Journal of Safety Research 77 (2021) 23–29

Contents lists available at ScienceDirect

Journal of Safety Research

journal homepage: www.elsevier.com/locate/jsr

A comparison of motorcycle instructor candidate selection practices in the United States

Donald L. Green

Ed.D. Rider Choices, Motorcycle Rider Education Consulting, 60 Pewter Cir., Chester, NY 10918, United States

ARTICLE INFO

Article history:
Received 18 February 2020
Received in revised form 27 September 2020
Accepted 27 January 2021
Available online 20 February 2021

Keywords:
Rider
Education
Coaching
Safety
Transportation
Emotional intelligence
Human resources

ABSTRACT

Introduction: An essential aspect of motorcycle rider education is how the instructor selection process impacts student learning, sometimes referred to as the human element, as it is a significant factor influencing curriculum success. Student and program achievements are partially contingent on instructors who understand the curriculum and facilitate student learning during instruction. Previous research on motorcycle rider education has emphasized a need for the examination of instructor selection and development, stating that quality education is reliant on instructors who are competent and qualified. *Method:* By applying an exploratory study method, state and military Motorcycle Safety Education Program Managers and Instructor Trainers were examined and compared through telephonic interviews to develop a greater understanding of instructor candidate selection criteria and vetting processes. *Results:* The results suggest that changes in instructor candidate selection systems may improve decisions about a candidate's job and organizational fit. *Conclusions:* Study conclusions indicate that use of multiple and thorough assessments to determine a candidate's motivation, social disposition, and emotional intelligence before preparation courses may better identify candidates and align potential job and organization fit within the discipline. *Practical Application:* Applications of the findings would include a standardized selection process with improved interviews and pre-course auditing, and candidate expectation management before the selection to attend preparation or certification courses. The efforts potentially decrease long-term costs and deficiencies when candidates have an inconsistent job or organizational fit, departing from organizations after short periods or by not providing consistent quality instruction to students. The study recommendations, when implemented, can improve most educational disciplines where instructors are selected for technical instructional positions where students risk injury or harm.

1. Introduction

An essential aspect of rider education is how instructor selection impacts student learning, a factor significantly influencing curriculum success (Daniello, Gabler, & Mehta, 2009; Senserrick et al., 2016, 2017). Student and program achievement are dependent on instructors who understand the curriculum and facilitate student learning during formalized instruction. Baldi, Baer, and Cook (2005) seminal research on motorcycle rider education emphasized a need for adequate supervision and training consumable by students, stating the quality is reliant on instructors who are competent and qualified. Moreover, a qualified instructor presents a defining model for students, placing value on increased consciousness, and good judgment while riding motorcycles to reduce risk and prevent harm (Arthur & Doverspike, 2001; Senserrick et al., 2016). Therefore, this exploratory study used interviews to attain how instructor selection is considered by state program administrators and instructor trainers during candidate selection to inform the rider education discipline.

1.1. Problem

A problem in formal motorcycle rider education is the thoughtful selection of instructor candidates who demonstrate a good job and organizational fit to support the quality delivery of well researched and effective curricula in training programs. Kardamanidis, Martiniuk, Ivers, Stevenson, and Thistlethwaite (2010) recommend the need for more rider education research based on previous methodological weaknesses. Baldi et al. (2005) note there is a sizeable gap in knowledge about the impact of instructors who are selected as a critical mechanism to facilitate

E-mail address: dgreen5@live.maryville.edu

https://doi.org/10.1016/j.jsr.2021.01.003
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student learning, potentially decreasing crashes (Daniello et al., 2009; Horswill, 2016; Senserrick et al., 2016).

1.2. Context and literature review

Studies on motorcycle rider education effectiveness have historically used motorcycle crash data in correlation with vehicle miles driven as a primary measure of efficacy. In doing so, researchers do not define the various factors, including instructor quality, which influence the delivery and retention of course content. Rarely considered in analysis is whether the rider received any rider education at all, measuring the possible effects of inappropriate judgment and behavior, no educational exposure, or poor knowledge transfer during a rider education course (Aupetit, Riff, Buttelli, & Espie, 2013; Haworth & Mulvihill, 2005).

As in all modes of safety instruction, it is challenging to research and document non-events or events of lessor severity caused by the effects of proper education. These events are sometimes referred to as lead events, as discussed by Loosemore, Raftery, Reilly, and Higgon (2006) as opposed to the lag events currently used to measure crash causation. While collecting evidence is considered problematic, an assumption in rider education is accidents and fatalities do decrease with proper education, although to what extent is unknown (NHTSA, 2009). Regardless, without an exploration of instructor candidate selection, meaningful consideration of instructors as a catalyst for knowledge transfer remains a gap in understanding efforts to improve rider education instruction as a prophylactic countermeasure to motorcycle crashes.

Daniello et al. (2009) advise the wrong instructor can lead to ineffectiveness for formal education. Supporting this in a study on teacher self-efficacy, Feldstein (2017) submits the effectiveness of quality teachers, improves the instruction, improves student achievement, and reduces teacher shortages. While measuring effectiveness is problematic, it is equally challenging measuring positive outcomes when an instructor with the wrong fit or quality employs a curriculum improperly.

Saskia de Craen (personal communication, June 12, 2018), a senior researcher at Stichting Wetenschappelijk Onderzoek Verkeersveiligheid (SWOV), The Netherlands Institute for Road Safety Research, explained that the quality of instructor is a crucial element for successful motorcycle rider training. Moreover, research on young driver training viewing identical curricula at different sites showed a negative impact by instructors who did not display job fit or trust in an organization or the curriculum's educational methods. By not preparing to give the course wholeheartedly, using the curriculum as intended or designed, the student outcomes became negatively impacted (de Craen, Vissers, Houtenbos, & Twisk, 2005).

Instructor competence is an essential cornerstone of any driver education, as described by Gregersen (2005). The knowledge to employ curricular lesson plans is necessary for creating a situation where instructors must not only understand the content but be able to explain most aspects of what the student should know and why that information is crucial. Moreover, quality instructors display the skill of pedagogical self-efficacy, best defined by a person's belief about being able to complete a specific task as described by Uhl-Bien, Schermerhorn, and Osborn (2014). Qualified and knowledgeable instructors use whatever tool is necessary to help individual students incorporate curricular material into their long-term memory and behavioral actions for continual use (Bandura, 1997; Danielson, 2007; Feldstein, 2017).

Guidance on instructor selection from the U.S. National Highway Traffic Safety Administration (NHTSA, 2014) recommends a national standard that includes qualification criteria, which are purposefully vague and flexible to accommodate the many different programs and curricula choices. However, state programs use the NHTSA recommended criteria for instructor selection in a manner that may have little to do with an instructor's ability to use pedagogical methods for relaying content. The recommendations may focus more on social compliance criteria than an ability to share information on wide-ranging topics and interacting well with others. As a result, Haworth and Mulvihill (2005) submit the matters associated with rider judgment, assessing risk, and developing motor skills are delivered differently from place to place, often affecting the curricular intent and the safe operation of motorcycles.

Another cogent problem is instructor quality and the impact on rider education to employ focused curriculum components effectively to individual students. Instructor ability necessitates consistency with an educational method to successfully facilitate student learning in an accelerated manner without losing a group or individual's attention (Akhmetova, Kim, & Harnisch, 2014; Senserrick et al., 2016, 2017). An instructor is a conduit for successful knowledge transfer between curriculum and students; an inappropriate or off-topic emphasis by the instructor may well affect the retainment of desired course content. When an instructor does not have the knowledge or ability to present the curricular material as intended, the student may leave with a piece of limited knowledge or worse – an inappropriate understanding of the content (Bandura, 1997; Senserrick et al., 2016, 2017). Dewey, 2015 made an essential clarification to this point when he explained that experience and education are not synonymous; not all experience is educational, and inappropriate experiences are counterproductive.

1.3. Purpose

Beyond the sphere of instructor influence, the novice rider course has historically been the main opportunity for formal education to enhance rider survivability since graduated motorcycle licensing or tiered training is not consistently used with motorcycling in the United States. Instructor selection and appropriate use of pedagogy then become the main factors for student learning and skill development provided during the educational process.

Haworth and Mulvihill (2005) describe the emphasis on motorcycle roadcraft control as a skill essential for students, yet also suggest other behavioral aspects of rider education emphasized haphazardly or not enough. Many consider judgment and risk management underrepresented in the teaching of course content (Aupetit et al., 2013; Dorn & Brown, 2003; Dorn, 2005; Rowden, Watson, & Haworth, 2012; Vidotto, Tagliabue, & Tira, 2015). The connection between content and sustainable knowledge transfer in rider education resides with a competent instructor able to analyze the learning environment and provide the appropriate direction to a student (Bandura, 1997; Danielson, 2007; Feldstein, 2017).

In a study by Bramley et al. (2018), a parallel is formed with Motor Learning Principles (MLPs) of Physical Therapy students in Canada. Findings suggest a knowledge-practice gap from programs where student learning is not fully supportive of the needs of a student MLP needs, focusing more on the neurological curriculum. If instructors do not understand or teach all relevant material, the student will focus mostly on what the instructor determines is most relevant. In rider education, MLPs are important and emphasized excessively; however, behavior and rider judgment are equally as important and typically accentuated less despite experts in traffic safety believing it is the primary cause for crashes (Breakwell, 2014; Dorn, 2005; Evans & Schwing, 1985; Evans, 1991, 2004).

Person organizational fit is desirable in teaching endeavors, and behavior specialists Uhl-Bien et al. (2014) suggest the combination of values, behaviors, and interests match well with the culture and professional requirements of an organization. An instructor with poor organizational fit can undermine the value of the culture and curricular material. Uhl-Bien et al. (2014) also define employee job fit as the interests, skills, and characteristics necessary to deliver the requirements associated with a position. If the improper instructor is selected, it may be considered antithetical to quality rider education. Either issue of fit could potentially endanger the well-being, health, and safety of students. Both organizational and job fit also relate to the competence of instructors, which helps to define what is considered a good employee or instructor fit. Oliveira (2015) describes employee [instructor] fit best as consistent with what the selector knows are the characteristics and attributes needed for the job and organization, as evidenced by a manager's extensive experience.

Although research on the efficacy of driver/rider education continues to produce mixed results, as previously stated, inquiries cite the variables of instructor impact as the topic leaving a gap in understanding (Aupetit et al., 2013; Baldi et al., 2005; Tagliabue, Gianfranchi, & Sarlo, 2017). A universal assumption is that a more knowledgeable motorcyclist can make better riding decisions. Quality entry-level motorcycle rider curriculum contains well-researched life-saving information, but the accurate relay of the lesson plans are contingent on instructors having the appropriate skills, characteristics, attributes, values, behaviors, and interests for facilitating knowledge transfer. Additionally, the instructor must match well with the culture and environment of the organization, modeling appropriate and safe riding behaviors as role models for students, demonstrating the need for a quality selection process to identify good candidate fit.

Before the risk of life or limb becomes a consequence of instructor guidance, programs that accurately assesses candidate fit could enhance the future educational process, improving preparation and certification course outcomes making the findings of this research beneficial.

1.4. Research questions

In the examination of the significant issues, three questions guided the qualitative interviews:

RQ1: How do motorcycle education program administrators and instructor trainers describe the criteria and vetting processes used to identify potential instructor candidates?

RQ2: How do motorcycle education program administrators and instructor trainers describe the quality characteristics and attributes of candidates?

RQ3: How do motorcycle education program administrators and instructor trainers describe the measure of candidates at the completion of the selection process?

The research questions provided an exploratory line of inquiry for understanding instructor candidate selection in motorcycle rider education in the United States. The results of this study establish a foundational perspective for future studies in rider education and other educational disciplines where instructors are integral to program and student success.

2. Method

An exploratory research method offered a more in-depth understanding of the views belonging to the more experienced and most informed program managers and instructor trainers in the profession. A 30-minute telephonic semi-structured interview used probing open-ended queries to answer the three research questions. By analyzing the thoughts and perceptions of multiple managers and trainers, the intent was to compare insights of the sample on the selection processes to identify useful selection models.

The transcribed interviews were verified by participants to ensure accuracy and trustworthiness through member checking. The sample was analyzed multiple times manually and by using NVIVO software to obtain a thematic sense of the information. Text segments were identified, annotated, and then divided into codes and end themes developed through the collective grouping of terms. In the absence of one exemplar candidate selection model to extract from the interviews, the information developed into a list of individual practices best reflected by administrators and trainers, further confirmed and supported by contemporaneous organizational behavior and human resource literature.

2.1. Participants

Recruiting of study participants was accomplished through emails garnered through state government agencies and public announcements on formal and informal social media websites. Limitations included program managers and instructor trainers between 30 and 65 years of age, with at least five years of motorcycle instructor trainer experience. Those who replied signed consent documents, verified they met the inclusion criteria, scheduled meetings, and participated in telephonic interviews. A total of 13 volunteer respondents were vetted and met the criteria included in the research, differentiated as eight Instructor Trainers (IT) and five Program Managers (PM) in the final sample.

Of the potential 60 possible administrators from 50 states, five military programs, and five independent organizational PMs in the United States, 20 administrators validated to have met the research inclusion criteria, with five opting to participate in the study. It is a particularly interesting note that two-thirds of the PMs have little or no experience instructing motorcycle rider education and-or have limited exposure to the necessary characteristics and attributes for instructing riders or for training instructors to instruct riders. Each of the 60 contacted PMs are monetarily compensated by government or motorcycle related entities for their positions to make competent decisions impacting instructor selection, ensuring the success of motorcycle rider education programs.

184 ITs received direct contact emails in the known IT population of over 214 trainers. Nine accepted invitations and did not follow through, 12 declined for various other reasons, and eight consented to participate. It is difficult to determine the activity and status of all ITs since personal data are maintained following personal privacy rules making them publicly inaccessible in many cases. Pay is also a variable difficult to determine based on multiple program structures but is generally attributable to the amount of work and geographical location of the organization having oversight. ITs serve the directed needs of sponsor organizations adjusting mostly for population density and geographical dispersion at two to five per organization or program. Some contactable ITs did not meet selection criteria, either with too little experience or presented as older than the IT selection criteria. One limitation based on research criteria highlighted the many ITs serving in the trade beyond the age of 65. Future studies should account for the possibility ITs serving well beyond typical United States retirement age.

The average age of participants in this research was 58 years, with the youngest being 39 years and the oldest 65 years of age. Based on the selection criteria, experience averaged 23 years with the least being nine years, and the most 37 years. Collectively, experience in Motorcycle Rider's Education was 301 years. Represented within the participants were two distinct curriculums, representatives from three distinct industry manufacturers, and trainers with experiences from 24 different states.

3. Results

The interview transcripts were analyzed by the researcher to develop themes providing an understanding of the participants' perceptions. The themes were determined primarily by the three research questions aligning with RQ1: instructor candidate selection and vetting process, RQ2: characteristics and attributes of instructor candidates, and RQ3: measure of candidates after the selection process (pre-certification). The noted representative comments exemplify the collective respondents' views, using the pseudonyms of Program Manager (PM##) and Instructor Trainer (IT##) to differentiate the multiple participants in their own words.

RQ1: Candidate selection and vetting processes

Qualitative interviews of State Motorcycle Safety Education PMs and ITs provided an understanding of instructor candidate selection criteria and vetting processes. A broad range of answers and methodologies signified the use of the consistent, yet minimal guidance proposed by NHTSA (2014). One state program administrator expressed:

> "My role in [candidate] selection in the state is very much one of leadership…The state accepts applications for any and all wishing to teach… All applications are routed through my office. Myself, [with] the support of my administrative team, we first vet the application to make sure the candidate at a minimum, passes the requirements set forth in the state program rules" (PM01, 2019).

In states without formal programs, ITs may act on behalf of private sites, the motorcycle industry, or U.S. military sites to handle the screening process. Three of five program managers and one in eight instructor trainers spoke of formal written standards for candidate recruitment and selection. Typically, programs use or build upon NHTSA (2014) written recommendations and curricular material:

> "The state has no requirements at all… [industry company] actually has no requirements other than they recommend [instructor] candidates are interviewed, and they meet some loose recommendations for a source of the candidates…but they make no recommendations beyond that. I do interview them [candidates], and it largely is based on [my] experience for having poorly selected candidates in the past. I've gradually learned what things I need to look for. In things actually than look for, things to listen for" (IT01, 2019).

All respondents discussed interviews citing at least a short phone conversation by state PMs or ITs. In other cases, informal collective information sessions or levels of interviews with multiple program team members was the policy. The candidate interview process was most commonly handled informally and inconsistently through day-to-day interactions, with some research participants questioning how useful they were.

Typical vetting questions were about general topics like "why do you want to become an instructor?" While others used information from written or electronic applications to discuss the applicant's motivations through probing, open-ended questions. More structured programs used multiple interviews by PMs, ITs, instructors, site providers, or site managers to develop stronger profiles of their candidates. While in at least some less structured programs, individuals were accepted merely upon meeting the NHTSA recommendations:

> "I wouldn't call it really a formal interview process. The requirements we have are, they're not super heavy… it's very rare that anybody does not qualify for the basic things, so we've never, I've never really done any one-on-one [interviews]. … we've never called candidates in for a face to face interview. … there's nothing else that we can do to eliminate a candidate. We have to go by the letter of [the] regulation" (PM04, 2019).
>
> "I contact every one of those folks who are interested in becoming instructors, I interview them. We spend quite a bit of time on the phone…once referred to the [training] site and the site decides to sponsor that instructor candidate… I'll have a second interview with them" (PM05, 2019).
>
> "It's almost a warm body theory out there to get them in the front door, and then you try to weed out who may not be the best candidate [during the instructor preparation course]" (IT02, 2019).
>
> "We joke about if you can fog a mirror, you can do that [be a candidate]" (IT04, 2019).
>
> "I get the honest impression that 99 percent of it was, in the beginning, a good ole boy type of thing. …the only real interviews that you got was what we did during the [instructor preparation course]" (IT08, 2019).

In some programs to explain the job requirements and expectations involved in being an instructor, information sessions or discussions informed candidates of the position. In some cases, PMs and ITs used the opportunity to discourage less motivated candidates by exposing the less glamorous side of the profession:

> "We are sometimes, to our own detriment, …dissuade anyone from actually carrying forward… We remind them that it does require a lot of upfront preparation, there is a financial investment, …as well as a considerable time investment. … it's not a lucrative profession, but rather one that is very gratifying emotionally" (PM04, 2019).
>
> "I am upfront and honest [to candidates] about what I think [their] liability might be" (PM01, 2019).
>
> "I make sure that they understand how much time they're committing and how it's going to affect them. Not only during the training program, but during the off days when they go home, and they've been working for 10 days in a row … between their personal jobs and this training just to see if they're willing to make some of those sacrifices. I will state to everyone how labor-intensive it is. I explain early on the time commitment" (IT06, 2019).

Some respondents discussed vetting a candidate through action as a method to assess the candidate's interest. If the candidate volunteered to observe or participate in courses as range aides before selection, they reasoned the candidate showed motivation, interest, and an inherent desire to be an instructor:

> "[Candidates] complete an online application. So that initiates the process…our applicant liaison will contact that person to set up a time to talk to them on the phone…signing [candidates] up for their audit assignment. …[candidates] do their audit assignment out in the field, the instructors that they audit also evaluate the applicant. …after the audit is complete when we have evaluation forms, and they're on assignment, then the training manager determines whether or not they're going to interview the candidate" (PM02, 2019).
>
> "Prior to them actually getting to [the] training they are encouraged to actually get out and interact with some of our team in a class environment. Observing and interacting with other instructors. So, that tends to give us some insight. …a lot of it is just gut impression during the interview process" (IT03, 2019).

The term most often used for this type of vetting was "auditing" a course as a student or range aide, to further develop an understanding of the requirements as an instructor. The task helped to vet those who were interested, potentially dissuading some candidates, yet identifying their desire and willingness to participate in the educational process. In some programs, the audit requirement is outlined in policy documents and expected of all candidates, whereas other programs merely suggest participation as a recommended way to prepare. Some programs did not have an audit process at all.

RQ2: Characteristics and attributes for candidates

Respondents used similar terms when describing the features and qualities of potential candidates. Although not always articulated concisely, the construct of Emotional Intelligence (EI), defined as the ability to manage oneself and one's relationships with others, was mentioned in varying ways by all respondents (Goleman, 2005; Mortiboys, 2011; Uhl-Bien et al., 2014). A high level of EI is considered an active component in being able to facilitate learning by creating bridges of understanding and using empathy as a tool to interact with others in adult learning:

> "The qualities that we look for, having the soft skills, people skills, to interact with students and represent the program in a positive light. You know, the kind of intangible things like integrity, honesty, and just being able to generally interact well with others…"(PM03, 2019).

> "I want a role model both, I want a boy scout or a girl scout. I want someone who has impeccable character, patience, and who can be a mentor to our students the same way the quality assurance specialist is a mentor to the [instructors]" (PM05, 2019).

> "Within the first five minutes, gauging their experience as far as teaching, mentoring, coaching, identifying the self-motivation, seeing where all that sits. …see if you can get emotional intelligence out of it, and that's you know, a conversation with them about things to see what their emotional intelligence is" (IT02, 2019).

Also mentioned, was the ability for potential candidates to be life-long learners capable and willing to seek new knowledge and continued growth as an individual and educator:

> "You can kind of get a general idea, is this something [they're] interested in? Do they have a positive attitude toward the whole thing? Their attitude and motivation [are] a big part, you know their willingness to come out and learn. …what extra work can they do to make them a better instructor down the road" (PM03, 2019)?

> "I listen for enthusiasm, I listen for curiosity, I listen for willingness to learn. …how readily they will reconsider a position based on something they've seen or something they've been told. …I look for flexibility" (IT01, 2019).

All respondents suggested that motorcycle riding skills and knowledge were necessary for being an instructor, but also acknowledged that they were secondary to high EI. Some respondents mentioned a necessity for candidates to have observation skills and provide proper guidance to students as highly desired characteristics and attributes of a model candidate.

RQ3: Measure of candidates at the completion of selection

Varying degrees of selection activities affect the determination of employability at the end of the candidate selection. Some programs use more thorough processes to vet potential candidates, while others by policy or choice, allow anyone who aspires to be an instructor to go directly to the instructor preparation course where formal certification uses a pedagogical vetting process. After the selection process, participant's expressions were consistent with the characteristics and abilities section of the study, even for those not having a selection and vetting process going beyond the NHTSA recommendations for instructor selection. Again, NHTSA recommendations have little to do with candidate quality or the ability to use pedagogical methods for delivering course content.

> "Selection is hard…It's choosing the right people. There is a qualitative factor. …the team perspective and if the group believes that this candidate is strong…we follow the group mentality. …someone who is seeking a job will say what they think you want to hear to get the job. So, the trick of it is to kind of listen to what's not being said. … it's an art and skill" (PM04, 2019).

> "[I want] an emotional commitment to both the training program, riding, riding safety in general, and to the team [before sending to prep]" (IT03, 2019).

> "So that's what I am talking about fit, somebody that's totally up-front and honest with you right off the get-go and they are who they say they are. Motivation and desire…to do that type of work…to be that help agent, to help somebody reach their goals" (IT05, 2019).

> "…to clarify, we don't ever compromise the end goal or the end of completion requirements, but we will keep weaker candidates through the training process when we have low numbers" (IT06, 2019).

The responses from participants provided an initial understanding of instructor candidate-job and organizational fit perceptions in the motorcycle education community. Once again, as discussed by Oliveira (2015), the manager's extensive experience is key to recognizing the characteristics and attributes necessary for a job and organizational fit. What was not definitively expressed by participants was a true measure of what a quality candidate should be, potentially opening the selection process to mismatches in personnel to a job and organizational fit.

4. Discussion

With the varying sizes of programs and differing regulatory or policy constraints among the states, it is difficult to use a one-size-fits-all approach for candidate selection. There are, however, best practices that, when implemented, show promise in selecting better candidates who are more suitable to represent program goals. The results identified areas of significant emphasis for improvement, given programmatic implementation of known best practices. Areas include: (a) enhanced recruiting efforts, (b) conducting multiple interviews with multiple team members, (c) more robust screening activities like auditing of courses for candidates, (d) comprehensive assessment of candidate EI, (e) detailed documentation of processes, and (f) further research within the field to fully measure selection outcomes.

The study results highlighted differences of opinion and knowledge between PMs and ITs where answers were incongruent regarding how screening processes were employed and the degree of success. Specifically, the use of selection interviews was a point of contention for ITs not thoroughly included in candidate selection vetting activities with PMs before certification courses. Written policies or requirements, often considered as common knowledge in the field, may not have been effectively documented or communicated to organizational levels below that of PMs, creating potential tensions. A strong recommendation is for programs to verify and detail all processes thoroughly, distribute the findings widely to prevent knowledge silos, ensure all personnel can understand the program's intent, and facilitate consistent usage and similar language by teams (Hannon, Hocking, Legge, & Lugg, 2018). Lemke (1995) supports the assertion by recommending well designed and implemented plans of induction raise retention rates from 50% to 85%.

The most thorough vetting systems included written or online applications as part of or immediately after recruitment. After recruitment, multiple levels of formal and informal interviews, requisite audits, evaluations, and preliminary written assignments display the potential of candidate efforts before preparation or certification courses. The least restrictive programs relied wholly on curriculum preparation and certification courses using assessment and qualitative selection criteria embedded in a minimal and often time-constrained process. By having a more robust system of screening candidates with multiple interviews, audits, and assignments, programs decrease the potential of selective screening bias as described by Uhl-Bien et al. (2014) and Oliveira (2015), where a limited portion of available candidate information enters the perception of a single candidate selector. A recommendation is to research further the differences between the most thorough and least restrictive methods of selection and quantifiably compare the outcome of selected candidates.

Respondents expressed a more developed EI as a desired attribute. The building blocks of EI, as defined by Goleman (2005), include self-awareness, self-regulation, motivation, empathy, and social skill, all characteristics described as desired in candidates by all participants in the interviews (Uhl-Bien et al., 2014). A recommendation is to increase the vetting and screening of applicants to assess candidate EI before admittance into expensive and time-consuming preparation courses. The practice could potentially decrease training costs, decrease the amount of turnover, decrease human resource management costs, and decrease instructor organizational fit tensions — the human factor.

Similarly, it is a consideration of longevity when a candidate minimally passes the preparation course or does not fit the culture necessary for adult learning, departing the program shortly after significant time and investment. A recommendation to achieve a better screening process includes multiple interviews or assessments by different levels of organizational members (Oliveira, 2015; Schuh, Jones, & Torres, 2017). By monitoring for inconsistencies in responses and actions, a complete valuation of the candidates EI, either through the interview process, formal assessments, or auditing, may be achievable before preparation course acceptance to clarify and help determine job and organizational fit.

Some respondents identified the need for accepting all candidates ostensibly to participate and act as filler candidates for courses to have enough participants. Although this practice may foster some success, a recommendation would be to recruit more viable candidates with stronger EI to enhance and accelerate learning in preparation courses. Interestingly, the characteristics and abilities most sought are those best fulfilled by professionals in the teaching, coaching, and education fields. When asked about the value of having an educational or teaching background, most participants expressed little significance.

This study exposed multiple variances in instructor candidate selection methods in motorcycle rider education in the United States, which can affect the quality of student and program outcomes. The most recent research recommended future study because of previous methodological weaknesses, this research considers the impact of candidates and potentially the instructors selected as a critical mechanism to facilitate student learning and also recommends deeper exploration of the topic (Baldi et al., 2005; Daniello et al., 2009; Kardamanidis et al., 2010; Horswill, 2016; Senserrick et al., 2016).

5. Conclusion

Individual programs must determine the advantages of additional selection requirements to improve quality. The effort and time spent on candidates who do not have the desired characteristics and abilities to fit with current culture or to complete a preparation course is considerable. Recruitment and screening practices commonly used in educational and human resource domains further reinforced by organizational behavior research, could be invaluable for determining stronger candidates as the need for competent instructors grows.

The results of this study identifies basic practices for the improvement of instructor selection processes, suggesting early candidate assessment might identify stronger emotional intelligence as a primary way to differentiate better instructor fit. By using basic interviewing techniques and auditing to assess candidates before preparation courses, emotional intelligence determination and motivations could substantially increase candidate quality, translating eventually into quality of student learning in motorcycle rider educational environments.

6. Practical application

Application of this research in motorcycle rider education and other instructor-led educational disciplines may potentially decrease the long-term effort and cost of sending candidates through preparation courses or overly extensive onboarding processes, ultimately resulting in poor outcomes. The practices, when implemented upfront, could improve instructor and organizational quality when selection addresses a holistic fit instead of meeting the minimal conventional compliance-based hiring criteria. Subsequent investigations can further this study by analyzing the impact of candidate selection on the longevity of instructor employment and some determination of instructor efficacy by monitoring student outcomes in a longitudinal study.

7. Presentation of results

Preliminary results of this research was presented at the 2019 Motorcycle Safety Foundations International Rider Education Training Systems Workshop in Columbus, Ohio, the 2019 National Association of State Motorcycle Safety Administrators Summit in Grand Rapids, Michigan, and the 2020 Institut fur Zweiradsicherheit Virtual 13th International Motorcycle Conference in Cologne Germany.

Funding

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Declaration of Competing Interest

The author declares he has that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

I would like to acknowledge Wayne "Bear" Steele, his mentorship and guidance changed my adult life and purpose providing the environment necessary to begin this journey. Wayne touched many lives and if nothing else, he left many with a deeper understanding of the human element. His departure came much too soon.

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Donald L. Green is the Proprietor of Rider Choices, Motorcycle Rider Education Consulting with over 30 years of training, operations, and organizational development experience. Dr Green holds an Ed.D. from Maryville University, Missouri, M.Ed. from Troy University, Alabama, and a B.S. in Computer Science from Central State University, Ohio. Serving for over 21 years in the military, including attending the Command and General Staff College at Leavenworth, Kansas. Dr Green is an annual presenter at the United States International Rider Education Training System Workshop (MSF) and presented at the 2020 13th International Motorcycle Conference (IFZ) in Cologne Germany.

Journal of Safety Research 77 (2021) 1–12

Contents lists available at ScienceDirect

Journal of Safety Research

journal homepage: www.elsevier.com/locate/jsr

Analyzing the safety impact of longer and heavier vehicles circulating in the European market

Jose I. Castillo-Manzano [a], Mercedes Castro-Nuño [a,*], Xavier Fageda [b]

[a] Applied Economics & Management Research Group, Universidad de Sevilla, Spain
[b] GIM-IREA, Universidad de Barcelona (Spain), Av. Diagonal, 690, 08034 Barcelona, Spain

ARTICLE INFO

Article history:
Received 27 April 2020
Received in revised form 17 September 2020
Accepted 25 January 2021
Available online 2 March 2021

Keywords:
Road accidents
Road fatalities
Freight transport
Longer and heavier vehicles
Megatrucks
Europe
Panel data

ABSTRACT

Introduction: The European Union (EU) has developed different strategies to internalize the costs of excessive motor traffic in the road freight transport sector. One of these is a relaxation of restrictions on the size and load capacity of trucks that circulate between member States and a proposal has been made for Longer and Heavier Vehicles (LHVs) to be allowed to circulate across borders. LHVs are the so-called "megatrucks" (i.e., trucks with a length of 25 meters and a weight of 60 tonnes). Megatrucks have allowed to circulate for decades in some European countries such as Norway, Finland, and Sweden, world leaders in traffic accident prevention, although the impact that cross-border traffic would have on road safety is still unknown. *Methods:* This article provides an econometric analysis of the potential impact on road safety of allowing the circulation of "megatrucks" throughout the EU. *Results:* The findings show that countries that currently allow megatrucks to circulate present lower traffic accident and fatality levels, on average. *Conclusions:* The circulation of this type of vehicle is only advisable in countries where there is a certain degree of maturity and demonstrated achievements in the field of road safety. *Practical applications:* European countries that have allowed megatruck circulation obtaining better road safety outcomes in terms of accidents, although the accident lethality rate seems to be higher. Consequently, introducing megatruck circulation requires a prior proper preparation and examination.

1. Introduction

Road traffic is currently the main mode of transport used in the European Union (EU) to address increasing freight demands. The European Commission (EC) expects that by 2030 the volume of road freight transportation could rise 83% over the 2005 level (Korzhenevych, Dehnen, Broecker, Holtkamp, Meier, Gibson, & Cox, 2014). However, the external costs associated with motorized transportation modes (accidents, congestion, noise, and pollution) that are generally attributable to heavier-duty vehicles (Alises & Vassallo, 2015; Piecyk & McKinnon, 2010) have led the EC to take decisive action to create a more efficient and safer transport logistics chain with less impact on the environment. The purpose of this paper is to evaluate one of these strategies, Longer and Heavier Vehicles (LHVs), and the related road safety issues.

The inclusion in EU policies of concepts such as multi-modality and inter-modality reflects the depth of the challenges facing the road transport sector (Teutsch, 2013). These policies aim to improve the individual modes of transport, to make better use of infrastructure, and to combine the different modes into multimodal chains to create a sustainable transport system to gain a competitive advantage (Liotta, Stecca, & Kaihara, 2015) within a framework of liberalization, deregulation, and competition (see e.g., Koliousis, Koliousis, & Papadimitriou, 2013). These issues are apparent in Transport Policy matters such as the *Eurovignette* Directive 2006/38/EC (see McKinnon, 2006); Short Sea Shipping (SSS) (Douet & Cappuccilli, 2011)—which has attracted a great deal of attention as a substitution mode for freight transportation (Suárez-Alemán, Trujillo, & Medda, 2014)—and, specifically, the Motorways of the Sea (MoS), designed to reduce long-distance inter-State land transport freight operations (Baindur & Viegas, 2011). The freight rail system also appears to offer an alternative to road freight transport that could reduce congestion, increase energy efficiency, and generate less pollution.

These expectations have not been fully met. According to Golinska and Hajdul (2012), the evidence shows that transportation policies have serious limitations and drawbacks, which suggests that there has still not been the widespread freight modal shift that was being sought. The EU has, therefore, considered another alternative to road freight transport based on the relaxation of the current

* Corresponding author.
E-mail addresses: jignacio@us.es (J.I. Castillo-Manzano), mercas@us.es (M. Castro-Nuño), xfageda@ub.edu (X. Fageda).

https://doi.org/10.1016/j.jsr.2021.01.001
0022-4375/

restrictions imposed by Directive 1996/53/EC (see http://eur-lex.europa.eu/legal-content/EN/TXT/?uri=celex:31996L0053)[1]. This would clear the way for the unrestricted circulation of longer heavier vehicles (LHVs) known as "megatrucks," gigaliners or eurocombis (up to 25 meters in length and 60 tonnes in weight). Larger freight vehicles have been circulating in some Scandinavian countries with underdeveloped rail systems (e.g., Norway, Sweden[2], and Finland) since the mid-1990s. Interestingly, these countries are also leaders in road safety. Subsequently, megatruck circulation has also been authorized in some other EU states, such as Spain (Ortega, Vassallo, Guzmán, & Pérez-Martínez, 2014). Several other countries have also carried out trials to test the effects of megatrucks on infrastructure capacity and fuel consumption, the implications for the environment and energy, and consequent changes in transportation costs (e.g., see Meers, van Lier, & Macharis, 2018 for Belgium and Sanchez-Rodrigues, Piecyk, Mason, & Boenders, 2015 for Germany). The results of almost all these pilot schemes have been positive and the EC has, therefore, proposed the legalization of cross-border megatruck circulation.

In June 2012, the EC announced the cross-border circulation of megatrucks between two member states that approved their use within their borders but strong opposition from the European Parliament and some member states eventually led to the initial Directive being amended by Directive EU/2015/719 (see http://eur-lex.europa.eu/legal-content/EN/TXT/?uri=uriserv%3AOJ.L_0.2015.115.01.0001.01.ENG). This amendment, which has still not been fully enacted in all EU countries, included a derogation from the maximum weights and lengths laid down in the original Directive to improve the safety and environmental emissions of heavy freight vehicles and also recommended that no changes should be made to restrictions on the cross-border movement of megatrucks laid down in Directive 1996/53/EC.

As the cross-border circulation LHV is currently a controversial issue in the EU (see e.g., Odeck & Engebretsen, 2014), this paper uses multivariate models to carry out an econometric exploration of the impact of megatruck circulation on road safety outcomes. Novel panel data are used for European countries (EU members + European Free Trade Association_EFTA_members) over the 1996–2014 period; i.e., the period between the two EU Directives that regulate the circulation of this type of vehicle. We aim to cover the gap in the literature on the impact of megatruck circulation on traffic safety as, to date, there has been no precedent that uses a rigorous econometric approach to address this topic globally for the entire European study case.

We estimate a multivariate regression model that controls for all explanatory variables that previous studies consider relevant for identifying the determinants of road accidents and fatalities. The use of country fixed effects allows us to control for time-invariant unobserved factors and the inclusion of a time trend allows us to control for unobserved shocks common to all countries. Finally, we apply the logic of differences in differences to enable the identification of changes in safety performance due to megatruck circulation in the treated countries (countries where megatrucks have been permitted to circulate at some point during the considered period) compared to the control countries (countries where the circulation of megatrucks has not been allowed).

Our main novel contribution to the literature is an empirical exploration of the implications of LHV circulation for safety performance. We consider a broad sample formed not of one specific country but of European countries (EU and others) that have allowed megatruck circulation. Countries where megatrucks do not circulate are used as a control group. Our research provides evidence of the potential consequences for safety of LHV fleet circulation in different states and these can be taken into consideration by policymakers designing measures to mitigate negative safety effects. This investigation also follows suggestions in earlier studies such as Sanchez-Rodrigues et al. (2015) as to the need to assess the impact of LHVs for more than a single country case.

Previous analyses of the effects of increasing the maximum weight and size of freight vehicles in Europe conducted by our research group in this line of research suggest that the largest trucks are not necessarily responsible for a higher mortality rate in Europe (Castillo-Manzano et al., 2015; Castillo-Manzano, Castro-Nuño, & Fageda, 2016). We now focus on responding to the following research questions: although part of the literature shows that megatrucks might be more efficient from the economic, logistical, and environmental points of view (Bergqvist & Behrends, 2011; Guzmán, Vassallo, & Hortelano, 2016; McKinnon, 2008; Ortega et al., 2014), can it also be stated that European highways are safer in places where these types of vehicles are allowed to circulate freely? Are countries where LHV or megatruck circulation is permitted safer when the impact is evaluated in terms of global road safety (i.e., involving all types of users and vehicle crashes)? Would it be advisable to allow megatrucks to circulate throughout Europe?

In short, our aim is that, via some practical managerial implications, our findings might shed some light on the road freight transport industry's skepticism around the introduction of LHVs due to a lack of sound information and knowledge.

This paper is organized as follows: after this Introduction, Section 2 sets out the state-of-the-art on LHV impacts; Section 3 describes the empirical analysis and methodology; Sections 4 present and discuss the results, Section 5 offers the conclusions of the study, followed by some relevant practical applications of the work in Section 6.

2. Literature review

Earlier researchers agree that differences in truck weight and configuration affect road safety (Castillo-Manzano et al., 2016; Corsi et al., 2012, 2014; Evgenikos et al., 2016). Specifically, much recent literature has addressed the effects of LHVs across Europe and evaluated certain states' experiences of implementing megatrucks or conducting trials; however, these have mostly been published as government or institutional reports (see e.g., ETSC, 2011; ITF, 2010; Knight et al., 2008; TML, 2008), with only a small number of academic papers (Knight, Burgess, Maurer, Jacob, Irzik, Aarts, & Vierth, 2010). Additionally, most scientific works analyzed the changes in truck dimensions and weight post-Directive 1996/53/EC, which raised these from 18.75 to 25.25 meters and 40 to 60 tonnes, respectively. The majority of these reports have focused on Scandinavian and Northern and Central European countries (Pålsson & Sternberg, 2018), including Sweden (Vierth, Lindgren, & Lindgren, 2018), the United Kingdom (Leach, Savage, & Maden, 2013; Liimatainen, Greening, Dadhich, & Keyes, 2018; McKinnon, 2005; Palmer, Mortimer, Greening, Piecyk, & Dadhich, 2018), Norway (Odeck & Engebretsen, 2014), Finland (Lajunen, 2014; Liimatainen, Pöllänen, & Nykänen, 2020; Lindt, Janka, & Dehdari, 2020; Palander, Haavikko, & Kärhä, 2018), Belgium (Meers et al.,

[1] This Directive allows the circulation of Heavy Goods Vehicles (HGV) with a maximum permitted length of 16.50 meters for articulated vehicles (semis) and 18.75 meters for road trains with a total combined weight of 40 tonnes but does not permit cross-border LHV traffic.

[2] Sweden has pioneered the use of Longer and Heavier Vehicle combinations and currently allows the circulation of heavier and longer road freight vehicles (maximum gross weight of 64 tonnes and length of 25.25 meters) than most European countries. The introduction of so-called High Capacity Vehicles (HCVs) has also recently been tested on certain segments of public roads. These are vehicles with a gross weight of 74 tonnes and a length of 34 meters (see Pålsson & Sternberg, 2018). HCVs with a gross weight of 76 tonnes and a length of 25.25 meters have been circulating on the road network in Finland since 2013 (Liimatainen & Nykänen, 2017).

2018), the Netherlands (Quak, 2012), and Germany (Burg, Neumann, Bühne, & Irzik, 2019; Sanchez-Rodrigues et al., 2015) and even specific corridors between countries such as Sweden and Germany (Vierth & Karlsson, 2014). Other papers have also investigated the most recent case: Spain (Guzmán & Vassallo, 2014; Guzmán et al., 2016; Ortega et al., 2014).

Considering all the evidence, the evaluations of LHV introduction can be grouped by their objectives. Several studies focus on the effects on infrastructure, highlighting increases in the cost of road maintenance and conservation caused by megatruck circulation, especially the strengthening of bridges and the replacement of fatigued road pavements (Christidis & Leduc, 2009; OBrien, Enright, & Caprani, 2008; UIC, 2014).

Another group of contributions explores the impact of LHVs on the modal split in logistics and provides evidence that the free movement of megatrucks in the EU would result in higher productivity and, therefore, the opportunity for road haulers to offer better prices (Christidis & Leduc, 2009; ITF, 2010; Ortega et al., 2014; Steer, Dionori, Casullo, Vollath, Frisoni, Carippo, & Ranghetti, 2013). Some studies determine that increasing truck dimensions and capacity would lead transport operators to consolidate and optimize loads with a consequent fall in the numbers of vehicles required (Nykänen & Liimatainen, 2014) due to the improved efficiency reducing the number of trips per freight tonne (McKinnon, 2005). This would translate into lower transport (McKinnon, 2011; Woodrooffe et al., 2010) and travel time costs (Pérez-Martínez & Vassallo, 2013; Proost et al., 2002). These changes might achieve a modal shift from rail and increase demand (Eom, Schipper, & Thompson, 2012; Knight et al., 2008; Nealer, Matthews, & Hendrickson, 2012) and more unfavorable consequences could also be generated for other collectives. For example, this measure might trigger the progressive transfer of a share of freight transport from rail to road, which would benefit LHVs (Meers et al., 2018; Rijkswaterstaat, 2010). The maritime transport sector might not be affected, however (Ortega et al., 2014). The introduction of the use of these vehicles might also have harmful effects for small haulage operators as the number of routes would be reduced and this could affect regional-level employment (Guzmán et al., 2016). Ortega et al. (2014) state that megatrucks would reduce costs per tonne-kilometer transported. This would have a knock-on effect with a cost reduction for the consumer, thus giving a boost to the economy. According to Vierth et al. (2018), all these arguments are inconclusive as results can vary depending on country-specific conditions and price elasticities. Other analysts predict a much more moderate modal split (Salet et al., 2010) that may even suggest a complementary relationship between LHVs and rail freight transport (Bergqvist & Behrends, 2011).

A third group of studies analyzes the impact of LHVs from an energy efficiency and environmental perspective based on energy consumption and greenhouse gas emissions. Several authors argue that the introduction of megatrucks (with lower freight transport operating costs) would lead to greater growth in road freight traffic than rail traffic, with a consequent increase in pollution (McKinnon, 2005; Palander, 2017). Other scholars such as Pålsson and Sternberg (2018) and Vierth et al. (2008) point to savings in fuel consumption and reductions in air pollutants per tonne-kilometer transported compared to HGVs due to the reduction in the number of journeys (Leach et al., 2013). Researchers such as Sanchez-Rodrigues et al. (2015) emphasize the key role of the effective payload to explain this environmental effect.

Finally, very little academic literature can be found that considers the effects of European megatrucks on road safety, which is the object of this article. Safety should be considered a key concern. According to Grïslis (2010), researchers have generally adopted two approaches to the study of LHV safety. The first concerns vehicle safety assessment and is focused on elements of vehicle engineering, operational characteristics, and design requirements (Debauche & Decock, 2007; Hanley & Forkenbrock, 2005; Knight et al., 2008).

The second approach considers the impact of LHVs on safety performance indicators (e.g., accidents, fatalities), although no study has been able to conclusively determine the real effect of their introduction (Grïslis, 2010). Some of the trial-based research (e.g., Backman & Nordström, 2002; Knight et al., 2008; Rijkswaterstaat, 2010) concludes that megatruck circulation should lead to a decrease in traffic, which would improve road safety (fewer accidents), especially if the stability and maneuverability of the vehicles were improved through the installation of certain technological advances (as suggested by Christidis & Leduc, 2009; Klingender, Ramakers, & Henning, 2009) or appropriate driver training (Sanchez-Rodrigues et al., 2015). Other analyses state that accident severity is expected to be higher when vehicles of this type are involved (Glaeser & Ritzinger, 2012; Glaeser, Kaschner, Lerner, Roder, Weber, Wolf, & Zander, 2006; Vierth et al., 2008), especially in some specific environments such as tunnels and bridges (McKinnon, 2008; Ortega et al., 2014) or on certain roads such as two-lane highways (Hanley & Forkenbrock, 2005). Other authors such as Debauche and Decock (2007) did not find any evidence of LHV circulation impacting safety.

Following Grïslis (2010) literature review, this lack of uniformity in safety findings for LHVs could be explained by the different methodologies used and statistical datasets that vary from country to country. In other cases, it may not be possible to find any empirical proof due to a lack of specific data on traffic accidents involving LHVs. Compared to two other studies that analyze LHVs and road safety (see Grïslis, 2010, for a literature review and Klingender et al., 2009, for a detailed safety method), our paper provides a novel quantitative evaluation based on an econometric analysis. The present research, therefore, pursues a line of research suggested by Sanchez-Rodrigues et al. (2015): a comparative study of a wide set of EU and non-EU European countries to generalize findings.

3. Empirical framework and method

The empirical regression used to estimate the impact of megatruck circulation on road safety takes the following form for country i during period t:

$$Y_{it} = \alpha + \beta_k X_{it} + \gamma_k Z_{it} + \lambda_k W_{it} + \mu_i + \nu \text{Time\_trend}_t + \varepsilon_{it} \quad (1)$$

In this equation, we consider two different dependent variables (Y_{it}) in two different regressions: the total number of fatalities (fatalities within 30 days of the accident, as per the Vienna Convention definition) and the total number of accidents (accidents involving personal injury, according to available statistical sources, see Table 1). Note that both of the endogenous safety variables are related to crashes involving any road user type to enable an assessment of the effects of megatruck circulation on all traffic safety, not only crashes involving trucks.

The model (1) also contains a vector X_{it} for the country's economic and demographic attributes; a vector Z_{it} that refers to the megatruck variable, and W_{it}, which represents road safety policy-related variables. μ_i are country fixed effects that control for omitted time-invariant country-specific variables; Time trend is an annual time trend that controls for unobserved shocks common to all countries, such as the evolution of oil prices, for example, and ε_{it} is a mean-zero random error.

We consider data for the 27 current European Union member countries (and also United Kingdom) and three EFTA countries (Iceland, Norway, and Switzerland). More specifically, we study European countries that allowed megatruck circulation or carried

Table 1
Variables used in the empirical analysis.

Variables	Description	Source	Type of data
Fatalities	Number of traffic fatalities	CARE (EU road accident database)	Dependent variable
Injury accidents	Number of traffic injury accidents	CARE (EU road accident database)	Dependent variable
Population	Number of inhabitants (in millions)	EUROSTAT	Country attribute
Motorization	Number of registered passenger cars per thousand inhabitants	UNECE, EUROSTAT (for population)	Country attribute
GDP per capita	Per capita Gross Domestic Product in Internationally Comparable Prices (US$ at 2005 prices and PPP)	EUROSTAT	Country attribute
Superhighway density	Number of kms of superhighway over country area in km^2	UNECE, EUROSTAT	Country attribute
Age	Median age of population (in years)	EUROSTAT	Country attribute
Population density	Number of inhabitants over country area in km^2	EUROSTAT	Country attribute
Passengers_km_railways	Number of rail passengers per km of track (in billions)	Eurostat, International Transport Forum, UNECE, Union Internationale des Chemins de Fer	Country attribute
Passengers_km_roads	Number of passenger-cars-km expressed in 1,000 million km	European Commission (Directorate General for Mobility and Transport)	Country attribute
Heating-degree_index	Index based on the number of cold days per year.	Eurostat	Country attribute
BAC	Maximum blood alcohol concentration rate allowed while driving in g/l	European Commission Road Safety Website	Road safety policy
Point_system	Dummy variable that takes a value of 1 if a point-based driving license system is in force; 0 otherwise	European Transport Safety Council (ETSC)	Road safety policy
Speed limit	Maximum speed limit allowed on superhighways (in km/h)	European Commission Road Safety Website	Road safety policy
Megatrucks	Dummy variable that takes a value of 1 when intra-border megatruck circulation is permitted; 0 otherwise	Directorate general for internal policies: a review of megatrucks (2013) and national legislations	Main explanatory variable

out trials during our timeframe, compared to a control group formed of the remaining countries, which did not. So, the megatrucks variable takes a value of one for the following countries in our sample (year megatruck circulation came into force in parentheses): Denmark (2008), Finland (1996), Germany (2010), Netherlands (2007), Norway (2008), Portugal (2014), Sweden (1996).

Given that the second Directive (which strengthened the first Directive) has still not been fully executed in all EU countries, we chose the 1996–2014 period for the study as it is the time period between the two EU Directives that regulate truck size and weight limits (i.e., Directive EU/1996/53 and Directive EU/2015/719).

The unit of observation is the country-year pair. Our panel data are unbalanced, as data for some variables are not available for some countries for all years. Tables 1 and 2 give the descriptions, information sources, descriptive statistics, and number of observations available for all of the variables used in the analysis.

Explanatory variables used in the analysis model were GDP per capita and the square of GDP per capita at the country level since a non-linear relationship is expected between a country's economic development and its road safety outcomes (Bishai, Quresh, James, & Ghaffar, 2006; Castillo-Manzano et al., 2014, 2015, 2016; Kopits & Cropper, 2005; Loeb & Clarke, 2007; Yannis, Papadimitriou, Mermygka, & Engineer, 2015). Countries where the economy is more developed may be affected by greater exposure to accidents. However, after reaching a certain wealth threshold, richer countries may have better infrastructure, vehicles, policies, and social attitudes, and so they may have better safety outcomes. The sign of the coefficient of the GDP variable is, therefore, expected to be positive and that of GDP^2, negative. Note also that the GDP variables allow us to control for the severe economic crisis that occurred during the considered period and which generated a great deal of debate about how the economic recession has influenced road safety (e.g., road user behavior, particularly among high-risk drivers) and road traffic in Europe (Antoniou, Yannis, Papadimitriou, & Lassarre, 2016; Wegman et al., 2017).

As in previous studies (Albalate & Bel, 2012; Castillo-Manzano et al., 2015, 2016; Kopits & Cropper, 2005), a further explanatory variable is included in the model as a proxy of the level of development of private transport: the number of passenger cars per capita (motorization). It is not clear which sign should be expected for this variable since, as in the case of the GDP variables, higher motorization rates may imply greater exposure to road traffic accidents but may also be linked to better and safer vehicles. We also take into account the influence of the quality of transport infrastructure by including a variable for superhighway density. The literature has proven a negative correlation between the quality of road infrastructure and safety outcomes, so a negative sign is expected for the coefficient of this variable (see, e.g., Castillo-Manzano et al., 2014; Jamroz, 2012; Wang, Quddus, & Ison, 2013). Another variable included in the model is the median age of the population. The sign that can be expected for this variable is not clear *a priori*. Younger road users may take more risks (Constantinou, Panayiotou, Konstantinou, Loutsiou-Ladd, & Kapardis, 2011; Langford, Methorst, & Hakamies-Blomqvist, 2006) but accidents may have a greater impact on older drivers (Koppel, Bohensky, Langford, & Taranto, 2011; Yee, Cameron, & Bailey, 2006).

The number of passengers-km on roads is an additional explanatory variable in our model. This variable seeks to capture road traffic intensity. We could expect a positive relationship between the amount of traffic and road fatalities since the total amount of driving is an indication of the population's exposure to road accident risks (Orsi et al., 2012). However, as Li, Graham, and Majumdar (2012) find, such a relationship could be dependent upon congestion levels.

A variable for the country's population density is also considered. We may expect that the proportion of urban journeys over total journeys will be higher in more densely populated countries. So, the number of accidents for urban journeys should be higher than for inter-urban journeys but the severity of accidents may be lower for urban journeys (Rakauskas, Ward, & Gerberich, 2009; Zwerling et al., 2005). Therefore, the sign that should be expected for the coefficient associated with this variable is not clear *a priori*. We also include a variable for the amount of traffic by rail (Passengers_km_railways). Given that the safety outcomes of rail journeys are systematically better than of cars and trucks (Bubbico, Di Cave, & Mazzarotta, 2004; Demir, Huang, Scholts, & Van Woensel, 2015; Forkenbrock, 2001), we can expect the coefficient for this variable to have a negative sign.

As in some previous studies (Albalate, 2008; Castillo-Manzano et al., 2015, 2016), several variables for specific road safety policies are also considered in the equation. A variable is included for the maximum permitted blood alcohol concentration. To capture the

Table 2
Descriptive statistics of variables used in empirical analysis.

Variables	Mean	Standard Deviation	Minimum value	Maximum value	Number of observations
Fatalities	1473.18	1942.12	4	8920	589
Injury accidents	43.52	76.17	0.58	395.69	585
Population_density	16.31	21.47	0.12	81.81	589
Motorization	422.37	115.91	103	667	589
GDP per capita	31092.33	13738.1	9249	87,873	579
Superhighway density	2207.76	3488.55	0	14,701	508
Age	38.59	2.62	31.1	45.6	584
Population density	158.72	228.35	2.7	1352.4	578
Passengers_km_railways	14.43	21.47	0.2	89.6	532
BAC	0.39	0.22	0	0.8	589
Point_system	0.57	0.49	0	1	589
Speed limit	120.06	14.11	80	130	589
Heating_degree_index	2909.386	1185.23	345.03	6179.75	513
Passengers-km-roads	150.58	238.06	1.7	920.8	589
Megatrucks	0.11	0.31	0	1	589

implementation of a point-based driving license, a dummy variable is included with a value of one if a penalty driving license system is applied. The introduction and application of any type of point system to driving licenses can lead to lower numbers of traffic fatalities and accidents (Castillo-Manzano & Castro-Nuño, 2012; Castillo-Manzano, Castro-Nuño, & Pedregal, 2011). A road traffic policy variable for the maximum speed limit allowed on superhighways is also considered. As one of the main effects of higher speed limits may be worse road safety performance (Elvik, 2012) (i.e., greater numbers of fatalities and accidents), a positive sign can be expected for the coefficient of this variable.

Regarding weather and meteorological conditions, country-level rain data are not available for the long period examined in this paper. We include the Heating Degree Days index (HDD) as a proxy of temperature. *HDD* measures cold severity during a specific time period and takes into consideration both *outdoor* and *average room* temperature. *HDD* calculation relies on the *base* temperature, defined as the lowest daily mean air temperature not leading to indoor heating. Although the base temperature depends on several factors associated with the building and the surrounding environment, the index adopts a general climatological approach and sets the value at 15 °C. With T_m^i as the mean (m) air temperature of day *i* (measured in °C), the *HDD* of a certain year is given by:

$$HDD = \begin{Bmatrix} \sum_i^I 18 - T_m^i & \text{for} T_m^i \leq 15 \\ 0 & \text{for} T_m^i > 15 \end{Bmatrix}$$

where *I* denotes the number of days in the considered year. For example, if the daily mean air temperature is 12 °C, the value of the HDD index for that day is 6 (i.e., 18 °C–12 °C). However, if the daily mean air temperature is 16 °C, the HDD index for that day is 0.

One limitation of this variable is that it is only available for European Union countries, which implies excluding relevant cases in our context such as Norway and the United Kingdom. So, we also report results of regressions omitting the HDD variable.

The main variable of interest in our analysis is a dummy variable that takes a value of one for countries where the use of megatrucks is permitted, as we have explained above.

We apply the logic of differences in differences (DiD), which is a common methodology used in the treatment evaluation framework (for details, see Angrist & Pischke, 2009; Gertler, Martinez, Premand, Rawlings, & Vermeersch, 2016). The identification strategy in a DiD analysis relies on collecting several years of data for two groups of observations: one group affected by the treatment/policy at some point during the considered period and a control group not affected by the policy in any year of the considered period. In our context, we have a panel dataset that includes countries where megatruck circulation is not permitted (control countries) and countries where megatrucks have been allowed to circulate at some point in the considered period or earlier (treated countries). Hence, the DiD variable in our analysis is a dummy variable that takes a value of one for countries where the use of megatrucks has been authorized since the year in which the policy was implemented. Therefore, if we control for all the relevant explanatory factors, we can identify changes in safety performance due to megatruck circulation in treated countries compared to the safety performance of the control countries. Examples of recent studies that evaluate policies in the transportation sector in the DiD framework include Aguirre, Mateu, and Pantoja (2019), Bernardo and Fageda (2017), Conti, Ferrara, and Ferraresi (2019, Haojie Li, Graham, and Majumdar (2012), Jiménez, Perdiguero, and García (2018), Oum, Wang, and Yan (2019), Wolff (2014).

According to previous studies (see Section 2, literature review), we are uncertain about the sign that this variable should take. The scarce literature that analyzes the safety impact of megatruck circulation for isolated cases in specific countries includes both scholars who argue an improvement in road safety due to the reduction in the number of traffic accidents resulting from fewer journeys made (e.g., Knight et al., 2008; Rijkswaterstaat, 2010) and studies that emphasize the greater severity of road accidents due to the vehicles' size and lack of maneuverability, especially in certain infrastructures (Ortega et al., 2014; Vierth et al., 2008).

4. Results

Table 3 shows the correlation matrix of the variables used in the empirical analysis. Multicollinearity can exaggerate estimates of the variance parameter and distort its statistical significance or even result in parameter estimates of implausible magnitude in the most extreme cases. Taking this into account, there are four variables that are highly correlated (Passengers-km-roads, Motorization, Superhighway density, Passengers-km-railways). The high correlation between the heating_degrees_index variable and the megatrucks variable must also be considered. To examine the influence of the high correlation between these variables, we report the results of various regressions. First, we include all the variables. Second, we exclude the heating_degrees_index variable, which also has the limitation of only being available for European Union countries. Then, we exclude the Passengers-km-roads variable. Further regressions also exclude the Motorization and Passengers-km-railways variables, respectively.

Heteroscedasticity and temporal autocorrelation problems may be present in the error term. Running the Wooldridge test for autocorrelation in our panel data shows that there may be an autocor-

Table 3
Correlation matrix of the variables used in the empirical analysis.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Fatalities (1)	1													
Accidents (2)	0.75	1												
Megatrucks (3)	−0.16	−0.01	1											
Heating_degree_index (4)	−0.36	−0.28	0.56	1										
Passengers_km_roads (5)	0.80	0.80	0.01	−0.30	1									
Motorisation (6)	0.13	0.36	0.20	−0.04	0.40	1								
Passengers_km_railways (7)	0.80	0.82	0.02	−0.26	0.97	0.33	1							
GDP per capita (8)	−0.05	0.14	0.22	−0.02	0.17	0.74	0.16	1						
Superhighway density (9)	0.70	0.78	0.02	−0.37	0.89	0.38	0.86	0.20	1					
Age (10)	−0.02	0.29	0.27	−0.01	0.27	0.47	0.24	0.16	0.27	1				
Population density (11)	0.19	0.34	−0.12	−0.37	0.27	0.23	0.27	0.34	0.24	0.06	1			
BAC (12)	0.12	0.25	0.06	−0.13	0.29	0.54	0.23	0.41	0.33	0.19	0.18	1		
Point_system (13)	0.13	0.18	0.05	−0.05	0.26	0.32	0.25	0.17	0.22	0.43	−0.01	0.17	1	
Speed limit (14)	0.27	0.21	−0.18	−0.40	0.23	0.11	0.26	0.12	0.16	−0.02	0.34	−0.10	0.24	1

relation issue and the Breusch–Pagan/Cook–Weisberg test indicates that we have a heteroscedasticity issue. We, therefore, run the regressions with standard errors robust to heteroscedasticity and specifying an AR (1) within-group correlation structure for the panels to address the autocorrelation issue. The variables used in the empirical analysis also have to be tested for normal distribution. We apply the Doornik–Hansen test for multivariate normality, which shows that our variables are not normally distributed.

The estimation is made using the population-averaged panel-data model with a negative binomial distribution. Count models are commonly used in the analysis of the determinants of road traffic fatalities (Albalate, Fernández, & Yarygina, 2013; Hauer, 1995; Johansson, 1996; Karlaftis & Tarko, 1998; Quddus, 2008). As is usual in road safety studies, we estimate a negative binomial model that is a standard count model. The advantage of negative binomial distribution is that it explicitly models the dependent variable as the number of occurrences and it takes into account the non-normality distribution of the variables. Note that the country population variable is included as an exposure variable, so its coefficient is restricted to one. This enables us to interpret the results in terms of rates per capita.

The sample considered in this study has been structured as panel data as we have information available for 31 countries and several years. The two main panel data models are random effects and fixed effects. The fixed-effects model is usually the preferred model because it controls for omitted variables that are correlated with the variables of interest and are time-invariant. For example, the effect of time-invariant variables such as latitude are already captured by the country fixed effects. Country fixed effects may also capture the fact that weather conditions are systematically worse for some countries than others. In contrast, the random-effects model may cause a bias in the estimation as the variables of interest may be correlated with the rest of the explanatory variables. The fixed-effects model identifies changes from one period to another, so it is the most appropriate method for the evaluation of the megatrucks policy. As it is based on the ("within") transformation of the variables as deviations from their average, the fixed-effects model allows us to compare changes in road safety outcomes in countries where megatrucks are permitted with countries where they are not. Note that we report the results of an F-test that confirms that the country fixed effects variable is statistically significant, which rules out the use of a pooled model.

Tables 4 and 5 reports the results of the different regressions described above. Table 4 considers traffic fatalities as the endogenous variable while that Table 5 considers traffic injury accidents as the endogenous variable

Note: Standard errors in parentheses (robust to heteroscedasticity). All regressions include country fixed effects. Regressions specify an AR (1) within-group correlation structure for the panels. Population is used as an exposure variable. Statistical significance at 1% (***), 5% (**), 10% (*).

Note: Standard errors in parentheses (robust to heteroscedasticity). All regressions include country fixed effects. Regressions specify an AR (1) within-group correlation structure for the panels. Population is used as an exposure variable. Statistical significance at 1% (***), 5% (**), 10% (*).

Regarding the control variables, we find evidence of a non-linear relationship between road traffic fatalities and the country's level of economic activity. This corroborates the findings of Bishai et al. (2006) and Kopits and Cropper (2005). A positive and statistically significant coefficient is obtained for the GDP variable, while GDP^2 is negative and statistically significant. Similar results are found when the dependent variable is traffic accidents, although the statistical significance of GDP^2 is more modest.

The motorization variable is generally not statistically significant. As argued by Castillo-Manzano et al. (2016), the sign of the effect of the motorization variable on safety outcomes may vary depending on the country's GDP level. The superhighway density variable is negative and statistically significant in most of regressions for traffic fatalities. There is, therefore, some evidence to support the hypothesis that more advanced infrastructure may reduce traffic fatalities (according to previous studies such as Castillo-Manzano et al., 2014; Wang et al., 2013, for example) but does not have a clear effect on injury accidents.

The rail traffic variable is negative and statistically significant in several regressions considering fatalities as the dependent variable. So, countries in which rail plays a greater role in mobility may have better safety outcomes, at least in terms of lower fatalities (as was expected, in line with e.g., Litman, 2007). More alcohol-tolerant policies seem to have generally negative effects both in terms of fatalities and injury accidents, which is in line with previous analyses such as Castillo-Manzano, Castro-Nuño, Fageda, and López-Valpuesta (2017). Higher speed limits may lead to higher fatalities, corroborating previous studies such as Castillo-Manzano, Castro-Nuño, López-Valpuesta, and Vassallo (2019) and Elvik (2012). The time trend is negative and statistically significant irrespective of the regression, which suggests an improvement in road safety outcomes even after controlling for all the observed factors that might affect these outcomes. Finally, we do not find any significant effects of the population density and point-system driving license variables. It may be that the variability in our sample is not high enough to identify any relevant effects for these variables.

As usual, the negative binomial uses a log-link function, so the coefficients can be interpreted in terms of elasticities. Taking this into account, we find that the coefficient of the megatrucks vari-

Table 4
Results of estimates (population-averaged panel-data model with negative binomial distribution).

Independent variables	Dependent variable: fatalities				
	Regression (1)	Regression (2)	Regression (3)	Regression (4)	Regression (5)
Megatrucks	0.19 (0.07)***	0.15 (0.06)***	0.15 (0.06)***	0.15 (0.06)***	0.12 (0.06)**
Heating_degree_index	−0.000008 (0.00005)	–	–	–	–
Passengers_km_roads	−0.0005 (0.001)	−0.001 (0.002)	–	–	–
Motorisation	−0.0006 (0.0003)*	−0.0004 (0.0003)	−0.0005 (0.0004)	–	–
Passengers_km_railways	−0.03 (0.007)***	−0.02 (0.01)**	−0.03 (0.01)**	−0.02 (0.01)*	–
GDP per capita	0.00004 (0.00001)***	0.00005 (0.00001)***	0.00005 (0.00001)***	0.00005 (0.00001)***	0.00005 (0.00001)***
GDP^2 per capita	−2.65e10 (1.01e-10)***	−3.31e10 (1.12e-10)***	−3.29e10 (1.11e-10)***	−3.00e10 (1.09e-10)***	−2.1e10 7.85e-11)***
Superhighway density	−0.0006 (0.00002)*	−0.0006 (0.00003)*	−0.0007 (0.00004)*	−0.0007 (0.00004)*	−0.00008 (0.00006)
Age	0.0006 (0.03)	0.0008 (0.03)	0.0003 (0.03)	−0.001 (0.03)	0.009 (0.03)
Population density	−0.001 (0.005)	0.003 (0.005)	0.004 (0.005)	0.005 (0.005)	−0.0011 (0.003)
BAC	8.62 (4.56)**	5.84 (5.22)	4.03 (1.43)***	4.03 (1.44)***	1.51 (0.45)***
Point_system	0.01 (0.04)	0.00005 (0.04)	0.003 (0.04)	−0.0001 (0.04)	0.08 (0.06)
Speed limit	−0.08 (0.06)	0.07 (0.04)*	0.08 (0.04)*	0.08 (0.04)*	0.04 (0.03)
Time_trend	−0.06 (0.009)***	−0.06 (0.009)***	−0.06 (0.009)***	−0.07 (0.009)***	−0.07 (0.01)***
Intercept	145.88 (16.82)***	120.92 (18.87)***	119.71 (19.69)***	122.94 (20.84)***	151.05 (20.60)***
Test joint sign (Wald χ^2)	1081.64***	367.13***	975.62***	257.80***	269.98***
Test F (Ho: Country fixed effects = 0)	88.63***	96.90***	105.37***	108.13***	93.27***
Breusch–Pagan/Cook–Weisberg test for heterogeneity (Ho: Constant variance)	235.88***	299.01***	267.51***	292.83***	298.76***
Wooldridge test for autocorrelation (Ho: No first-order autocorrelation)	416.22***	375.91***	348.07***	348.56***	309.73***
Doornik–Hansen test for multivariate normality	40632.90***	40184.35***	39321.40***	39017.66***	40007.85***
No. of observations	413	464	464	464	494

Note: Standard errors in parentheses (robust to heteroscedasticity). All regressions include country fixed effects. Regressions specify an AR (1) within-group correlation structure for the panels. Population is used as an exposure variable. Statistical significance at 1% (***), 5% (**), 10% (*).

able is positive and statistically significant in all regressions where the dependent variable is fatalities per capita. More precisely, we find an impact that ranges between a 12–19% increase in traffic fatalities in countries where megatrucks have been permitted post-1996. Finally, we do not find any clear change in traffic injury accidents associated with the authorization of megatruck circulation, as the corresponding variable is not statistically significant in the regressions where the dependent variable is road accidents.

As a robustness check, we re-do our analysis by applying propensity score matching. The matching procedure pairs observations in the treated countries (where megatrucks are allowed to circulate) with control countries (where megatrucks are not allowed to circulate) with similar characteristics in terms of traffic density and latitude (as a proxy of weather conditions). Following Rosenbaum and Rubin (1983), we first estimate the probability of being treated, conditional on traffic density and climate, to obtain a propensity score for each observation. In a second step, we use the first nearest neighbor algorithm to match the observations in the treated and control groups with respect to the propensity score. Then, we drop all the observations without common support and re-estimate the model using the matching sample. The matching sample only includes treated and control countries comparable in terms of traffic density and climate.

Table 6 shows the results of the regressions that use the matching sample. In our context, one clear limitation of propensity score matching is that the number of observations that have common support is small. In particular, the main source of variability in the reduced matching sample is whether countries allow or do not allow the circulation of megatrucks. This may explain why most of the control variables are not statistically significant. However, propensity score matching is a sound robustness check given that the megatrucks variable remains positive and statistically significant with an estimated impact on the increase in fatalities ranging from 11% to 17%. Furthermore, we find no evidence of a relevant impact of megatrucks on traffic accidents.

Megatrucks may not have led to an increase in traffic accidents as they need to circulate on "better" roads due to their specific technical features or because they incorporate safer technological advances or drivers are more appropriately trained, as suggested by Sanchez-Rodrigues et al. (2015). However, the presence of megatrucks increases the severity and lethal consequences of accidents, as is the case for all types of heavier and larger trucks (Castillo-Manzano et al., 2016; Forkenbrock & Hanley, 2003; Glaeser & Ritzinger, 2012; Glaeser et al., 2006; Hanley & Forkenbrock, 2005). So, our wide set of European countries (EU + EFTA) corroborates the specific findings for megatrucks found in previous studies for individual countries such as Spain (Ortega et al., 2014; Pérez-Martínez & Vassallo, 2013) and the United Kingdom (Knight et al., 2010).

Our results might represent a European case extension of the af Wåhlberg (2008) U.S. meta-study, which concludes that as larger trucks replace higher numbers of smaller vehicles, heavier trucks

Table 5
Results of estimates (population-averaged panel-data model with negative binomial distribution).

Independent variables	Dependent variable: accidents				
	Regression (1)	Regression (2)	Regression (3)	Regression (4)	Regression (5)
Megatrucks	0.03	−0.02	−0.02	−0.02	−0.07
	(0.08)	(0.09)	(0.09)	(0.09)	(0.08)
Heating_degree_index	1.96e-06	–	–	–	–
	(0.00005)				
Passengers_km_roads	−0.0008	−0.001	–	–	–
	(0.002)	(0.002)			
Motorisation	−0.0008	−0.0007	−0.0009	–	–
	(0.0006)	(0.007)	(0.0008)		
Passengers_km_railways	−0.04	−0.03	−0.03	−0.03	–
	(0.01)***	(0.01)*	(0.02)	(0.02)	
GDP per capita	0.00005	0.00005	0.00006	0.00004	0.00005
	(0.00002)***	(0.00002)***	(0.00002)***	(0.00002)**	(0.00001)***
GDP^2 per capita	−2.73e-10	−3.83e-10	−3.83e-10	−3.20e-10	−2.90e-10
	(1.83e-10)	(1.78e-10)**	(1.85e-10)**	(1.96e-10)*	(1.71e-10)*
Superhighway density	−0.00001	−0.00005	−0.00006	−0.00009	−0.00006
	(0.00003)	(0.00004)	(0.00005)	(0.00005)	(0.00008)
Age	0.07	0.07	0.07	0.07	0.08
	(0.05)	(0.06)	(0.06)	(0.06)	(0.07)
Population density	−0.01	−0.005	−0.003	−0.002	−0.01
	(0.008)*	(0.08)	(0.01)	(0.01)	(0.006)*
BAC	8.17	8.59	5.80	5.80	2.59
	(5.52)	(6.44)	(2.15)***	(2.16)***	(0.78)***
Point_system	0.06	0.05	0.06	0.05	0.12
	(0.06)	(0.06)	(0.06)	(0.06)	(0.08)
Speed limit	−0.01	0.006	0.02	0.02	−0.05
	(0.08)	(0.07)	(0.08)	(0.08)	(0.05)
Time_trend	−0.04	−0.04	−0.04	−0.04	−0.06
	(0.01)***	(0.01)***	(0.01)***	(0.01)***	(0.02)***
Intercept	90.08	80.31	78.67	84.05	124.45
	(31.15)***	(30.34)***	(31.06)***	(32.95)***	(38.90)***
Test joint sign (Wald χ^2)	99.21***	85.42***	93.10***	103.24***	81.14***
Test F (Ho: Country fixed effects = 0)	256.13***	234.48***	424.85***	424.35***	338.16***
Breusch–Pagan/Cook–Weisberg test for heterogeneity (Ho: Constant variance)	639.74***	592.44***	698.48***	668.32***	678.27***
Wooldridge test for autocorrelation (Ho: No first-order autocorrelation)	51.12***	49.66***	36.06***	36.05***	36.87***
Doornik–Hansen test for multivariate normality	9685.79***	9705.83***	9795.09***	10191.20***	11649.58***
No. of observations	413	464	464	464	494

Note: Standard errors in parentheses (robust to heteroscedasticity). All regressions include country fixed effects. Regressions specify an AR (1) within-group correlation structure for the panels. Population is used as an exposure variable. Statistical significance at 1% (***), 5% (**), 10% (*).

are involved in a greater number of fatal accidents due to their specific maneuverability issues, especially in some particular environments such as urban settings.

Note: Standard errors in parentheses (robust to heteroscedasticity). All regressions include country fixed effects. Regressions specify an AR (1) within-group correlation structure for the panels. Population is used as an exposure variable. Statistical significance at 1% (***), 5% (**), 10% (*). Propensity score matching uses passengers_km_roads in the baseline period and latitude of the capital city in each country as predictors of the probability of being treated. Treated countries are Denmark, Germany, Netherlands and Norway. Control countries are Estonia, France, Poland and United Kingdom. Note that some control variables are not considered; GDP per capita^2 is omitted because testing the non-linear relationship between traffic fatalities and income requires a sample with a large number of countries. BAC and speed variables are excluded because they do not have variability over time in the matching sample. Finally, traffic density and climate conditions are already captured in the matching procedure.

5. Conclusions

The debate that has emerged around cross-border Longer and Heavier Vehicle (LHVs)/megatruck circulation on European roads to reduce excessive motorized transportation costs is a topic that affects a wide range of interest groups linked to the road freight sector and has sparked a growing interest in the literature as to its economic, environmental and logistics impacts. Authorizing the circulation of megatrucks would doubtlessly result in greater productivity and, consequently, better prices for road haulers, due to a reduction in costs per tonne-kilometer transported. However, one serious consequence of this measure is that it might trigger a dynamic process that would result in a large amount of freight transport switching from rail to road. As far as infrastructure is concerned, everything points to the introduction of megatrucks possibly influencing investments in infrastructure maintenance and conservation as, for example, Ortega et al. (2014) and Pérez-Martínez and Miranda (2016) find for Spain, Sanchez-Rodrigues et al. (2015) suggest for Germany, and Vierth and Haraldsson (2012) analyze for the Swedish case.

It is noticeable that several earlier studies consider the influence of megatrucks on road safety to be considerably lower but the results of their analyses are, to some extent, inconclusive, as their conclusions on this matter are not unanimous. As previous scholars state (e.g., Sanchez-Rodrigues et al., 2015), a better understanding and assessment of the benefits and risks of LHVs are needed. The present article has, therefore, pioneered the application of multivariate econometric analysis to *ad-hoc* panel data for a sample of European Union and EFTA countries.

To close the gap on the potential safety consequences of megatrucks (in terms of road safety performance indicators), the current research contributes to the literature by providing an original study case focused not on one single country (as is usually the case) but on a set of European countries, some of which permit LHVs to circulate on their national road networks, and others that do not. Our results point to European countries that have allowed

Table 6
Results of estimates: matching sample (population-averaged panel-data model with negative binomial distribution).

Independent variables	Dependent variable: fatalities			Dependent variable: accidents		
	Regression (1)	Regression (2)	Regression (3)	Regression (4)	Regression (5)	Regression (6)
Megatrucks	0.11 (0.05)**	0.13 (0.05)***	0.17 (0.09)*	−0.005 (0.05)	0.06 (0.03)*	0.11 (0.08)
Motorisation	−0.0007 (0.001)	-	-	−0.002 (0.001)**	-	-
Passengers_km_railways	−0.02 (0.02)	−0.02 (0.02)	-	−0.03 (0.02)*	−0.03 (0.01)	-
GDP per capita	0.00001 (0.00003)	0.00001 (0.00004)	0.00004 (0.00002)**	0.00002 (0.00003)	0.00001 (0.00004)	0.00004 (0.00002)
Superhighway density	−0.0001 (0.0001)	−0.0001 (0.0001)	−0.0001 (0.0002)	−0.0002 (0.0001)	−0.0002 (0.0001)	−0.0001 (0.0002)
Age	0.08 (0.12)	0.08 (0.12)	0.07 (0.12)	0.15 (0.12)	0.15 (0.13)	0.14 (0.14)
Population density	0.01 (0.01)	0.01 (0.01)	0.004 (0.01)	−0.001 (0.01)	0.002 (0.01)	−0.005 (0.009)
Point_system	−0.04 (0.13	−0.04 (0.12)	0.15 (0.10)	−0.26 (0.12)**	−0.24 (0.13)*	−0.007 (0.10)
Time_trend	−0.07 (0.04)*	−0.07 (0.03)**	−0.11 (0.02)***	−0.02 (0.03)	−0.05 (0.03)	−0.09 (0.02)***
Intercept	138.53 (82.00)*	152.58 (69.35)**	219.06 (39.75)***	48.43 (67.10)	95.34 (64.45)	177.15 (47.68)***
Test joint sign (Wald χ^2)	26.33***	24.12***	25.08***	18.44***	17.32***	12.21***
Test F (Ho: Country fixed effects = 0)	91.18***	89.90***	59.21***	834.80***	926.05***	707.34***
Breusch–Pagan/Cook–Weisberg test for heterogeneity (Ho: Constant variance)	11.76***	8.22***	0.19	41.69***	35.21***	3.79**
Wooldridge test for autocorrelation (Ho: No first-order autocorrelation)	58.01***	56.23***	46.66***	8.42**	8.45**	7.09
Doornik–Hansen test for multivariate normality	470.76***	487.08***	529.94***	506.59***	525.54***	617.72***
No. of observations	137	137	137	137	137	137

Note: Standard errors in parentheses (robust to heteroscedasticity). All regressions include country fixed effects. Regressions specify an AR (1) within-group correlation structure for the panels. Population is used as an exposure variable. Statistical significance at 1% (***), 5% (**), 10% (*). Propensity score matching uses passengers_km_roads in the baseline period and latitude of the capital city in each country as predictors of the probability of being treated. Treated countries are Denmark, Germany, Netherlands and Norway. Control countries are Estonia, France, Poland and United Kingdom. Note that some control variables are not considered; GDP per capita^2 is omitted because testing the non-linear relationship between traffic fatalities and income requires a sample with a large number of countries. BAC and speed variables are excluded because they do not have variability over time in the matching sample. Finally, traffic density and climate conditions are already captured in the matching procedure.

megatruck circulation obtaining higher accident lethality rates. This highlights the need to develop a parallel set of specific strategies that, as part of a country's road safety policy, are designed to mitigate the likely ensuing increase in the mortality rate.

Finally, some issues need to be clarified regarding our research object. First, we are assessing an item on the policymaker agenda that is still unresolved, ongoing, and currently under examination. This could be considered both a natural limitation of our study and, also, a future line of research as new countries introduce LHVs and new statistical data become available. Second, our paper analyzes the impact of megatruck circulation on road safety performance in our wide sample of European countries (i.e., on crashes involving all road users, not just an evaluation of crashes involving megatrucks). This is due to separately-classified statistical data for LHV traffic accidents only being available for the United States, where LHV trucks are allowed by law. Third, before our findings are generalized, it should be noted that a variety of trials and temporary planning strategies were implemented in the countries where megatrucks are permitted before they were introduced, so some caution is required when extending their authorization to other countries or regions. In this line, if at all possible, it would be interesting to extend this analysis to evaluate other dimensions derived from the introduction of LHVs (environmental, modal split, infrastructure, logistics costs), with a comparison of safety issues in European Union and non-European Union countries, as in this paper.

Other recent phenomena in the European continent that could potentially affect road freight transportation in general and megatruck circulation in particular, such as the United Kingdom's exit from the EU or the application of the *Eurovignette* Directive, might present future research opportunities to complement this paper's findings.

6. Practical application

The positive impact of megatruck circulation might be enhanced through measures that maximize logistics efficiency gains and minimize the consequences of fatal accidents. As road freight companies are likely to be interested in using longer vehicles and, especially, bearing in mind that traffic safety depends on multiple parameters related to vehicles' technical characteristics, infrastructure design, and driver behavior (Douglas, Swartz, Richey, & Roberts, 2019), among others, a set of multi-approach actions can be recommended to ensure that the introduction of megatrucks compensates any stakeholders who would be negatively affected. By way of example, strategies might include warning other drivers of the danger of being involved in an accident with a megatruck or adapting post-accident emergency medical care protocols to crashes involving LHVs. It would also be advisable to implement legislative measures to make truck manufacturers raise the minimum safety technical requirements for LHVs and/or stricter training program requirements for LHV drivers.

Considering the potential generalization of LHV authorization to other states and the possibility of LHV cross-border circulation, a better enforcement and surveillance framework (such as, e.g., Teoh, Carter, Smith, & McCartt, 2017 have concluded for U.S. states) should be applied to ensure that these vehicles comply with the maximum load, size, and speed regulations, among others.

Megatruck circulation is a strategy that requires proper preparation and proper examination before it is applied. In this case, unlike other measures such as the point-system driver's license that also originated in the international benchmark countries of northern Europe, the imitation effect in other countries may be more doubtful. Extrapolation to countries with high accident rates and/or the lack of a high capacity road network/superhighways, which are the ideal natural habitat for this type of LHV, is not a simple matter.

Conflict of interest

Authors declare no conflict of interest.

Acknowledgements

The authors would like to express their gratitude to the Dirección General de Tráfico (Spanish Road Traffic Directorate General) for the human and financial resources provided for this study (grant reference: SPIP20141274).

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Jose I. Castillo-Manzano is a full professor in the Faculty of Economics and Business at the University of Seville. His research interests include safety research, transportation research, or policy evaluation. He has published almost 70 papers in journals with JCR impact factor, including Accident Analysis and Prevention; Economic Modelling; International Journal of Sustainable Transportation; Journal of Safety Research; Journal of Transport Geography; Regional Studies; Transport Policy; Transportation; Transportation Research: parts A, D, E and F or Safety Science.

Mercedes Castro-Nuño is associate at the University of Seville. Her research focuses on road safety; transport economics and sustainable mobility; tourism studies; innovative communication technologies; Europeanization and meta-analysis. She has published more than 30 papers in journals with JCR impact factor, including Accident Analysis and Prevention; Transport Policy; Economic Modelling; Journal of Safety Research; Journal of European Public Policy; Transportation Research: Parts D, E & F or Safety Science.

Xavier Fageda is associate professor at the University of Barcelona. His areas of expertise are transport economics, road safety and policy evaluation. He has been involved in several competitive research projects and research contracts with firms and public agencies. He has published several of his works in most of the leading journals in the transportation field. He holds a PhD in economics from the University of Barcelona (Spain) and a Msc in Economics from the University of Warwick (UK).

Journal of Safety Research 77 (2021) 114–124

Contents lists available at ScienceDirect

Journal of Safety Research

journal homepage: www.elsevier.com/locate/jsr

An in-depth analysis of self-reported cycling injuries in single and multiparty bicycle crashes in Denmark

Mehdi Hosseinpour[a,*], Tanja Kidholm Osmann Madsen[b], Anne Vingaard Olesen[b], Harry Lahrmann[b]

[a] School of Engineering & Applied Sciences, Western Kentucky University, 1906 College Heights Blvd., Bowling Green, KY, United States
[b] Department of the Built Environment, Aalborg University, Thomas Manns Vej 23, 9220 Aalborg, Denmark

ARTICLE INFO

Article history:
Received 8 July 2020
Received in revised form 24 October 2020
Accepted 12 February 2021
Available online 10 March 2021

Keywords:
Bicycle crashes
Injury severity
Self-reported crashes
Crash type
Multilevel logistic model

ABSTRACT

Introduction: Cycling is one of the main forms of transportation in Denmark. However, while the number of traffic crash fatalities in the country has decreased over the past decade, the frequency of cyclists killed or seriously injured has increased. The high rate of serious injuries and fatalities associated with cycling emphasizes the increasing need for mitigating the severity of such crashes. *Method:* This study conducted an in-depth analysis of cyclist injury severity resulting from single and multiparty bicycle-involved crashes. Detailed information was collected using self-reporting data undertaken in Denmark for a 12-month period between 1 November 2012 and 31 October 2013. Separate multilevel logistic (MLL) regression models were applied to estimate cyclist injury severity for single and multiparty crashes. The goodness-of-fit measures favored the MLL models over the standard logistic models, capturing the intercorrelation among bicycle crashes that occurred in the same geographical area. *Results:* The results also showed that single bicycle-involved crashes resulted in more serious outcomes when compared to multiparty crashes. For both single and multiparty bicycle crash categories, non-urban areas were associated with more serious injury outcomes. For the single crashes, wet surface condition, autumn and summer seasons, evening and night periods, non-adverse weather conditions, cyclists aged between 45 and 64 years, male sex, riding for the purpose of work or educational activities, and bicycles with light turned-off were associated with severe injuries. For the multiparty crashes, intersections, bicycle paths, non-winter season, not being employed or retired, lower personal car ownership, and race bicycles were directly related to severe injury consequences. *Practical Applications:* The findings of this study demonstrated that the best way to promote cycling safety is the combination of improving the design and maintenance of cycling facilities, encouraging safe cycling behavior, and intensifying enforcement efforts.

1. Introduction

Cycling is one of the main forms of non-motorized transportation (NMT) system, which is commonly used for commuting, recreation, and access to short-distance destinations. Compared to motorized transport systems, cycling is healthy, inexpensive, and sustainable mode of transport, providing benefits to the society by reducing pollution emissions, energy consumption, and travel cost (Eluru, Bhat, & Hensher, 2008; De Geus et al., 2012; Klassen, El-Basyouny, & Islam, 2014; Palmer et al., 2014; Useche, Montoro, Alonso, & Tortosa, 2018). Cycling is one of the main forms of transportation in Denmark, where 16% of all trips and 24% of trips below 5 km are made by bicycles (Cycling Embassy of Denmark, 2010). However, while the number of traffic crash fatalities in Denmark has decreased over the past decade, the proportion of cyclists killed or seriously injured has increased. The percentage of cyclist fatalities among total traffic deaths increased from 13% in 2008 to 16% in 2018 (IRTAD, 2019). The high rate of serious injuries and fatalities associated with cycling emphasizes the increasing need for mitigating the severity of bicycle-involved crashes. To do so, it is necessary to first understand and control factors associated with the risk of cyclist-involved crashes and their injury outcomes. This helps gain a better understanding of bicycle-related crash causes and develop effective countermeasures.

It should be noted that police-reported records for bicycle crashes are seriously subject to underreporting, especially for crashes resulting in less severe consequences (Veisten et al., 2007; Heesch, Garrard, & Sahlqvist, 2011; De Geus et al., 2012; Beck et al., 2016; Janstrup, Kaplan, Hels, Lauritsen, & Prato, 2016; Vanparijs, Panis, Meeusen, & De Geus, 2016; Chen et al., 2017;

* Corresponding author.
E-mail addresses: h_mehdi61@yahoo.com, mehdi.hosseinpour@wku.edu (M. Hosseinpour).

https://doi.org/10.1016/j.jsr.2021.02.009

Debrabant et al., 2018). Based on the reported crash statistics in Denmark for the year 2014, 16,481 cyclists were either treated in Danish hospitals or registered by the police. Of these, only 830 were reported to the official Danish crash statistics (Statistics Denmark, 2014; Lahrmann, Madsen, & Olesen, 2018). This means that the official crash statistics registers only 5% of bicycle crashes reported by either hospitals or the police. Moreover, bicycle crash data provided by hospital or emergency departments are often incomplete and biased towards more serious crashes, and also fail to record the cause and circumstances of crash events. Therefore, it may be difficult to identify the factors affecting bicycle crashes when using hospital crash database (Heesch et al., 2011; Juhra et al., 2012; Vanparijs et al., 2016; Chen et al., 2017). In addition, the rate of underreporting of single-bicycle crashes is even higher than that of bicycle crashes involving other road users. As a result, most previous studies have excluded single-bicycle crashes from the analysis (Lujic, Finch, Boufous, Hayen, & Dunsmuir, 2008; Boufous, De Rome, Senserrick, & Ivers, 2013; Kaplan, Vavatsoulas, & Prato, 2014).

One way to cope with the aforementioned issues is to deploy self-reported data acquisition method in which participants are asked to report their crash involvement. An advantage of using self-reported information is that it allows researchers to obtain more detailed information than would have been possible using police or hospitals reports (Hertach, Uhr, Niemann, & Cavegn, 2018). There are a number of studies in the literature that have examined cycling safety. However, research efforts devoted to cyclist injury severity are still limited. In addition, the majority of previous studies have focused on bicycle-motor vehicle collisions, while little research has been conducted to investigate single-bicycle crashes and the severity consequences. Therefore, this study aimed at adding to the existing literature by examining the risk factors associated with the injury severity of cyclists in single and multiparty bicycle-related crashes. In this study, multiparty crashes were defined as bicycle collisions involving other road users, such as motor vehicle, bicycle, motorcycle/moped, and pedestrian, whereas single crashes (e.g., falls or fixed-object collisions) involve only a bicyclist (Schepers et al., 2015).

The main hypothesis behind the separate analysis of cyclist injury severity in single and multiparty crashes is that the causes and mechanisms of crash events and consequences may vary between these two crash types. In other words, different risk factors are associated with the occurrence and severity outcomes of single and multiparty crashes. Several previous studies have supported this argument (Chen & Chen, 2011; Boufous et al., 2013; Martínez-Ruiz et al., 2013; Islam, Jones, & Dye, 2014; Wu et al., 2014; Uddin & Huynh, 2017; Hosseinpour, Sahebi, Zamzuri, Yahaya, & Ismail, 2018). The current study considered a large set of potential determinants of bicycle injury severity, including cyclist socio-demographic and behavioral attributes, roadway characteristics, environmental conditions, bicycle factors, and crash characteristics. To accomplish the objective of this study, detailed information on the above-mentioned factors was collected using self-reported bicycle crashes undertaken between 1 November 2012 and 31 October 2013. A two-level logistic regression model was applied to relate cyclist injury severity to the aforementioned factors.

The remainder of the paper is organized as follows: Section 2 gives a review of previous studies on bicycle-involved crashes. Section 3 describes the characteristics of the data collected in this study. Section 4 explains the methodology used for analyzing cyclist injury severity. In Section 5, the estimation results and the interpretation of the findings obtained are presented. Finally, Section 6 summarizes the key findings and gives recommendations for future research.

2. Literature review

Several previous studies have been conducted to analyze different aspects of cycling safety, such as crash frequency (Siddiqui, Abdel-Aty, & Choi, 2012; Kaplan & Giacomo Prato, 2015; Amoh-Gyimah, Saberi, & Sarvi, 2016), injury severity (Johnson et al., 2010; Juhra et al., 2012; Washington, Haworth, & Schramm, 2012; Kaplan, Janstrup, & Prato, 2017; Zhao, Carstensen, Nielsen, & Olafsson, 2018; Katanalp & Eren, 2020), cyclist behavior (Useche, Montoro, Alonso, & Oviedo-Trespalacios, 2018; Kaplan, Luria, & Prato, 2019; Poulos et al., 2019; Useche, Alonso, Montoro, & Esteban, 2019), or the safety effectiveness of cycling facilities or specific treatments (Jensen, 2008; Dill, Monsere, & Mcneil, 2012; Goodno, Mcneil, Parks, & Dock, 2013; Madsen, Andersen, & Lahrmann, 2013; Pulugurtha & Thakur, 2015; Digioia, Watkins, Xu, Rodgers, & Guensler, 2017; Madsen & Lahrmann, 2017; Lahrmann, Madsen, Olesen, Madsen, & Hels, 2018). In this section, a review of previous studies on cycling injury severity is presented. These studies used different statistical methods, such as standard ordered logit or probit models, mixed logit model, random-parameters ordered models, and generalized ordered models, to establish a relationship between cyclist injury severity and different risk factors.

For example, Kim, Kim, Ulfarsson, and Porrello (2007) applied a multinomial logit model to determine the key factors affecting the injury severity of bicyclists in bicycle–motor vehicle crashes that occurred between 1997 and 2002 in North Carolina. The results showed inclement weather, darkness with no streetlights, morning peak time, head-on collision, vehicle speeds, truck involved, intoxicated driver, bicyclist age 55 or over, and intoxicated bicyclist increased the probability of a bicyclist suffering a fatal injury in an crash. Using the same modeling approach, Moore, Schneider Iv, Savolainen, and Farzaneh (2011) examined the impacts of those factors affecting the injury severity of cyclists in bicycle-involved crashes that occurred at intersection and non-intersection locations in Ohio between 2002 and 2008. The results showed that injury severity levels were different at intersection and non-intersection locations. Nevertheless, the risk of severe cyclist injuries at both types of locations was higher for female cyclists, when the driver was under the influence of alcohol, when the vehicle was a heavy-duty truck, when the front of the motor vehicle impacted the side of the bicycle, and when the roadway pavement was dry. In another similar study, Bahrololoom, Young, and Logan (2020) examined bicyclists' injury severity in bicycle-car crashes that occurred at intersections in Victoria, Australia. A mixed binary logit model was developed using the Transport Accident Commission (TAC) crash database. The results demonstrated that speed and mass of both the car and bicycle, not wearing a helmet, and bicyclists aged 65 years old or more were associated with higher bicyclist injury severity.

Using the 2004 General Estimates System (GES) database, Eluru et al. (2008) adopted a mixed generalized ordered logit model to identify the risk factors associated with the injury severity of pedestrians and bicyclists in traffic crashes in the United States. The authors found that male cyclists, the elderly, alcohol consumption, higher speed limits, non-intersection locations, vehicle type (SUVs and pickups are overinvolved than vans in severe injuries), and time-of-day (darker periods lead to higher injury severity) were associated with more serious injuries. Boufous, De Rome, Senserrick, and Ivers (2012) used a logistic regression model in order to investigate the injury severity of bicycle crashes in Victoria, Australia. Variables found to increase the probability of cyclist injury severity were cyclist age (50 years and above), not wearing helmet, dark unlit roadway conditions, 70 km/h or above, curved roadway sections, rural locations, run-off-road crashes due to loss of control, and striking the door of a parked vehicle on paths. Using the same database, Boufous et al. (2013) conducted a further analysis to compare trends, circumstances and outcomes of bicycle crashes between single- and multi-vehicle bicycle crashes occurred in the state of Victoria, Australia. The authors found that the risk of single-vehicle crashes was higher in dark lighting condition, on wet surface conditions, and in rural areas.

Klassen et al. (2014) applied a spatial mixed logit model to examine the severity of bicycle-motor vehicle crashes. Four years (2006–2009) of crash data were collected in Edmonton, Canada. The existence of partial crosswalks and bicycle signs, and the bicyclist' gender and age were found to significantly affect bicycle severities at intersections. For mid-block sections, roadway classification, on-street parking, and driver's age contributed to bicycle crash severities. Wang, Lu, and Lu (2015) studied the factors associated with the severity of bicycle–motor vehicle crashes that occurred at unsignalized intersections in Kentucky, USA, between 2002 and 2012. The results indicated that stop-controlled intersections, one-lane approaches, helmet usage, and lower speed limits were correlated with decreased injury severity, while uncontrolled intersections, older (age > 55) drivers and bicyclists, child (age < 16) bicyclists, foggy and rainy weather, poor lighting in dark conditions, and wet road surfaces were associated with increased injury severity.

Using bicycle crash data from the State of New Hampshire between 2002 and 2013, Chen et al. (2017) evaluated the relationship between different risk factors and bicycle crash frequency and injury severity. With respect to bicycle crash injury severity, the results suggested that cyclists' level of traffic stress, darkness, two-way direction roadways, crashes that happened before the year 2005, straight and level roadway segments, and crashes where a traffic signal was present increased the probability of severe injury of bicycle-involved crashes. Robartes and Chen (2017) examined risk factors for bicyclist injuries in crashes that occurred in the state of Virginia. An ordered probit model was applied using police-reported crash data from 2010 to 2014. It was found that bicyclist and driver intoxication, bicycle and motor vehicle speeds, obscured automobile driver vision, vertical roadway grades, horizontal curves, and vehicle type (SUV, truck, and van) increased the probability of severe injury for the cyclist. Fischer, Nelson, Laberee, and Winters (2020) examined cycling injury severity reported to BikeMaps.org, which is a global crowd-sourced platform for reporting cycling incidents. The study included a total of 281 cycling crashes that occurred in the City of Victoria, Canada, between 2005 and 2019. The authors found that hitting fixed objects (such as fixed signs/posts or train tracks), collisions with animals, the 41–50 age group, moderate ridership, downhill terrain, cyclist traveling straight, and left-turning motor vehicles were found to be the most important factors increasing the risk of cyclists' more severe injury.

A number of studies used self-reporting crash data to study bicycle-involved crashes. Washington et al. (2012), for example, examined self-reported bicycling injuries in Queensland, Australia. A sample of 2,500 self-reported crash data was used in the study for the period between October 2009 and the end of March 2010. The results demonstrated that perceived risk did not influence injury rates. Also, wearing helmets and increased riding frequency were associated with decreased injury. In another similar study using self-reported crash data, Hertach et al. (2018) evaluated the crash risk and injury severity of single crashes involving e-cyclists in Switzerland. A survey was conducted among 3658 e-cyclists in 2016. With regard to cyclist injury severity, it was found that fast-moving e-bikes (up to 45 km/h), females, older riders, speeding, and intoxicated e-cyclists had an increased likelihood of suffering a serious injury. Useche et al. (2019) conducted a cross-sectional analysis to study the effects of demographic characteristics and cycling risky behaviors on the traffic safety outcomes of cyclists. The authors used self-reported crash data collected from 1,064 bicycle users across 20 different countries in Latin America, Europe, and North America. The results indicated the presence of a significant relationship between individual characteristics, cycling habits (e.g., cycling intensity), risk perception, knowledge of traffic rules, cycling risky behaviors (errors and violations), and self-reported bicycle crashes.

The overview of the existing literature indicates that the majority of previous studies were generally focused on bicycle-motor vehicle crashes, while little research has been devoted to single bicycle crashes. Furthermore, most of the past studies neglected to take into consideration cyclists' socioeconomic and behavioral characteristics in analyzing bicycle safety. Additionally, the use of self-reported crash data, which is relatively new in traffic safety, has been least covered by the past research (notable exceptions are Washington et al. (2012), Hertach et al. (2018), and Useche et al. (2019)).

3. Data collection

In order to identify the risk factors associated with the injury severity of single and multiparty bicycle-involved crashes, the current study used self-reported data undertaken from 1 November 2012 to 31 October 2013. Participants of the study were recruited through social media coverage (e.g., TV, radio, newspapers) and direct contact (e.g., email, telephone contact). Participants aged 18 years or older who used their bicycles frequently when signing up were recruited. When registering for the study, participants were asked to complete a web-based questionnaire containing information about socio-demographic characteristics (age, gender, education level, civil status, etc.), car ownership, bicycle-specific factors (e.g., bicycle type, cycling frequency).

An important behavioral-specific factor considered in this study is cyclists' risk-taking behavior. Because of social desirability biases and self-deception tendency associated with self-reporting of crash involvement, it is difficult to collect information on riding violations when a cyclist gets involved in a crash event (Af Wåhlberg, Dorn, & Kline, 2010). To cope with this problem and to measure cyclist risk-taking behavior, participants were further asked to state how often they make errors or violate traffic rules when they ride at different situations. For this purpose, a set of nine questions representing riding errors, consisting of four items, and traffic violations, composing of five items, was designed and included in the questionnaire (see Appendix A). A global score of risk-taking behavior was calculated through summing and averaging the respondents' answers to these items (Useche, Montoro, Alonso, et al., 2018; Useche et al., 2019).

In total, 6,793 participants confirmed their participation. Of these, only participants who experienced crash during the study period were finally selected for the current study. To minimize the effect of recall bias, each month the participants were asked whether or not they had experienced any crash in the previous month. In the case of a positive response, they were then asked to fill out a questionnaire containing details about crash information, for example crash time and location, personal injury severity level, crash counterpart (e.g. bicyclist, motor vehicle), road surface condition (e.g., wet), weather (e.g. snowing), and whether the crash was reported to the police, whether the crash had required a visit to the hospital emergency department or to general practitioner. In terms of injury severity sustained, bicycle crashes were split into two main groups, namely severe and non-severe crashes. A severe crash was a crash that resulted in injury severity more than bruising or required medical treatment (e.g. visits to emergency department or hospitalization) (De Geus et al., 2012, Lahrmann, Madsen, Olesen, et al., 2018).

Table 1 presents detailed information about the participants' sociodemographic attributes, crash characteristics, environmental conditions at the time of crash, and bicycle factors. During the study period, a total of 693 crashes were reported by the participants. Of these, 349 (50.4%) crashes were reported as single crashes, of which 176 (51%) resulted in severe injury outcomes. The remaining crashes, 344 (49.6%) were multiparty crashes, of which 125 (36%) implied severe injuries. The review of the participants' self-reporting crash records showed that the share of crashes that were reported to police, insurance companies, and hospitals were, 3.3%, 13.9%, and 17.3%, respectively, These figures confirm that these three sources represent a high rate of underreporting of bicycle crashes.

4. Methodology

In this study, a multilevel (hierarchical) logistic regression (MLL) model was applied to estimate the probability of severe injury outcome. There are multi-hierarchical features in crash data at road-segment-level or at-area level (Jones & Jørgensen, 2003; Savolainen, Mannering, Lord, & Quddus, 2011). The MLL model assumes that crash observations from the same geographical unit (e.g., zip code, municipality, area) share common unobserved characteristics, implying that crash records are not independent from one another. Such unobserved characteristics might result from unmeasured factors, such as quality of cycling facilities, cyclist populations, pavement condition, vehicular traffic. Due to these unobserved factors, bicycle crashes occurring in the same geographical unit may be correlated. Ignoring to account for such interdependencies results in biases in parameter estimation and misinterpretation of the results (Kim et al., 2007; Cervero & Kang, 2011; Sharman & Roorda, 2013; Xiong, Tobias, & Mannering, 2014). A standard logistic (SLO) model assumes that the model residuals are independent across crash observations, failing to accommodate the presence of intercorrelation among crash observations within the same group.

This study applied a two-level logistic model, where bicycle-involved crashes within the same zip codes were hypothesized to represent similar features in terms of crash severity patterns[1]. For more details on the MLL specification, the reader is referred to the work of Kim, Lee, Washington, and Choi (2007), Cervero and Kang (2011), Sharman and Roorda (2013), Xiong et al. (2014), Huang, Liu, Xue, Li, and Shi (2018), and Ko, Lee, and Byun (2019).

In this study, the Intra-class Correlation Coefficient (ICC) was employed to measure the ratio of the between-zip code variance to total variance in the MLL model (Kim, Kho, & Kim, 2017):

$$\mathrm{ICC} = \frac{Var(\upsilon_j)}{Var(\upsilon_j) + \sigma^2} \tag{2}$$

where $\mathrm{Var}(\mathrm{v_j})$ is the variance among the zip codes, captures the between-group variation; σ^2 is the variance component at the crash level, accounts for the within-group variation ($\sigma^2 = \frac{\pi^2}{3}$) (Kim et al., 2007; Huang et al., 2018).

The ICC is an indicator of the magnitude of the within-crash correlation (Huang, Chin, & Haque, 2008). If the ICC approaches 1, the MLL model is necessary. If the ICC approaches 0, the ordinary logit model is sufficient. A relatively large value of ICC implies that a multilevel model is more appropriate for the data (Park, Kim, Kho, & Park, 2017; Huang et al., 2018; Ko et al., 2019). A likelihood ratio test (LR test) was used to compare the MLL over the SLO model. The LRT, which is based on the differences in the log-likelihood of these two models, follows a chi-square distribution with one degree of freedom, as follows:

$$\mathrm{LRT} = 2 \times (LL_{MLL} - LL_{SLO}) \cong \chi^2_{(d.f.=1)} \tag{3}$$

where LL_{MLL} is the log-likelihood at converge of the MLL model, and LL_{SLO} is the log-likelihood at converge of the SLO model.

This study developed three distinct MLL models to estimate the likelihood of cyclist injury severity separately for the total, single, and multiparty crashes. An additional LRT was undertaken to examine the statistical justification of estimating cycling injury severity separately in the present study. The LRT statistic of the three MLL models is calculated as follows:

$$LRT_{MLL} = -2 \times (LL_{\beta}^{total} - LL_{\beta}^{single} - LL_{\beta}^{multi}) \cong \chi^2_{(d.f.)} \tag{4}$$

$$d.f. = \left(\beta^{multi} + \beta^{single} - \beta^{total}\right) \tag{5}$$

where LL_{β}^{total}, LL_{β}^{single}, and LL_{β}^{multi} are, respectively, the log-likelihood at convergence of the models estimated for the total, single, and multiparty crashes.

The test statistic follows a chi-square distribution with the degrees of freedom equal to the summation of the number of estimated parameters in the separate models (single and multiparty crashes) minus the number of estimated parameter in the total model. A significant value of the LRT statistic justifies the necessity of modeling and analyzing single and multiparty crashes separately in the present study (Chen & Chen, 2011; Islam et al., 2014; Wu et al., 2014; Uddin & Huynh, 2017). All statistical analyses of this study were conducted using STATA, version 15 (StataCorp, 2018).

Prior to the development of injury severity models, a correlation analysis was conducted to check the presence of multicollinearity among the study independent variables. Using Pearson's correlation coefficient, no evidence of high pairwise collinearity was found among independent variables included in the analysis.

5. Results and discussion

The modeling results of the MLL models for the single, multiparty, and total bicycle-involved crashes are shown in Table 2. As can be seen from the table, several explanatory variables were found to be statistically significant in determining the injury severity of cyclists in these three models. For example, multiparty crashes, roundabout, slippery/frozen surface, number of fines received, and riding to/from shopping were found to be associated only with the total crash model. Urban area was the only variable significant in all the three models, while crash location (intersections and bike paths), autumn and winter seasons, time of day (evening and night), strong wind, car ownership, urban bicycle type, and bicycles with light turned-on were found to be significant only in the single or multiparty crash model.

In terms of crash type, the total model shows that single-bicycle crashes were more likely to result in severe injuries than multiparty bicycle crashes did. A possible reason for this finding is that bicycle routes in Denmark are mainly segregated from the motorized or pedestrian traffic. On such devoted facilities, cyclists tend to ride at higher speed and more aggressively. Hence, the risk of a sole bicycle crash with severe consequences is high. Furthermore, because of intensive use of bicycles in Denmark, drivers and pedestrians are aware of the presence of cyclists on shared paths and roads. Therefore, the risk of a severe collision between a bicycle

[1] It should be noted that this study initially utilized a multilevel random-parameters logistic model, which is believed to be more superior to the MLL model in dealing with unobserved heterogeneity. However, due to the convergence problem associated with the calibration of the aforementioned model, the MLL model was ultimately chosen for estimating cyclist injury severity.

Table 1
Descriptive statistics of explanatory variables.

Variable Name	Variable Description	Single Crashes (%)	Multiparty Crashes (%)
Bicycle Crashes:			
Non-severe Crash	If true = 1, otherwise = 0	25.0	31.6
Severe Crash	If true = 1, otherwise = 0	25.4	18.0
Crash characteristics			
Single vs. Multiparty	Multiparty crash: if the crash involved another road user	50.4	49.6
Type of other party involved (only for multiparty crashes):			
Light	If light counterpart (bicycle or pedestrian) = 1, otherwise = 0	–	24.5
Motorized	If motorized counterpart (e.g., passenger car, motorcycle, bus, truck, etc.) = 1, otherwise = 0	–	25.1
Area Type:			
Rural	If crash occurred in rural area = 1, otherwise = 0	16.9	9.3
Semi-urban	If crash occurred in semi-urban area (i.e., small towns) = 1, otherwise = 0	20.6	15.4
Urban	If crash occurred in urban area = 1, otherwise = 0	62.5	75.3
Crash Location:			
On road	If crash occurred on road = 1, otherwise = 0	27.5	19.2
Cycle lane	If crash occurred on-road marked cycle lane = 1, otherwise = 0	2.9	3.2
Intersection	If crash occurred at intersection = 1, otherwise = 0	22.6	39.8
Bicycle path	If crash occurred on cycle path = 1, otherwise = 0	40.1	32.8
Roundabout	If crash occurred at roundabout = 1, otherwise = 0	4.0	4.1
Other	If crash occurred at other location (e.g., parking lot) = 1, otherwise = 0	2.9	0.9
Side Friction	If the level of interaction between cyclist and pedestrian was high = 1, if low = 0	3.7	10.8
Road Surface Condition:			
Dry	If road surface was dry at the time of crash = 1, otherwise = 0	31.5	76.7
Slippery/frozen	If road surface was slippery or frozen at the time of crash = 1, otherwise = 0	49.6	7.8
Wet	If road surface was wet at the time of crash = 1, otherwise = 0	18.9	15.4
Environmental conditions			
Season of Year:			
Autumn	If crash occurred in autumn (i.e., September through November) = 1, otherwise = 0	22.1	36.0
Winter	If crash occurred in winter (i.e., December through February) = 1, otherwise = 0	48.1	20.9
Spring	If crash occurred in spring (i.e., March through May) = 1, otherwise = 0	14.0	23.3
Summer	If crash occurred in summer (i.e., June through August) = 1, otherwise = 0	15.8	19.8
Time of Day:			
Morning	If crash occurred in the morning = 1, otherwise = 0	41.8	37.5
Noon	If crash occurred at noon = 1, otherwise = 0	14.3	14.8
Afternoon	If crash occurred in the afternoon = 1, otherwise = 0	25.2	40.4
Evening	If crash occurred in the evening = 1, otherwise = 0	10.9	5.2
Night	If crash occurred at night = 1, otherwise = 0	7.7	2.0
Weather Condition:			
Clear	If it was clear at the time of crash = 1, otherwise = 0	69.6	84.9
Rain	If it was raining at the time of crash = 1, otherwise = 0	9.2	8.1
Strong winds	If it was strong wind at the time of crash = 1, otherwise = 0	3.4	2.6
Snow	If it was snowy at the time of crash = 1, otherwise = 0	16.9	3.5
Fog	If it was foggy at the time of crash = 1, otherwise = 0	0.9	0.9
Lighting Condition:			
Daylight	If it was daylight = 1, otherwise = 0	52.1	75.9
Lowlight	If it was dawn, dusk, or dark-streetlight = 1, otherwise = 0	17.8	12.2
Darklight	If it was dark without supplemental lighting = 1, otherwise = 0	30.1	11.9
Cyclist Characteristics			
Age Group:	Cyclist age group		
18–24	If cyclist age was between 18 and 24 years = 1, otherwise = 0	5.4	7.0
25–44	If cyclist age was between 25 and 44 years = 1, otherwise = 0	35.2	43
45–64	If cyclist age was between 45 and 64 years = 1, otherwise = 0	54.2	44.5
65+	If cyclist age was 65 years old or more = 1, otherwise = 0	5.2	5.5
Gender	If cyclist was male = 1, otherwise = 0	59.0	63.4
Civil Status:			
With others	If cyclist lived with others (e.g., spouse, family, friends) = 1, otherwise = 0	80.5	76.7
Alone	If cyclist lived alone = 1, otherwise = 0	15.8	20.3
Unknown	If civil status was not specified = 1, otherwise = 0	3.7	2.9
Education Level:			
School	If school-educated = 1, otherwise = 0	22.9	23.0
College	If college-educated or higher degree = 1, otherwise = 0	73.6	75.0
Unknown	If education level was not specified = 1, otherwise = 0	3.4	2.0
Occupation			
Unemployed	If cyclist was unemployed = 1, otherwise = 0	2.3	1.7
Employed	If cyclist was employed = 1, otherwise = 0	78.8	78.2
Retired	If cyclist was retired = 1, otherwise = 0	7.7	8.1
Student	If cyclist was student = 1, otherwise = 0	7.7	9.9
Unknown	If occupation level was not specified = 1, otherwise = 0	3.4	2.0
Cycling Frequency	Cyclist's bike use rate, explained on a 5-point Likert scale ranging from 1 (monthly) to 6 (daily), (mean: 3.593, standard deviation: 0.635)	–	–
Risk-taking Behavior	Cyclist' risk-taking behavior ranging from 1 (never) to 6 (always) (see Appendix A), (mean: 2.294, standard deviation: 0.612)	–	–
Number of Fines	Number of fines the cyclist had received over the past 5 years, (mean: 0.113, standard deviation: 0.401)	–	–

Table 1 (*continued*)

Variable Name	Variable Description	Single Crashes (%)	Multiparty Crashes (%)
Car Ownership:			
No car	If cyclist had no car = 1, otherwise = 0	23.8	28.2
One car	If cyclist had one car = 1, otherwise = 0	65.0	57.6
Two or more cars	If cyclist had two or more cars = 1, otherwise = 0	11.2	14.2
Car Use Rate	Cyclist's car use rate, explained on a 5-point Likert scale ranging from 1 (never) to 5 (daily) (mean: 3.531, standard deviation: 1.121)	–	–
Main Reason for Cycling:			
To/from discretionary activities	If cyclist rode for discretionary activities (e.g., leisure, exercise, visiting family/friends) = 1, otherwise = 0	15.5	14
To/from work/education	If cyclist rode for mandatory activities (e.g., work or education) = 1, otherwise = 0	81.7	83.1
To/from shopping	If cyclist rode for shopping = 1, otherwise = 0	2.3	1.7
For other purposes	If cyclist rode for other purposes = 1, otherwise = 0	0.6	1.2
Brightly-colored Clothing Worn	If yes = 1, otherwise = 0	35.0	25.3
Helmet Use	If helmet was worn = 1, otherwise = 0	81.9	79.1
Bicycle Characteristics			
Bicycle Type:			
Urban bicycle	If urban bicycle = 1, otherwise = 0	34.7	40.4
Classic bicycle	If classic bicycle = 1, otherwise = 0	23.5	14.2
Race bicycle	If race bicycle = 1, otherwise = 0	20.6	24.7
Mountain bicycle	If mountain bicycle = 1, otherwise = 0	12.3	8.4
Unknown	If not specified = 1, otherwise = 0	8.9	12.2
Bicycle Light Turned-on	If bicycle light was turned on when cycling = 1, otherwise = 0	65.9	48.3

and other road users is relatively low when compared to the severity outcomes of single bicycle crashes. Several previous studies have also confirmed that single-vehicle crashes involving bicycles result in more casualties (Jacobson, Blizzard, & Dwyer, 1998; Heesch et al., 2011; Schepers & Den Brinker, 2011; De Rome et al., 2014; Fischer et al., 2020).

The values of deviance statistic for all the three models are statistically significant at the 1% level, which rejects the null hypothesis that these three models yield the same performance as that of their respective constant-only counterparts. The LRT comparing the MLL versus SLO models show that the former is favored to the latter at the 1% significance level for all the three models. This result strongly rejects the null hypothesis that the MLL models developed had explanatory power equal to their respective SLO counterparts. According to the ICC values, the zip-level random-effect variance for the single, multiparty, and total crashes explains, respectively, 24.3%, 19.4%, and 6.8% of the total variance. This result indicates the presence of unobserved heterogeneity in bicycle crash severity among the same group, which cannot be explained using a SLO model (Park et al., 2017). In this condition, the MLL model is an appropriate approach to accommodate this issue. An additional LRT was used to test the appropriateness of the separate models (single and multi-party models) over the total model. The result shows that the separate models result in better prediction performance than the total model (LRT = 52.94, d.f. = 8). As a result, the outcomes of single and multi-party crashes were analyzed and are discussed in the following. To ease the interpretation of the effect of each variable on the severity of single and multi-party crashes, marginal effects (MEs) were estimated, and are shown in Table 2. For categorical variables, the marginal effect represents the difference in probability of severe injury as the variable changes from zero (the reference case) to one. For continuous variables, the marginal effect gives the difference in probability of severe injury as the variable changes from the mean to one standard deviation above the mean (Robartes & Chen, 2017).

5.1. Crash characteristics

With regard to area type, crashes occurring in urbanized areas resulted in less severe consequences compared to other areas. This finding is not surprising as there are high traffic volumes and strict enforcement in urban areas. Therefore, cyclists tend to ride at lower speeds and more carefully in such areas. Another reason for this effect is that rural areas are less cycling-friendly, with poor connectivity, higher vehicular speeds, and longer time delays for emergency services to injured cyclists. Therefore, crashes occurring in rural areas may result in more serious injuries. A similar finding was achieved in other studies (Zahabi, Strauss, Manaugh, & Miranda-Moreno, 2011; Boufous et al., 2012, 2013; Hamann, Peek-Asa, Lynch, Ramirez, & Hanley, 2015; Kaplan & Giacomo Prato, 2015).

Regarding crash location, intersections (95% CI: 0.465, 2.092) were strongly associated with severe multiparty crashes. This finding is intuitive as the number of conflicts between cyclists and motorists at intersections are significantly high. A number of previous studies drew similar findings that intersections are the riskiest locations for cyclists (Räsänen & Summala, 1998; Wang & Nihan, 2004; Kim et al., 2007; Martínez-Ruiz et al., 2013; Kaplan & Giacomo Prato, 2015; Hamann & Peek-Asa, 2017). Similarly, multiparty crashes occurring on bicycle paths (95% CI: 0.422, 2.026) were more serious. A possible explanation for this finding is that because of a false sense of safety potentially induced by bicycle paths, cyclists tend to ride at high speeds on such devoted facilities, and hence due to shorter reaction time attributed with higher riding speeds, the risk of bicycle-to-bicycle or bicycle-to-pedestrian crashes increases. Several previous studies have indicated that bicycle paths do not necessarily increase cycling safety when compared to other cycling facilities, like on-road cycling (Loo & Tsui, 2010; Heesch et al., 2011; De Rome et al., 2014; Beck et al., 2016).

Regarding road surface conditions, riding on wet surfaces (95% CI: 1.265, 3.429) was more associated with serious single crashes. The interpretation of this effect is that the probability of slipping and losing the control of bicycle on wet roads is high, which together increase the risk of falls or fixed-object collisions. This finding is in line with that of previous studies (De Geus et al., 2012; Schepers & Wolt, 2012; Boufous et al., 2013; Wang et al., 2015; Vanparijs et al., 2016).

5.2. Environmental characteristics

In terms of seasonal effect, the results showed that single bicycle crashes were more likely to be severe in autumn (95% CI: 0.203,

Table 2
Estimation results of the MLL models for the single, multiparty, and total bicycle crashes.

Variable	Single Bicycle Crashes					Multiparty Bicycle Crashes					Total Bicycle Crashes			
	Coeff.	*P*-value	95% C.I.*		ME*	Coeff.	*P*-value	95% C.I.		ME	Coeff.	*P*-value	95% C.I.	
			Lower limit	Upper limit				Lower limit	Upper limit				Lower limit	Upper limit
Constant	−13.446	<0.001	−14.621	−12.270		−11.162	<0.001	−12.300	−10.025		−11.219	<0.001	−12.079	−10.358
Crash characteristics														
Multiparty Crash											−0.970	<0.001	−1.392	−0.548
Area Type:														
Urban	−0.914	0.016	−1.655	−0.172	−0.153	−0.753	0.047	−1.496	−0.011	−0.138	−0.656	0.003	−1.088	−0.224
Crash Location:														
Intersection						1.279	0.002	0.465	2.092	0.234				
Bicycle path						1.224	0.003	0.422	2.026	0.224				
Roundabout											−1.004	0.038	−1.952	−0.057
Road Surface Condition:														
Slippery/frozen											−0.869	0.001	−1.380	−0.359
Wet	2.347	<0.001	1.265	3.429	0.392						0.625	0.018	0.109	1.142
Environmental cond.														
Season:														
Autumn	1.051	0.015	0.203	1.899	0.176									
Winter						−0.803	0.033	−1.539	−0.067	−0.147				
Summer	1.218	0.010	0.285	2.150	0.204						0.584	0.021	0.090	1.078
Time of Day:														
Evening	1.205	0.021	0.179	2.230	0.201									
Night	1.524	0.015	0.293	2.754	0.255									
Weather Condition:														
Strong winds	−3.057	0.006	−5.231	−0.883	−0.511									
Cyclist Characteristics														
Age Group: 45–64	0.966	0.003	0.321	1.610	0.161						0.410	0.031	0.037	0.784
Gender: Male	0.777	0.023	0.108	1.447	0.130						0.505	0.009	0.125	0.885
Occupation:														
Employed						−1.508	0.001	−2.390	−0.626	−0.276	−1.179	<0.001	−1.756	−0.602
Retired						−1.360	0.039	−2.650	−0.069	−0.249	−1.548	0.001	−2.491	−0.605
Number of Fines											−0.518	0.041	−1.015	−0.022
Car Ownership: Two or more cars						−0.892	0.049	−1.779	−0.006	−0.163				
Main Reason for Cycling:														
To/from work/education	1.065	0.025	0.135	1.995	0.178						0.591	0.044	−0.003	1.181
To/from shopping											1.536	0.028	0.163	2.910
Bicycle Characteristics														
Bicycle Type:														
Urban bicycle						−0.864	0.014	−1.555	−0.173	−0.158				
Race bicycle						1.169	0.004	0.365	1.974	0.214	0.850	<0.001	0.380	1.320
Bicycle Light Turned-on	−0.924	0.018	−1.689	−0.159	−0.154									
Random-effect Parameter (ρ)	1.527	<0.001	0.970	2.406	1.527	1.077	0.001	0.600	1.934	1.077	0.638	0.001	0.359	1.135
GOF Summary	**Single Bicycle Crashes**					**Multiparty Bicycle Crashes**					**Total Bicycle Crashes**			
No. of level 1 units (crash)	349					344					693			
No. of level 2 units (zip code)	148					141					217			
ICC (%)	24.3%					19.4%					6.8%			
No. of Parameters ($\boldsymbol{\beta}$)	13					11					16			
Log-likelihood at zero ($\boldsymbol{LL_0}$)	−267.878					−249.256					−518.992			
Log-likelihood at convergence ($\boldsymbol{LL_\beta}$)	−217.288					−218.538					−462.298			
Deviance = −2*($\boldsymbol{LL_\beta}$ - $\boldsymbol{LL_0}$), (*P*-value)	101.18 (<0.001)					61.44 (<0.001)					113.39 (<0.001)			
LRT (MLL vs. SLO), d.f. = 1, (*P*-value)	20.79 (<0.001)					9.41 (0.002)					6.83 (0.009)			
LRT (Total vs. Separate models), (*P*-value)	$LRT_{MLL} = -2 \times (LL_\beta^{total} - LL_\beta^{single} - LL_\beta^{multi}) = -2 \times (-462.298 - (-217.288) - (-218.538))$ $= 52.94 d.f. = \left(\beta^{single} + \beta^{multi} - \beta^{total}\right) = 13 + 11 - 16 = 8 (P-value)_{(\mathrm{LRT}=52.94,\mathrm{d.f.}=8)} < 0.001$													

* 95% C.I. stands for the 95% confidence interval; ME stands for marginal effect

1.899) and summer (95% CI: 0.285, 2.150) months. Because of fine weather conditions and shorter period of darkness during the autumn and summer months in Denmark, more people are attracted to riding, thus bearing more exposure to bicycle-involved crashes. Another possible reason is that those who ride in these seasons tend to ride at higher speeds and more aggressively mainly due to the absence of inclement weather. Hence, they are more likely to get involved in severe injury crashes. This fining is consistent with previous studies (Moore et al., 2011; Prati, Pietrantoni, & Fraboni, 2017). In contrast, multiparty crashes occurring in winter (95% CI: −1.539, −0.067) had a lower probability of severe outcomes. This is because winter months (i.e., December through February) are associated with adverse weather conditions, and under such conditions cyclists are more likely to ride at lower speeds. Hence, they are less likely to be involved in multiparty crashes resulting in severe consequences. Regarding the time of crash, single crashes that occurred in the evening (95% CI: 0.179, 2.230) or at night (95% CI: 0. 0.293, 2.754) were more likely to result in severe injuries. This effect is mainly due to the reduced visibility associated with evening and night times. As a result, the probability of a single crash resulting in serious outcome increases. This finding was also supported by several previous studies (Eluru et al., 2008; Boufous, Rome, Senserrick, & Ivers, 2011; Boufous et al., 2012, 2013; Wang et al., 2015; Chen et al., 2017). Regarding weather condition at the time of crash, strong winds (95% CI: −5.231, −0.883) contributed negatively to the probability of sustaining a severe injury in single bicycle crashes. This result can be reasoned by the fact that cyclists tend to ride more carefully during adverse weather conditions.

5.3. Cyclist characteristics

Cyclists aged between 45 and 64 (95% CI: 0.321, 1.610) were overinvolved than other age groups in serious single crashes. A potential explanation for this finding is that aging is directly associated with slower reaction time and greater fragility, which together increase the probability of severe injuries when an crash occurs (Bíl, Bílová, & Müller, 2010; Weber, Scaramuzza, & Schmitt, 2014; Wang et al., 2015; Hertach et al., 2018; Useche, Montoro, Alonso, et al., 2018).

Male cyclists (95% CI: 0.108, 1.447) had a higher probability of severe injuries in single bicycle crashes. This finding is partly attributed to speeding and aggressive riding behavior among male cyclists. Therefore, they are more prone to severe crashes. This result is in line with that of previous studies (Bíl et al., 2010; Hertach et al., 2018). With regard to occupation status, employed (95% CI: −2.390, −0.626) and retired (95% CI: −2.650, −0.069) individuals were less likely to be seriously injured when they were involved in multiparty crashes. This result may be explained by the fact that retired and employed individuals ride more carefully and at lower speeds when compared to other groups, like students, thus decreasing the likelihood of more severe injuries.

Cyclists owning two or more cars (95% CI: −1.779, −0.006) were less likely to get involved in serious multiparty crashes. This effect might be because individuals owning two or more cars were less likely to ride, especially in the case of mandatory trips, such as work or school trips. Therefore, they were less exposed to the risk of being involved in bicycle crashes.

Regarding the purpose of cycling, cyclists who rode their bicycles for work or education purposes (95% CI: 0.135, 1.995) had a higher risk of serious injuries in single crashes. This is expectable as individuals with work- or education-related purposes use their bicycles more frequently. Therefore, they are more exposed to being involved in a severe bicycle crash. This finding is in line with previous studies (De Geus et al., 2012; Hertach et al., 2018).

5.4. Bicycle characteristics

With regard to the effect of bicycle type on the severity of multiparty crashes, urban bicycles (95% CI: −1.555, −0.173) were found to be less involved in serious injuries, while race bicycles (95% CI: 0.365, 1.974) were overinvolved in severe consequences. A possible reason for the association of race bicycles in severe crashes is that cyclists on race bicycles tend to ride at high speeds, hence increasing the risk of a crash with severe outcome. Another finding related to bicycle characteristics is that a bicycle with lights turned-on (95% CI: −1.689, −0.159) had a lower probability of being involved in serious single crashes. This finding is intuitive as bicycle lights increase bicyclists' sight distance during dark lighting condition, hence assisting the cyclist to avoid an unexpected harmful event, such as striking a fixed object.

A brief overview of the modeling results shows that there are several parallels and differences between single and multiparty bicycle crashes in terms of the injury severity and factors associated. For example, wet surface condition, autumn and summer seasons, evening and night periods, strong winds, middle-aged cyclists (45–64), male cyclists, riding for the purpose of getting to/from work, and bicycles with lights turned-on were associated with the injury severity of single bicycle crashes only, while intersections, bike paths, winter season, cyclist occupation status (retired and employed individuals), car ownership, and bicycle type (urban and race bicycle types) were found to affect the severity of multiparty crashes only. "Urban area" was the only factor that affected cyclist injury severity in both single and multiparty crashes. These findings can help safety officials understand the causes and circumstances resulting in cyclist injury severities for single and multiparty crashes and to develop effective ways of improving cycling safety. For example, a noteworthy finding of this study is that the risk of severe multiparty crashes was higher on bike paths and at intersections. Although segregated bike paths encourage cycling, such cycling-devoted facilities do not necessarily increase the safety. Therefore, further analysis is warranted to thoroughly examine the effects of bike path-specific characteristics on bicycle crashes and severity outcomes. Moreover, further in-depth study is recommended to examine the effect of intersection-specific characteristics, such as signal timing, road geometric design, as well as collision type, on bicycle-vehicle crashes.

6. Conclusions and suggestions for future research

The aim of this study was to analyze risk factors associated with the injury severity of bicyclists in single and multiparty crashes. Based on self-reported crash data collected across Denmark between 1 November 2012 and 31 October 2013, separate MLL models were developed to estimate the probability of cyclist injury severity in single and multiparty crashes. The modeling results demonstrated that the MLL models clearly led to a superior fit over the SLO models for both single and multiparty bicycle-involved crashes. This indicates the presence of correlation among the crash observations within the same zip code, supporting the use of the MLL model. The LRT comparing the total model versus the separate models (single and multiparty crashes) showed that the latter was significantly favored over the former, implying that the analysis of injury severities of crashes should be separately carried out by crash type. This finding was also supported through comparing the association of different risk factors on the injury severity associated with single and multiparty crashes.

The results showed that single bicycle crashes resulted in more severe outcomes compared to multiparty crashes. The findings also demonstrated that there were various factors contributed to the probability of severe injuries. For both single and multiparty bicycle crashes, urban area was negatively associated with bicycle injury severity. For the single crashes, wet surface condition, autumn and summer seasons, evening and night periods, non-adverse weather conditions, cyclists aged between 45 and 64 years, male sex, riding for the purpose of work or educational activities, and bicycles with light turned-off were associated with severe injuries. For the multiparty crashes, intersections, bicycle paths, non-winter season, not being employed or retired, lower personal car ownership, and race bicycles increased cyclist injury severity. The findings of this study can help public health and road safety practitioners to gain a better understanding of bicycle injury severities in bicycle-involved crashes and to develop effective countermeasures aiming at improving cycling safety. In general, the findings of this study suggest that the injury severity of cyclists involved in traffic crashes could be reduced by developing different intervention programs, such as the safety improvement of intersections and bicycle paths, promoting cycling facilities in rural areas, speed reduction in areas prone to speeding by both motorists and cyclists, improving roadway lighting, and enforcing traffic rules and legislations. From the research, the best way to promote cycling safety is the combination of improving the design and maintenance of cycling facilities, encouraging safe cycling behavior, and intensifying enforcement efforts.

This study represents at least two contributions, which should be acknowledged here. First, this research used self-reporting crash data containing a wide range of explanatory variables, some of which, such as cyclist risk-taking behavior, civil status, occupation status, education level, car ownership, car use rate, and bicycle-specific attributes (e.g., type of bicycle, bicycle lights turned on or off), have rarely been investigated in the bicycle safety literature. This could be a contribution of this research because bicycle crashes are subject to underreporting, especially in Denmark, where bicycle trips are increasing, yet the rate of underreporting of bicycle crashes also remains high. Another contribution of this study is that it analyzed the injury severity of cyclists separately for single and multiparty crashes.

This study supports the use of self-reporting crash data as an effective way to overcome the issue of crash underreporting. Accordingly, further research is recommended on how to interconnect and match details of self-reporting crash data with those reported by the police. This could effectively reduce the high rate of underreporting of bicycle-involved crashes. A limitation associated with the current study is that it did not investigate other potential factors, such as knowledge of traffic rules, riding violations (e.g., speeding, red-light running), impaired riding, and distraction (e.g., using mobile phone when riding) on cycling injury severity. This is because information about the aforementioned factors was not available in the current database. In this regard, further research is warranted to investigate the effect of riding violations on bicycle crashes through considering more risk behavior items.

Acknowledgements

The study was financially supported by the Danish Foundation TrygFonden. The authors would like to thank TrygFonden for their funding of this study.

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Dr. Mehdi Hosseinpour: Dr. Mehdi Hosseinpour is a Postdoctoral Research Fellow at Western Kentucky University (WKU). His main interests are traffic crash analysis, road user safety behavior, and the application of state-of-the-art statistical models to transportation studies.

Dr. Tanja Kidholm Osmann Madsen: Dr. Tanja Kidholm Osmann Madsen is an Assistant Professor of Transportation Engineering in the Department of the Built Environment at Aalborg University, Denmark.

Dr. Anne Vingaard Olesen: Dr. Anne Vingaard Olesen is an Associate Professor of Transportation Engineering in the Department of the Built Environment at Aalborg University, Denmark.

Associate Professor Harry Lahrmann: Harry Lahrmann is an Associate Professor in the Department of the Built Environment at Aalborg University, Denmark.

APPENDIX A: Cyclist risk-taking behavior questionnaire

Indicate how often you ride with regard to the following items (For each item, participants were asked to answer the question according to a 6-point Likert scale ranging from 1 (never) to 6 (always)):

Items indicating riding errors:

- I ride inattentively
- I ride recklessly
- I ride impatiently
- I ride intolerantly

Items representing traffic violations:

- Going through a red light
- Listening to music while riding
- Using the mobile phone to talk or text whilst riding
- Talking on hands-free while cycling
- Riding on sidewalks/pathways

Journal of Safety Research 77 (2021) 241–254

Contents lists available at ScienceDirect

Journal of Safety Research

journal homepage: www.elsevier.com/locate/jsr

Assessing disabling and non-disabling injuries and illnesses using accepted workers compensation claims data to prioritize industries of high risk for Oregon young workers

Liu Yang [a,*], Adam Branscum [a], Viktor Bovbjerg [a], Curtis Cude [b], Crystal Weston [b], Laurel Kincl [a]

[a] Oregon State University, College of Public Health and Human Sciences, United States
[b] Oregon Health Authority, Public Health Division, United States

ARTICLE INFO

Article history:
Received 3 July 2020
Received in revised form 22 December 2020
Accepted 9 March 2021
Available online 30 March 2021

Keywords:
Young workers
Workers' compensation
Disabling claims
Non-disabling claims
Work-related injury and illness

ABSTRACT

Introduction: Young workers are especially vulnerable to occupational injuries and illnesses. There is a continued need to investigate injury burden among young workers across demographics and industry to inform targeted interventions. Workers compensation (WC) claims are important for quantifying work-related injuries and illnesses, however published studies have focused on disabling claims. This study extended previous research on Oregon young workers by including the most recent WC claims data to identify patterns of injury and high risk industries. *Methods:* We obtained all accepted disabling claims (N = 13,360) and a significant portion of non-disabling claims (N = 24,660) on workers aged 24 years and under from 2013 to 2018. Claim count, rate and cost were calculated by year, age, gender, industry, and injury type. A prevention index (PI) method was used to rank industries in order to inform prevention efforts. *Results:* Average annual disabling and non-disabling claim rates were 111.6 and 401.3 per 10,000 young workers. Workers aged 19–21 (disabling: 119.0 per 10,000 and non-disabling: 429.3) and 22–24 years (115.7 and 396.4) and male workers (145.3 and 509.0) had higher claim rates than workers aged 14–18 (80.6 and 297.0) and female workers (79.8 and 282.9). The most frequent injury types were "struck by/against" (35.6%) and "work-related musculoskeletal disorders (WMSDs)" (19.5%). High risk industries included agriculture, construction, and manufacturing for both genders combined. For female young workers, the highest risk industry was healthcare. *Conclusions:* This study demonstrated the added value of non-disabling WC claims data. Using both disabling and non-disabling data and PI method, agriculture, construction, manufacturing and healthcare industries were identified as priority workplaces to prevent common and costly injuries among Oregon young workers. *Practical Applications:* While the industries identified are considered hazardous for all workers, findings in this study can guide targeted research and prevention efforts specific to young workers.

1. Introduction

Adolescents and young adults make up a significant portion of the workforce in the United States. In 2018, there were about 19.4 million young workers aged 24 years and under nationally and more than 200,000 young workers in the State of Oregon, representing 12% of the total workforce in the country and the state (Institute, 2019). In general, U.S. state and federal laws regulate child labor laws, and youth aged 14 years and above are allowed to work. In 2019, the proportion of youth aged 16 to 24 years participating in the labor force was 38% for those enrolled in school and 81% for those not in school. College students had higher participation rates than high school students (50% vs. 22% in 2019) (U.S. Department of Labor, Bureau of Labor Statistics, 2019). While working is a key developmental milestone for many adolescents and young adults, risk of occupational exposures and injuries can be a serious threat to not only their immediate health but also long-term development and ability to work throughout adulthood (Breslin, Koehoorn, Smith, & Manno, 2003; Pratt, Cheesman, Breslin, & Do, 2016). Ensuring a safe and healthy working environment is essential to protect young workers and enable them to be productive through their working life.

Youth are vulnerable to occupational hazards and injuries (National research Council, 1998; Breslin et al., 2005; Windau & Samuel, 2005). Young workers, especially males, are at up to two

* Corresponding author.
E-mail address: yangliu@oregonstate.edu (L. Yang).

https://doi.org/10.1016/j.jsr.2021.03.007
0022-4375/© 2021 The Authors. Published by the National Safety Council and Elsevier Ltd.

times higher risk of injuries at work as compared to their older counterparts (Bena, Leombruni, Giraudo, & Costa, 2012; Breslin & Smith, 2005; Centers for Disease Control and Prevention, 2006; Hanvold, Kines, Nykänen, Safety, & Workers, 2018; Salminen, 2004). Occupational injury risk factors often differ between young and adult workers. Young workers often hold temporary jobs and work irregular hours (Breslin et al., 2005; Hanvold, 2016; Paterson, Clarkson, Rainsird, Etherton, & Blevvett, 2015). They tend to work in certain industry sectors such as wholesale and retail trades, services, and agriculture, and their jobs often require higher levels of physical exertion (Breslin & Smith, 2005; Breslin et al., 2005; Hanvold et al., 2018; Hanvold, 2016; Layne, Castillo, Stout, & Cutlip, 1994; Miller & Kaufman, 1998). Moreover, young workers often receive inadequate safety training and supervision (Breslin, Polzer, MacEachen, Morrongiello, & Shannon, 2007; Dragano, Barbaranelli, & Reuter, 2018; Runyan et al., 2007).

A growing body of research further highlights the heterogeneity in young workers subgroups defined by age, gender, and other potential factors such as training and job skills. Workplace safety and health experiences may vary across subgroups (Hanvold et al., 2018; Nielsen, Dyreborg, Kines, Nielsen, & Rasmussen, 2013). Studies have shown that male young workers had higher injury rates as compared to female young workers (Breslin & Smith, 2005; Breslin et al., 2003; Horwitz & McCall, 2005; Layne et al., 1994; Miller & Kaufman, 1998; Mujuru & Mutambudzi, 2007). Male and female workers tend to have different job tasks and experience different types of injuries (Laberge & Ledoux, 2011; Parker, Carl, French, & Martin, 1994). For example, one study on adolescents reported that few females did farm work, while few males worked in health care facilities (Parker et al., 1994). Compared with males, females are more likely to have jobs that require very fast repetitive motions and static standing for extended time periods, which are associated with musculoskeletal injuries (Breslin et al., 2007). There is a continued need to investigate injury burden among young workers across age, gender, and industry to identify vulnerable subgroups for targeted interventions.

A number of data sources have been examined to characterize the injury burden and nature among young workers, including administrative and hospital data such as workers compensation (WC) claims data, emergency department (ED) visits data, trauma registry data, census data and survey-based data (Breslin et al., 2003; Brooks & Davis, 1996; Brooks, Davis, & Gallagher, 1993; Graves, Sears, Vavilala, & Rivara, 2013; Horwitz & McCall, 2005; Layne et al., 1994; Mujuru & Mutambudzi, 2007; US Bureau of Labor Statistics, 2019a, 2019b; Windau & Samuel, 2005). Each of these data sources are subject to potential coverage and completeness issues and no single data source captures all injuries to young workers (National research Council, 1998). WC claims data have long been used as a population-based data source for research and surveillance of work-related injuries and illnesses (Breslin et al., 2003; Council of State and Territorial Epidemiologists, 2019; Morassaei, Breslin, Shen, & Smith, 2014; Radi, Benke, Schaafsma, & Sim, 2016; Tarawneh, Lampl, & Robins, 2013). The state of Oregon uses WC claims data to document the incidence and characteristics of injuries and illnesses among young and adult workers (Mccall & Horwitz, 2004; McCall, Horwitz, & Carr, 2007; Walters, Christensen, Green, Karam, & Kincl, 2010). However, earlier efforts focused on disabling claims (i.e., claims involving compensation for lost work time or permanent disability or death), which generally represent more severe injuries. Non-disabling claims involving injuries and illnesses without lost work time were generally not available to researchers and public health surveillance in many states including the state of Oregon (Utterback, Meyers, & Wurzelbacher, 2014).

Minor injuries and illnesses occur frequently among young workers (Breslin et al., 2007; Miller & Kaufman, 1998; Parker et al., 1994; Tucker, Diekrager, Turner, & Kelloway, 2014; Turner, Tucker, & Kelloway, 2015). One study suggested that young workers had been experiencing minor injuries so frequently that they saw them as a normal part of their everyday work (Breslin et al., 2007). Another study on both disabling and non-disabling WC data in the state of Washington showed that only 15% of claims from adolescents involved compensation for lost work time (Miller & Kaufman, 1998). Oregon has been working to improve the completeness of occupational surveillance by obtaining non-disabling claims data. A previous study conducted by Walters et al. (2010) on Oregon young workers found the crude injury rate almost doubled when adding data from a portion of non-disabling claims from a commercial insurer in Oregon. However, we consider this rate as conservative and underestimated since the insurer providing the non-disabling claims did not include all of Oregon businesses.

This present study aimed to further the understanding of non-disabling injury and illness burden among Oregon young workers and comprehensively document both disabling and non-disabling injuries and illnesses in recent years to guide injury prevention efforts for Oregon young workers.

2. Methods

The study includes non-disabling WC claims data from the State Accident Insurance Fund Corporation (SAIF), the largest WC insurance provider in Oregon (SAIF, 2020). Using the most recent disabling and non-disabling WC claims data, the present study reported work-related injuries and illnesses from 2013 to 2018 among Oregon young workers aged $\leq$24 years, with two specific objectives: (a) quantify and compare disabling and non-disabling injuries and illnesses by demographics, industry and injury characteristics; (b) identify industry sectors of high disabling and non-disabling injury risk for young workers using a prevention index (PI). The PI takes into account multiple metrics such as injury count, rate, and associated cost to systematically compare injury risk across industry sectors to inform research and prevention priorities (Anderson, Bonauto, &, Adams, 2013; Bonauto, Silverstein, Adams, & Foley, 2006).

The study obtained ethics review approval by the Institutional Review Board at Oregon State University (Review#: IRB-2019-0448).

2.1. Data sources

2.1.1. Workers' compensation (WC) claims data

Oregon law requires most employers to provide workers' compensation coverage to their employees, including hourly and part-time employees (Oregon State Legislature, 2019). Oregon employers can choose to have WC insurance for their employees by self-insurance, insurance through a private insurance company, or insurance through SAIF. In 2018, SAIF's market share in Oregon was 54%, whereas the private insurers covered 34% and self-insured employers and employer groups had 12% of the market share (Department of Consumer and Business Services, 2020).

Disabling WC claims in Oregon are defined as involving missing three or more days of regularly scheduled work, overnight hospitalization, likely permanent disability, or death (Oregon State Legislature, 2019). Non-disabling claims refer to those in which the injured workers do not receive any compensation for lost work days (i.e., time lost from work is generally less than three days) or experience permanent disability (Michael Vogt & Chuck Easterly, SAIF corporation, March, 2019, written communication). All Oregon insurance companies are required to report their accepted disabling claims to the Workers' Compensation Division of the Oregon

Department of Consumer and Business Services (DCBS), while accepted non-disabling claims are not required to be reported.

The DCBS manages the Oregon disabling WC claims data system and provides the data for research purposes on request. The present study obtained 2013–2018 de-identified accepted disabling WC claims data from the DCBS for workers of all ages. Through a research project agreement, SAIF provided 2013–2018 de-identified accepted non-disabling claims data for workers aged 24 and under.

2.1.2. Employment data

To calculate claim rates, the Quarterly Workforce Indicators (QWI) data were used as employment data. The QWI covers 95% of U.S. private sector jobs and includes a wide variety of record-level data sources such as the Unemployment Insurance data and Quarterly Census of Employment and Wages data (US Census Bureau Center for Economic Studies, 2020). The QWI data have been used in previous studies on Oregon's young workers as well as for other published studies (Syron, Kincl, Yang, Cain, & Smit, 2017; Walters et al., 2010). The publicly available QWI data provide estimates for the number of workers aged 14 years old and above, stratified by industry and demographics. For this study, data for Oregon workers from 2013 to 2018 were used.

2.2. Data variables and coding

Both the accepted disabling and non-disabling claims datasets contain the following variables used in this study: injury year, worker's demographics (age and gender), employer's industry, injury characteristics (nature, body part, and event/cause), and compensated medical cost.

2.2.1. Age group

The worker's age was recorded in years in both WC claims datasets. To match age groups in the QWI employment data, workers were grouped into: <10, 10–13, 14–18, 19–21, 22–24, and >24 years (in the disabling claims dataset only).

2.2.2. Industry sector and group

Employer's industry in the WC claims raw data was coded using the North American Industry Classification System (NAICS) (US Census Bureau, 2020). We further coded nine industry sectors based on National Occupational Research Agenda (NORA, the second-decade) definitions using NAICS codes up to 4 digits (Centers for Disease Control and Prevention, 2019). We combined the NORA sector, "Oil and gas extraction" with "Mining (except oil and gas extraction)" into one sector, "Mining" because they are related and both sectors had a small number of claims.

2.2.3. Injury characteristics

DCBS coded injury characteristics (i.e., nature, event and body part affected) in the disabling claims data using the Occupational Injury and Illness Classification System (OIICS) version 2.01 (Centers for Disease Control and Prevention, 2019). However, SAIF coded the non-disabling data using the Workers Compensation Insurance Organizations (WCIO) coding system (Organizations, Table, Part, & Nature, 2020). The study team drafted a WCIO-OIICS crosswalk independently and then compared with two other crosswalks proposed for research purposes to amend the crosswalk (Laura Syron, NIOSH, January 2020, written communication; Steve Wurzelbacher, NIOSH, January 2020, written communication). Conflicting results were resolved by consensus among the study team. We used the final WCIO-OIICS crosswalk to code injury characteristics of non-disabling WC claims to OIICS.

2.2.4. Injury types

Based on previous studies (Anderson, Bonauto, & Adams, 2014; Anderson et al., 2013), we further coded claims into 17 types based on injury and illness characteristics (i.e., nature and event). OIICS codes in version 1.01 used in previous studies were reviewed and converted into codes in version 2.01 by consensus among the study team. We used the Bureau of Labor Statistics definition for work-related musculoskeletal disorders (WMSDs) (in OIICS code version 2.01) (US Bureau of Labor Statistics, 2016).

2.2.5. Medical cost

Medical costs were standardized to the 2018 U.S. dollar based on inflation information from the Bureau of Labor Statistics (BLS) website (Bureau of Labor Statistics, 2017).

2.3. Data analysis

To characterize work-related injuries and illnesses among Oregon young workers, we counted claims by year, age group, gender, industry, injury nature and injury type for disabling claims and non-disabling claims separately. We also calculated median medical costs associated with the injuries and illnesses for each grouping.

Claim rates were estimated by year, age group, gender and industry for disabling and non-disabling claims separately, expressed as the number of claims per 10,000 workers. We chose the unit of workers to facilitate the comparison with previous studies on Oregon young workers. Disabling claim counts and rates for adult workers (25 years and above) were also calculated to provide a point of reference.

To adjust for under-coverage in calculating non-disabling claim rates, we weighted the QWI employment data at the 2-digit level NAICS industry using the percentage of SAIF-covered disabling claims over the total number of disabling claims in each industry in a similar study period from 2014 to 2018 (proportion data provided by DCBS). The proportions ranged from 13.5% (NAICS code 22, "Utilities") to 90% (NAICS code 11, "Agriculture, forestry, fishing and hunting"), with an average of 55.6%. An implicit assumption is that similar percentages hold for non-disabling claims. Specifically, we assumed that these proportions reflected SAIF's market share, that is, the percentage of workers covered under its premium in these industry sectors.

To rank industries of high risk, we adapted the prevention index (PI) methodology developed by researchers in the state of Washington (Anderson et al., 2013; Bonauto et al., 2006). This method has been used in a number of studies as an effective way to systematically rank industry sectors to inform research and prevention priorities (Anderson et al., 2014, 2013; Bonauto et al., 2006; Fouquet, Bodin, Chazelle, Descatha, & Roquelaure, 2018; Silverstein, Viikari-Juntura, & Kalat, 2002). Each industry is ranked by injury count, injury rate and associated medical cost, and arithmetic means of these ranks are calculated to obtain PI, a composite index reflecting the industry's risk rank.

The basic PI was calculated using the following formula. In case of a tie in basic PI, rate rank was used as the tiebreaker (Anderson et al., 2013; Bonauto et al., 2006).

$$\text{Basic PI} = \frac{count\ rank + rate\ rank}{2}$$

To reflect injury severity, the expanded PI further adds medical cost rate rank, in which the medical cost rate was calculated as the total medical cost incurred in an industry sector over the total employment in this sector (per 10,000 workers). The expanded PI was calculated using the following formula. In case of a tie in expanded PI, cost rank was used as the tiebreaker (Anderson et al., 2013; Bonauto et al., 2006).

$$Expanded\ PI = \frac{count\ rank + rate\ rank + cost\ rank}{3}$$

We calculated basic and expanded PIs for each NORA sector for disabling claims and non-disabling claims separately. In calculating PI ranks, we excluded categories with cases less than 10 claims over the study period from the analysis due to small sample size. PI ranks were also calculated for strata by selected factors including age group, gender and major injury types.

Due to the very small number of claimants aged below 14 years, separate statistics are not reported in this paper. We excluded claims with age below 10 years in age related calculations because ages were likely incorrectly coded in these claims. For analyses involving claim rates, claims with age below 14 years were excluded as no employment data (denominator) were available.

All statistical analyses were performed using R software (version 3.5.1). A two-sided 95% confidence level was applied when appropriate.

3. Results

3.1. Injury frequency and rate

There were 13,360 accepted disabling claims and 24,660 accepted non-disabling claims among Oregon young workers over the six-year study period from 2013 to 2018 (Table 1). Nine claims involved fatal injuries. There were no important differences between disabling claims and non-disabling in terms of claimants' gender and age group distribution (Table 1).

The overall disabling claim rate from 2013-2018 was 111.6 per 10,000 workers (95% Confidence Interval (CI): 109.7–113.5) (Table 1). The overall non-disabling claim rate was 401.3 per 10,000 workers (95% CI: 393.6–406.4), which was 3.60 times higher than the disabling claim rate (95% CI: 3.52–3.67). The median medical cost for disabling claims was $1,758, while the median medical cost for non-disabling claims was $499.

Table 1
Oregon workers' compensation disabling and non-disabling claims frequency, rate, medical cost by year and demographics, 2013–2018.

	Disabling Claims			Non-disabling Claims		
	#Claims (%)	Claim rate/10,000 (95% CI)	Rate ratio (95% CI)	#Claims (%)	Claim rate/10,000 (95% CI)	Rate ratio (95% CI)
Total	13,360 (100)	111.6 (109.7, 113.5)	/	24,660 (100)	401.3 (396.3, 406.4)	/
Year						
2013	2000 (15.0)	113.1 (108.2, 118.1)	1	3258 (13.2)	360.8 (348.6, 373.3)	1
2014	2157 (16.1)	115.4 (110.6, 120.3)	1.02 (0.96, 1.08)	3793 (15.4)	397.0 (384.5, 409.8)	1.10 (1.05, 1.15)
2015	2234 (16.7)	112.5 (108.0, 117.3)	1.00 (0.94, 1.06)	4016 (16.3)	396.0 (383.9, 408.4)	1.10 (1.05, 1.15)
2016	2417 (18.1)	116.7 (112.1, 121.4)	1.03 (0.97, 1.10)	4255 (17.3)	400.6 (388.7, 412.8)	1.11 (1.06, 1.16)
2017	2410 (18.0)	113.5 (109.1, 118.1)	1.00 (0.95, 1.07)	4519 (18.3)	413.4 (401.4, 425.5)	1.15 (1.10, 1.20)
2018	2142 (16.0)	99.3 (86.0, 95.1)	0.88 (0.83, 0.93)	4819 (19.5)	431.6 (419.5, 443.9)	1.20 (1.14, 1.25)
Gender						
Female	4926 (36.9)	79.8 (77.6, 82.1)	1	8890 (36.1)	282.9 (277.1, 288.9)	1
Male	8433 (63.1)	145.3 (142.3, 148.5)	1.82 (1.76, 1.89)	15,284 (62.0)	509.0 (501.0, 517.1)	1.80 (1.75, 1.85)
Age group						
14–18	1473 (11.0)	80.6 (76.6, 84.8)	1	2853 (11.6)	297.0 (286.3, 308.1)	1
19–21	5167 (38.7)	119.0 (115.8, 122.3)	1.48 (1.39, 1.56)	9470 (38.4)	429.3 (420.7, 438. 0)	1.45 (1.39, 1.51)
22–24	6719 (50.3)	115.7 (113.0, 118.5)	1.44 (1.36, 1.52)	11,807 (47.9)	396.4 (389.3, 403.6)	1.33 (1.28, 1.39)

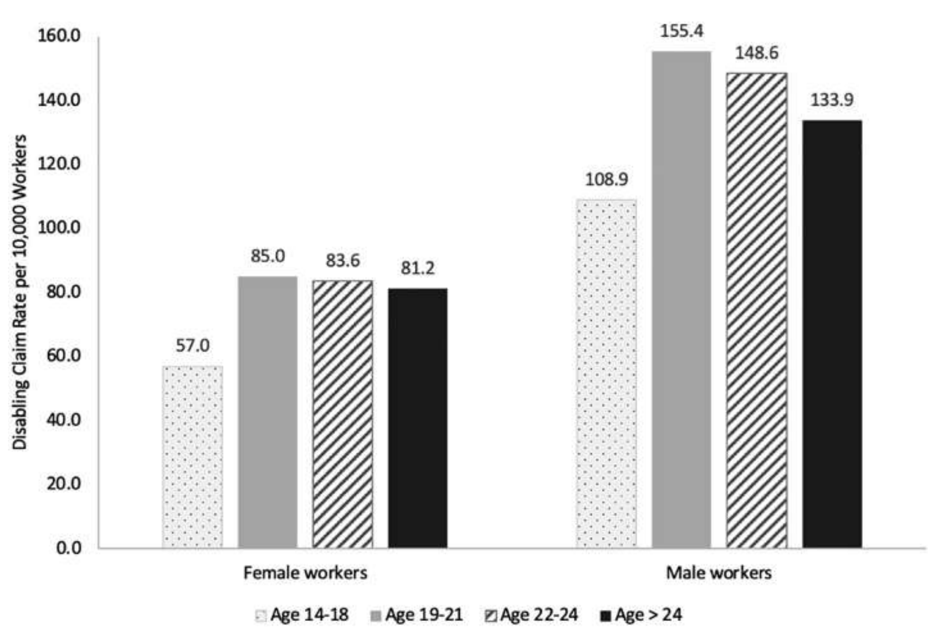

Fig. 1. Disabling injury rate by age group (including adult worker group) and gender, Oregon accepted disabling claims (2013–2018) (Female workers: N = 568 (14–18), 1904 (19–21), 2454 (22–24), 36,714 (>24); Male workers: N = 905 (14–18), 3263 (19–21), 4264 (22–24), 64,931 (>24)).

Table 2
Oregon workers' compensation claims frequency, proportion and medical cost by injury type, for young workers, 2013–2018.

Injury type	All Claims		Disabling Claims			Non-disabling Claims		
	#Claims	%Claims	#Claims	%Claims	Median Medical Cost	#Claims	%Claims	Median Medical Cost
Struck by/against	13,535	35.6	3235	24.2	1414.9	10,300	41.8	507.4
WMSDs	7425	19.5	4231	31.7	1793.6	3194	13.0	692.4
Fall on same level	3470	9.1	1702	12.7	1703.4	1768	7.2	552.7
Violence	2493	6.6	614	4.6	1548.7	1879	7.6	406.8
Others	2470	6.5	361	2.7	1757.5	2109	8.6	499.1
Caught in/under/between	1934	5.1	761	5.7	2659.7	1173	4.8	550.8
Rubbed or abraded	1402	3.7	47	0.4	965.9	1355	5.5	367
Transportation	1300	3.4	672	5.0	2835.7	628	2.5	295.5
Fall to lower level	1278	3.4	760	5.7	2247.2	518	2.1	666.6
Extreme temperature	1156	3.0	339	2.5	787.4	817	3.3	392.5
Toxic	851	2.2	125	0.9	936.1	726	2.9	338.5
Overexertion	398	1.0	304	2.3	5154.5	94	0.4	530.2
Bodily reaction	250	0.7	181	1.4	7984.2	69	0.3	788.8
Fire and explosion	58	0.2	28	0.2	2468.8	30	0.1	580.8

An increasing trend of both the claim count and rate during the study period was observed for non-disabling claims, with an estimated 1.03 times increase in injury rate each year (95% CI: 1.02–1.04). The trend in disabling claim rate remained fairly constant from 2013 to 2017 but dropped substantially in 2018. This drop in 2018 is likely due to data incompleteness in this year given less maturation time, which is a common phenomenon in disabling WC claims dataset (Yang et al., 2020).

Workers aged 19–21 (disabling: 119.0 per 10,000 workers and non-disabling: 429.3) and 22–24 years (115.7 and 396.4) had higher claim rates than the youngest workers aged 14–18 (80.6 and 297.0) (Table 1). Males had higher claim rates (disabling: 145.3 per 10,000 workers and non-disabling: 509.0) than females (79.8 and 282.9). For both disabling and non-disabling claims, the injury rate ratio comparing male and female workers decreased with increasing age (Rate Ratio (RR): >1.91 in age group 14–18 vs. <1.78 in age group 22–24, data not shown).

Fig. 1 further displays disabling claim rates by gender for all age groups, including adult workers aged above 24 years. The age group 19–21 years had the highest injury rates in both genders. Compared to female and male adult workers, injury rates in females and males in this age group were 1.05 (95% CI: 1.00–

Table 3
Claim rate for young workers, by injury type and NORA industry sector, Oregon workers' compensation accepted disabling ((N = 13360) and non-disabling claims (N = 24660), 2013–2018.

Injury type	All	Agriculture	Construction	Healthcare	Manufacturing	Mining	Public Safety	Service	Transportation	Wholesale & Retail
Disabling Claims (Per 10,000 workers, (95% Confidence Interval))										
WMSDs	35 (34, 36)	56 (49, 65)	46 (41, 53)	67 (63, 72)	59 (54, 65)	60 (19, 140)	52 (37, 71)	18 (17, 19)	120 (108, 133)	36 (33, 38)
Struck by/against	27 (26, 28)	90 (80, 101)	76 (68, 84)	12 (10, 14)	60 (54, 65)	30 (5, 93)	28 (17, 42)	19 (18, 20)	60 (51, 69)	24 (22, 26)
Caught in/ under/between	6.4 (5.9, 6.8)	27 (22, 33)	15 (12, 19)	1.3 (0.8, 2.0)	28 (25, 32)	60 (19, 140)	2.9 (0.5, 9)	3.4 (2.9, 3.9)	13 (9, 17)	4.8 (4, 5.6)
Rubbed or abraded	0.4 (0.3, 0.5)	3 (1.5, 5.4)	0.9 (0.3, 2.0)	/	2.1 (1.2, 3.3)	/	/	0.2 (0.1, 0.3)	0.4 (0, 1.6)	0.2 (0.1, 0.4)
Fall on same level	14 (14, 15)	47 (40, 55)	19 (15, 23)	15 (13, 17)	20 (17, 24)	15 (1, 66)	25 (15, 38)	12 (11, 13)	31 (25, 38)	11 (9, 12)
Fall to lower level	6.3 (5.9, 6.8)	27 (22, 33)	42 (37, 49)	2 (1.5, 3)	7.7 (5.9, 9.9)	15 (1, 66)	8.7 (3.5, 18)	4.1 (3.6, 4.7)	16 (11, 21)	3.2 (2.6, 3.9)
Transportation	5.6 (5.2, 6.1)	21 (17, 27)	12 (9, 16)	4.2 (3.2, 5.3)	4.5 (3.1, 6.1)	/	16 (8, 27)	4.3 (3.8, 4.9)	17 (12, 22)	5 (4.3, 5.9)
Violence	5.1 (4.7, 5.5)	7.3 (4.8, 11)	1.7 (0.8, 3.2)	27 (24, 30)	0.5 (0.2, 1.2)	/	34 (22, 49)	2.2 (1.9, 2.6)	2.1 (0.8, 4.3)	1.2 (0.8, 1.7)
Non-disabling Claims (Per 10,000 workers, (95% Confidence Interval))										
WMSDs	52 (50, 54)	66 (57, 76)	59 (51, 67)	105 (99, 112)	101 (92, 111)	123 (49, 249)	33 (18, 54)	29 (27, 31)	53 (40, 69)	50 (46, 55)
Struck by/against	168 (164, 171)	257 (239, 276)	420 (399, 442)	71 (65, 77)	371 (352, 389)	430 (272, 641)	51 (32, 76)	136 (132, 140)	146 (123, 172)	155 (147, 162)
Caught in/ under/between	19 (18, 20)	35 (28, 42)	33 (27, 39)	11 (8.5, 13)	63 (56, 71)	82 (25, 190)	18 (8, 34)	12 (11, 13)	19 (12, 29)	21 (18, 24)
Rubbed or abraded	22 (21, 23)	41 (34, 48)	85 (76, 95)	5 (3.7, 6.7)	84 (75, 93)	123 (49, 249)	15 (6, 31)	11 (10, 13)	25 (17, 37)	16 (14, 18)
Fall on same level	29 (27, 30)	52 (44, 61)	31 (25, 37)	36 (33, 41)	34 (28, 39)	41 (7, 126)	41 (24, 64)	25 (24, 27)	36 (25, 49)	22 (19, 25)
Fall to lower level	8.4 (7.7, 9.2)	37 (31, 45)	37 (31, 43)	2.9 (1.9, 4)	11 (8.3, 15)	62 (15, 159)	2.5 (0.1, 11.2)	4.2 (3.6, 5.0)	18 (11, 28)	5.5 (4.2, 7.1)
Transportation	10 (9.4, 11)	24 (18, 30)	21 (16, 26)	8 (6.3, 10)	8.8 (6.2, 12)	41 (7, 126)	5.1 (0.8, 16)	7.8 (6.8, 8.8)	32 (22, 45)	11 (8.7, 13)
Violence	31 (29, 32)	55 (47, 64)	8.9 (6.2, 12.4)	121 (114, 128)	6.4 (4.2, 9.1)	/	36 (20, 58)	16 (15, 17)	9.5 (4.6, 17)	8.9 (7.2, 11)

NORA: National Occupational Research Agenda.

Table 4
NORA industry sectors ranked by prevention index (PI) for young workers, Oregon workers' compensation accepted disabling ($N = 13360$) and non-disabling claims ($N = 24660$), 2013–2018.

NORA Sector Description	Disabling Claims					Non-disabling Claims				
	Claim Count	Claim Rate/ 10,000 Workers	Cost Rate/ 100 Workers	Basic PI	Expanded PI	Claim Count	Claim Rate/ 10,000 Workers	Cost Rate/ 100 Workers	Basic PI	Expanded PI
Agriculture, Forestry & Fishing (except Wildland Firefighting and including seafood processing)	1017	310.2	20965.9	1	1	1959	668.9	7031.8	5	4
Construction	1086	234.5	14666.1	2	3	2614	730.7	6359.1	1	3
Healthcare & Social Assistance (including Veterinary Medicine/Animal Care)	1988	138.6	5125.5	5	6	4640	531.7	4841.0	3	5
Manufacturing (except seafood processing)	1535	201.5	10762.4	4	5	2975	726.6	6514.1	2	1
Mining	15	225.6	37458.1	8	4	44	901.6	10200.9	4	2
Public Safety (including Wildland Firefighting)	126	183.4	11288.4	9	8	119	302.4	3009.5	9	9
Services (except Public Safety and Veterinary Medicine/Animal Care)	4212	71.8	3031.9	7	9	8760	286.2	2278.1	7	8
Transportation, Warehousing & Utilities	806	284.5	15190.0	3	2	346	366.2	3587.2	8	7
Wholesale and Retail Trade	2548	92.4	3789.7	6	7	3176	313.7	2598.9	6	6

1.10) and 1.16 times (95% CI: 1.12–1.20) higher. The youngest age group (14–18) had the lowest injury rates, which were 0.70 (95% CI: 0.65–0.76) and 0.81 (95%CI: 0.76–0.87) times those of female and male adult workers.

3.2. Injury nature and major types

Most claims involved the injury nature, "traumatic injuries and disorders" (92.6% in both disabling and non-disabling claims combined), followed by "infectious and parasitic diseases" (4.6%) and "diseases and disorders of body systems" (2.0%). Other and multiple diseases, conditions, disorders, and symptoms accounted for less than 1% of the claims; however, they incurred much higher medical cost. For example, the median medical cost in these injury natures was $10,656 as compared with $1,722 in the above three more common injury natures in disabling claims.

Regarding injury types, "struck by/against" was the most common type accounting for 35.6% of disabling and non-disabling claims combined, followed by WMSDs (19.5%), "fall on same level" (9.1%), and violence (6.6%) (Table 2). Non-disabling claims involved a higher proportion of "struck by/against" (41.8% vs. 24.2%) and violence (7.6% vs. 4.6%) injuries relative to the disabling claims. Young workers had more "struck by/against" injuries (36.0% vs. 13.8%) and less WMSDs (19.5% vs. 35.7%) as compared to adult workers (in disabling claims). Considering medical cost, WMSDs tended to have higher medical cost compared to other injury types, which was especially evident in non-disabling claims (Table 2).

Claim rates by major injury types and the nine NORA sectors are presented in Table 3. The "agriculture, forestry & fishing" (hereinafter referred to as agriculture) sector had much higher than average rates for all major injury types. Although the mining sector did not have claim records for all these major injury types, it had high rates in the injury types that had claims. WMSDs had high rates in nearly all NORA sectors, with "healthcare & social assistance" (hereinafter referred as healthcare), manufacturing, and mining sectors having the highest rates for both disabling and non-disabling claims. Disabling WMSDs rate was exceptionally high in the "transportation, warehousing & utilities" (hereinafter referred as transportation) sector (RR: 3.4; 95% CI: 3.04–3.79, compared with the average disabling WMSDs rate). "Struck by/against" injuries were concentrated in production sectors such as agriculture, construction and manufacturing. It is worth noting that violence injuries were concentrated in few sectors including healthcare, agriculture and public safety, while the other sectors had extremely low rates.

3.3. Identifying industries of high risk

Nine NORA industry sectors were ranked using the basic and expanded PIs (Table 4). For disabling claims, the agriculture sector ranked the highest with both the basic and expanded PIs, followed by construction, transportation, and manufacturing. The mining sector ranked among the lowest with basic PI, however it ranked high on expanded PI, which incorporates medical costs. For non-disabling claims, the manufacturing and construction sectors had the highest ranks with both basic and expanded PIs. Compared to disabling claims, the agriculture and transportation sectors ranked relatively lower. Again, mining sector ranked high with expanded PI. In both disabling and non-disabling claims, "services (except public safety and veterinary medicine/animal care)" (hereinafter referred to as services) and "wholesale and retail trade" ranked fairly low given their low injury rates.

Stratified by gender, for both disabling and non-disabling claims, the healthcare sector ranked the highest for female workers but among the lowest for male workers (Tables S1 and S2 in Appendix 1). Both the ranks of claim count and rate of this industry were very high among female workers. On the other hand, construction and agriculture were among the top ranked sectors for male workers but among the lowest ranked for female workers, as decided by the low count and rate ranks of the two industries among female workers. Further examination showed that male claimants dominated the construction and agriculture sectors (>87%), while there were mostly female claimants in the healthcare sector (80%) (Tables S3–S5).

We further ranked industry groups based on NAICS 4-digit codes. These results are included in Appendix 2 (Tables S6–S8) but not discussed in this paper.

4. Discussion

Injury is the leading cause of death as well as years of potential life lost for children and young adults (Graitcer, 1987). Preventing work-related injuries and illnesses among young workers continues to be a critical need. The present study explored the use of both disabling and non-disabling WC claims data to document patterns of work-related injuries and illnesses among Oregon young workers aged 24 years and under from 2013 to 2018. Using a prevention index method, the study systematically prioritized industry sectors with a high injury risk for young workers.

4.1. Trend and types of injuries and illnesses among young workers

The study identified an overall disabling injury rate of 111.6 per 10,000 workers for young workers, which is slightly lower than the reported disabling injury rate of 122.7 per 10,000 workers for Oregon young workers from 2000-2007 in the previous study (Walters et al., 2010). Consistent with other studies, workers aged 19–21 and 22–24 had higher rates than adult workers, and this was particularly evident among male workers (Breslin et al., 2003; Centers for Disease Control and Prevention, 2006; Salminen, 2004; Walters et al., 2010). The study quantified a non-disabling injury rate approximately four times the rate of disabling injuries among Oregon young workers, which has not been reported before. Findings from the study highlighted the importance of using both disabling and non-disabling WC claims data for a more complete description of injuries and illnesses among young workers (Tables S6–S8).

Common injury types identified for Oregon young workers were similar to those for Oregon adult workers in this study, as well as to those reported in the state of Washington for workers of all ages combined (Anderson et al., 2013). Consistent with existing studies (Breslin & Smith, 2005; Breslin et al., 2003; Laberge & Ledoux, 2011), we found that the overall proportion of WMSDs among young workers was less than that among adult workers. Young workers may have less time to develop impaired musculoskeletal functioning compared with older workers (Breslin et al., 2003), however, a progressive history of WMSD and other musculoskeletal conditions accumulated since young age may lead to higher risk to more injuries and permanent disability (Breslin et al., 2003; Saha & Sadhu, 2013). WMSDs accounted for a higher proportion in disabling claims than non-disabling claims among young workers, showing that WMDS injuries occurred to young people were more severe and costly.

In contrast to WMSDs, "struck by/against" injuries were more common among young workers than adult workers. They were more prevalent in non-disabling claims, indicating this type of injury may be less severe but happen more often among young workers. "Struck by/against" injuries refer to those produced by forcible contact or impact between the injured person and sources. Most injuries of this type involved open wounds or surface wounds and bruises (80.9%). "Struck by/against" injuries were concentrated in production sectors such as agriculture, construction, and manufacturing, where young workers often work with machinery and equipment tools. These machines may be particularly dangerous to young workers, especially the younger age group, as they are usually not designed to fit young workers' physical body frames, leading to awkward postures and injuries (Runyan & Zakocs, 2000). Young workers often hold jobs with fast-pace and higher levels of physical exertion, lack experience, access to training and appropriate supervision (Breslin et al., 2005; Dragano et al., 2018; Hanvold et al., 2018; Laberge & Ledoux, 2011; Runyan et al., 2007; Salminen, 2004). Education and other intervention programs to increase young people's safety skills and knowledge and awareness of workplace hazards, as well as development and adoption of workplace equipment and arrangement that are safer to young workers help to reduce their vulnerability to many workplace injuries including "struck by/against."

4.2. Prioritizing industries for prevention intervention

No previous study has systematically ranked high-risk industries for young workers. This study reported high ranked NORA sectors in both disabling and non-disabling claims. The findings can inform research and intervention targets by integrating injury count, rate, and cost burden. Previous studies commonly reported agriculture, manufacturing, trade and service sectors as hazardous for adolescent and young adult workers (Belville, Pollack, Godbold, & Landrigan, 1993; Horwitz & McCall, 2005; McCall et al., 2007; Walters et al., 2010). Our study suggested that agriculture, construction, and manufacturing sectors should be priority targets as they had fairly high injury counts and rates, as well as high medical cost associated with the injuries and illnesses. It is of note that the mining sector had high expanded PI ranks due to its very high claim rate and cost rate, despite that it was ranked low with basic PI due to the fewest claim counts. Although the mining industry has historically been seen as one of the most dangerous industries in the United States for its high death toll and high injury rate for all ages (Margolis, 2010), few previous studies highlighted concern on the mining sector for young workers. Given the high injury rate and associated medical cost among Oregon young workers, more research is needed to investigate young workers' safety and health in these industries at the state and local level. Prevention efforts in these industries must consider how to target young workers or create provisions specific for younger workers.

4.3. Gender difference

In line with most studies on gender difference regarding work-related injuries (Breslin & Smith, 2005; Breslin et al., 2003; Horwitz & McCall, 2005; Layne et al., 1994; Miller & Kaufman, 1998; Mujuru & Mutambudzi, 2007; Walters et al., 2010), the study showed that male young workers had the most injuries with almost doubled injury rate compared with their female counterparts. Recognizing the high burden of injury and illness among male workers, researchers also pointed out a bias in occupational health that it tends to emphasize injuries and risk factors typically associated with male workers and overlook those associated with women (Breslin et al., 2007; Laberge & Ledoux, 2011; Taylor, Neis, Messing, & Dumais, 1996). Our study showed that male young workers dominated in most high rank sectors. In fact, the high ranked industries for both genders combined mostly represented patterns of male young workers. For example, agriculture and construction, ranked high for males, were ranked low for females. On the other hand, the healthcare sector, ranked the highest for females, was listed low in the combined list. By making lists specifically for female workers, the study revealed industries and injury types that contributed disproportionately to occupational injury and illness in female young workers.

4.4. Limitations

Despite the strength of including both disabling and non-disabling claims data, injuries and illnesses are likely to be underestimated due to under-coverage and under-reporting issues with WC claims (Azaroff, Levenstein, & Wegman, 2002; Biddle, Roberts, Rosenman, & Welch, 1998; Oregon State Legislature, 2019; Shannon & Lowe, 2002; Tucker et al., 2014). Young workers are more likely to be under-counted as they often engage in temporary or seasonal work, or self-employment arrangements such as farm work or with family businesses, which are not covered by Oregon WC (Oregon State Legislature, 2019).

Without data on the number of workers covered by SAIF, we had to weight employment data using claims proportion based on the assumption that the workforce covered by SAIF was the same as that by other insurers, defined by factors of the study's interest such as age and gender. We understand that this assumption might not hold true. However, we think the estimation is appropriate for this explorative study, given the fact that SAIF is the largest WC provider in Oregon and covers the majority of Oregon employers. Data interoperability in disabling and non-disabling data was another challenge in this study. Despite our best effort to develop a crosswalk between WCIO and OIICS, misclassification was unavoidable in certain codes that cannot be perfectly matched.

5. Conclusions and practical applications

The study explored the expanded use of WC data by including both disabling and non-disabling claims data in a recent 6-year period from 2013 to 2018 in describing young workers' injury burden. The findings of this study complement previous studies with a more complete report on work-related injuries and illnesses among young workers.

In summary, young workers experienced significantly more non-disabling injuries than disabling injuries across different industry sectors, age and gender groups. For both disabling and non-disabling claims, male young workers and workers aged 19–21 and 22–24 years had a greater injury burden than female workers and workers aged 14–18. Common injury types included "struck by/against," WMSDs, "fall on same level," and violence, with differences observed between disabling and non-disabling claims, and across industries and genders. The study is the first to report a systematic ranking of industry sectors with high injury risk among young workers as a whole as well as in sub-groups.

The study has practical applications for young workers' occupational safety and health. A more complete picture of work-related injuries and illnesses based on multiple data sources provides evidence to both develop and evaluate targeted prevention interventions for Oregon young workers. High ranked industry sectors including agriculture, construction, manufacturing, and healthcare sectors should be priority targets to reduce both the number and rate of injuries and illnesses among young workers. Interventions targeting certain industry could aim for major injury types that are prevalent in the sector and consider the applicability and acceptance of intervention among young workers. For example, WMSDs and violence injuries should be the focus in healthcare sector, but an intervention for a younger worker may include additional emphasis on the recognition of musculoskeletal discomfort as a precursor to future cumulative trauma. The study team has been actively working on disseminating up-to-date and interpretable information based on this study to young workers and to help guide appropriate intervention actions through connection with field practitioners. For example, interpretable information has been disseminated through the Oregon Young Employee Safety Coalition (O[yes]), which works to prevent injuries and illnesses to young workers through outreach and sharing of resources (Oregon Young Employee Safety Coalition (O[yes]), 2020).

Exploring non-disabling claims data from commercial WC insurers and the use of the prevention index methodology enhances OSH surveillance of young workers, as well as other worker groups. Continued efforts to obtain non-disabling data and to examine data representativeness would increase the completeness and accuracy in monitoring injuries and illnesses among young workers. The study methodology could be adopted by other states to inform prevention efforts with state WC data.

6. Authors' contributions

L.Y. substantially worked on conception and design of the study, analysis and interpretation of data, writing of the manuscript. L.K. guided the study. L.K., A.B., V.B., C.C. and C.W. substantially contributed to analysis and interpretation of data. C.C., C.W. L.Y. and L.K. substantially contributed to the acquisition of data. All authors worked on revising of the manuscript critically for important intellectual content, and final approval to be published.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

This work was supported by the U.S. Centers for Disease Control and Prevention (CDC), the National Institute for Occupational Safety and Health (NIOSH) [Grant number: 5 U60 OH00872-15-00 (formerly 5 U60 OH00872-14)].

Funding

This work was supported by the Centers for Disease Control and Prevention, the National Institute for Occupational Safety and Health [Grant number: 5 U60 OH00872-15-00 (formerly 5 U60 OH00872-14)].

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Liu Yang MS, MPH, PhD completed this work as a graduate student at Oregon State University. She received an M.S. in Environmental Engineering, MPH in Biostatistics and Ph.D. in Public Health. She has more than 10 years of experience in occupational safety and health research and practice. Her research focuses on workplace injuries and illnesses and associated risk factors for vulnerable populations including construction workers and young workers, as well as occupational safety and health surveillance methods and evaluation.

Adam Branscum PhD is a Professor and Director of Biostatistics in the College of Public Health and Human Sciences at Oregon State University. He received an M.S. in Epidemiology and Ph.D. in Statistics from UC Davis in 2005. He is Associate Editor of *Biometrics*. Previously he was Editor of *Statistical Methods in Medical Research* and Associate Editor of *The American Statistician* and *Bayesian Analysis*. He co-authored the book *Bayesian Ideas and Data Analysis*. His research focuses on nonparametric Bayesian methodology.

Viktor Bovbjerg MPH, PhD is a Professor of Epidemiology at Oregon State University. His research focuses on injury control and prevention, including injuries in high risk occupational settings. He has extensive experience using data ranging from in-person interviews to secondary data from healthcare settings in order to assess risk and to identify high risk activities and settings.

Curtis Cude BS is a program manager in the Environmental Public Health section of the Oregon Health Authority. He has over 25 years of experience in the fields of occupational health, environmental health, water quality protection and information systems development. He is the Principal, Multi- or Co-Investigator on several CDC, EPA, NIH and state-funded grants. His research focuses on occupational health surveillance, environmental health interventions and water insecurity.

Crystal Weston MPA serves as the Program Coordinator for the Occupational Public Health and Pesticide Exposure Safety and Tracking programs at the Oregon Health Authority. In this role she coordinates partnerships and manages research and surveillance projects that improve the health of Oregonians. She has over 15 years of experience designing and managing health initiatives, as a community health worker, and in health research. She has a BS in Psychology (University of California) and an MPA with a concentration in Management from the University of Oregon.

Laurel Kincl PhD, CSP is an Associate Professor of Environmental and Occupational Health at Oregon State University. She has more than 15 years of experience in research, outreach, and educational programs related to occupational health and safety. Her research focusses on quantifying, communicating, and controlling occupational exposures to health and safety hazards with the goal to reduce adverse health outcomes. She is the Principal or co-Investigator on several NIH and CDC funded grants and has completed research in a variety of high risk industries including commercial fishing, logging, construction and health care.

Appendix 1

Table S1
NORA industry sectors ranked by prevention index (PI) for **male** young workers, Oregon workers' compensation accepted disabling (N = 8433) and non-disabling claims (N = 15284), 2013–2018.

NORA Sector Description	Claim Count	Claim Rate/ 10,000 Workers	Cost Rate/ 100 Workers	Basic PI	Expanded PI	Claim Count	Claim Rate/ 10,000 Workers	Cost Rate/ 100 Workers	Basic PI	Expanded PI
	Disabling Claims					Non-disabling Claims				
Agriculture, Forestry & Fishing (except Wildland Firefighting and including seafood processing)	887	375.8	26357.7	1	1	1651	782.5	7908.8	3	4
Construction	1050	262.3	16495.2	2	3	2478	801.2	6849.2	2	2
Healthcare & Social Assistance (including Veterinary Medicine/Animal Care)	397	125.1	4162.2	9	9	859	445.0	3561.3	7	5
Manufacturing (except seafood processing)	1219	223.5	12082.0	4	5	2503	853.6	7312.3	1	1
Mining	14	236.5	41408.4	8	4	41	942.5	11198.1	4	3
Public Safety (including Wildland Firefighting)	92	245.0	15070.7	7	6	85	396.5	3166.3	9	9
Services (except Public Safety and Veterinary Medicine/Animal Care)	2493	94.0	3955.0	6	8	5059	366.9	2771.4	6	8
Transportation, Warehousing & Utilities	645	314.2	17184.1	3	2	279	406.3	3800.9	8	7
Wholesale and Retail Trade	1618	115.5	4865.1	5	7	2311	442.2	3541.0	5	6

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Table S2
NORA industry sectors ranked by prevention index (PI) for **female** young workers, Oregon workers' compensation accepted disabling (N = 4926) and non-disabling claims (N = 8890), 2013–2018.

NORA Sector Description	Claim Count	Claim Rate/ 10,000 Workers	Cost Rate/ 100 Workers	Basic PI	Expanded PI	Claim Count	Claim Rate/ 10,000 Workers	Cost Rate/ 100 Workers	Basic PI	Expanded PI
	Disabling Claims					Non-disabling Claims				
Agriculture, Forestry & Fishing (except Wildland Firefighting and including seafood processing)	130	141.4	7094.7	6	4	276	336.7	4392.5	4	3
Construction	36	57.5	2992.2	8	8	87	179.8	2370.8	7	5
Healthcare & Social Assistance (including Veterinary Medicine/Animal Care)	1590	142.3	5396.1	1	3	3689	542.7	5017.4	1	1
Manufacturing (except seafood processing)	316	146.9	7470.5	3	2	426	368.4	3725.1	2	2
Mining	/					/				
Public Safety (including Wildland Firefighting)	34	109.1	6721.1	7	6	25	139.5	1185.7	8	8
Services (except Public Safety and Veterinary Medicine/Animal Care)	1719	53.4	2270.1	5	7	3510	208.7	1683.8	3	4
Transportation, Warehousing & Utilities	161	207.6	10002.9	2	1	53	206.4	1749.8	6	6
Wholesale and Retail Trade	930	68.5	2679.5	4	5	816	166.5	1430.4	5	7

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Appendix 2

Table S3
Top 5 NAICS Industry groups ranked by prevention index (PI) for young workers, Oregon workers' compensation accepted disabling and non-disabling claims, 2013–2018.

NORA sector	4-digit NAICS	Industry group (4-digit NAICS Description)	Claim Count	Claim Rate/10,000 Workers	Cost Rate/100 Workers	Basic PI	Expanded PI
Disabling Claims							
Agriculture	1133	Logging	217	788.8	79941.6	1	1
Agriculture	1153	Support Activities for Forestry	191	481.1	33162.7	2	2
Healthcare	2381	Foundation, Structure, and Building Exterior Contractors	273	429.2	31059.1	3	3
Manufacturing	3219	Other Wood Product Manufacturing	179	433.7	21519.0	4	4
Wholesale & Retail	4244	Grocery and Related Product Merchant Wholesalers	198	329.9	19507.7	5	6
Non-disabling Claims							
Healthcare	6239	Other Residential Care Facilities	643	8712.7	71249.1	1	1
Healthcare	6231	Nursing Care Facilities (Skilled Nursing Facilities)	1377	2356.7	26040.7	2	2
Construction	2383	Building Finishing Contractors	778	1373.6	11955.9	3	5
Manufacturing	3331	Agriculture, Construction, and Mining Machinery Manufacturing	178	5562.5	49842.6	4	3
Manufacturing	3211	Sawmills and Wood Preservation	322	1816.1	18314.5	5	4

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Table S4
Top 5 NAICS Industry groups ranked by prevention index (PI) for **male** young workers, Oregon workers' compensation accepted disabling and non-disabling claims, 2013–2018.

NORA sector	4-digit NAICS	Industry group (4-digit NAICS Description)	Claim Count	Claim Rate/10,000 Workers	Cost Rate/100 Workers	Basic PI	Expanded PI
Disabling Claims							
Agriculture	1133	Logging	216	835.9	85001.3	1	1
Construction	2381	Foundation, Structure, and Building Exterior Contractors	268	469.8	34186.6	2	2
Agriculture	1153	Support Activities for Forestry	184	525.7	34440.0	3	3
Manufacturing	3219	Other Wood Product Manufacturing	159	457.8	22283.9	4	5
Transportation	4931	Warehousing and Storage	156	424.0	30393.0	5	4
Non-disabling Claims							
Healthcare	6239	Other Residential Care Facilities	179	6884.6	53307.1	1	1
Manufacturing	3331	Agriculture, Construction, and Mining Machinery Manufacturing	159	5845.6	46271.8	2	2
Construction	2383	Building Finishing Contractors	739	1512.8	12388.6	3	5
Manufacturing	3211	Sawmills and Wood Preservation	291	1796.3	18456.4	4	3
Manufacturing	3219	Other Wood Product Manufacturing	297	1590.8	12939.6	5	7

NORA: National Occupational Research Agenda.

Table S5
Top 5 NAICS Industry groups ranked by prevention index (PI) for **female** young workers, Oregon workers' compensation accepted disabling and non-disabling claims, 2013–2018.

NORA sector	4-digit NAICS	Industry group (4-digit NAICS Description)	Claim Count	Claim Rate/ 10,000 Workers	Cost Rate/100 Workers	Basic PI	Expanded PI
Disabling Claims							
Healthcare	6231	Nursing Care Facilities (Skilled Nursing Facilities)	252	334.3	11642.9	1	1
Healthcare	6221	General Medical and Surgical Hospitals	293	268.6	9774.7	2	3
Healthcare	6232	Residential Intellectual and Developmental Disability, Mental Health, and Substance Abuse Facilities	201	293.6	11255.1	3	3
Transportation	4921	Couriers and Express Delivery Services	56	525.3	26491.1	4	2
Healthcare	6233	Continuing Care Retirement Communities and Assisted Living Facilities for the Elderly	415	179.5	6889.8	5	10
Non-disabling Claims							
Healthcare	6239	Other Residential Care Facilities	443	9229.2	74996.9	1	1
Healthcare	6231	Nursing Care Facilities (Skilled Nursing Facilities)	1177	2509.6	28178.2	2	2
Healthcare	5419	Other Professional, Scientific, and Technical Services	292	1334.6	8217.7	3	3
Healthcare	8129	Other Personal Services	130	797.6	5419.0	4	8
Healthcare	6212	Offices of Dentists	244	638.4	4400.7	4	11

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Table S6

Top 5 NAICS Industry groups by major NORA industry sector ranked by prevention index (PI) for young workers, Oregon workers' compensation accepted **disabling** claims, 2013–2018.

NORA sector	4-digit NAICS	Industry group (4-digit NAICS Description)	Claim Count	Claim Rate/ 10,000 Workers	Cost Rate/ 100 Workers	Basic PI	Expanded PI
Agriculture, Forestry & Fishing (except Wildland Firefighting and including Seafood Processing)	1133	Logging	217	788.8	79941.6	1	1
	1153	Support Activities for Forestry	191	481.11	33162.7	2	2
	1119	Other Crop Farming	123	301.32	24426.0	3	3
	1151	Support Activities for Crop Production	156	284.46	14363.3	3	4
	1121	Cattle Ranching and Farming	65	319.88	16977.2	5	5
Construction	2381	Foundation, Structure, and Building Exterior Contractors	273	429.18	31059.1	1	1
	2361	Residential Building Construction	197	257.89	15746.2	2	2
	2383	Building Finishing Contractors	169	230.5	15333.2	3	3
	2389	Other Specialty Trade Contractors	91	209.05	11439.7	4	5
	2382	Building Equipment Contractors	184	164.29	8028.9	4	6
Healthcare & Social Assistance (including Veterinary Medicine/Animal Care)	6231	Nursing Care Facilities (Skilled Nursing Facilities)	275	292.8	10004.2	1	1
	6221	General Medical and Surgical Hospitals	383	278.59	9819.1	1	2
	6232	Residential Intellectual and Developmental Disability, Mental Health, and Substance Abuse Facilities	262	261.35	9727.5	3	4
	6233	Continuing Care Retirement Communities and Assisted Living Facilities for the Elderly	476	157.3	6005.1	4	6
	6222	Psychiatric and Substance Abuse Hospitals	49	1195.12	23106.6	5	3
Manufacturing (except Seafood Processing)	3219	Other Wood Product Manufacturing	179	433.73	21519.0	1	1
	3362	Motor Vehicle Body and Trailer Manufacturing	106	436.93	17362.8	2	2
	3211	Sawmills and Wood Preservation	104	315.34	20099.4	3	3
	3114	Fruit and Vegetable Preserving and Specialty Food Manufacturing	157	258.18	10731.6	4	9
	3371	Household and Institutional Furniture and Kitchen Cabinet Manufacturing	58	270.02	16277.9	5	7
Services (except Public Safety and Veterinary Medicine/Animal Care)	5613	Employment Services	740	201.19	9533.1	1	2
	5617	Services to Buildings and Dwellings	333	222.64	10931.3	2	1
	8111	Automotive Repair and Maintenance	138	145.68	7108.3	3	5
	9241	Administration of Environmental Quality Programs	23	297.54	24270.1	4	3
	9231	Administration of Human Resource Programs	23	165.83	8134.6	5	7
Transportation, Warehousing & Utilities	4811	Scheduled Air Transportation	85	840.75	29126.3	1	1
	4841	General Freight Trucking	115	359.38	23004.2	2	2
	4931	Warehousing and Storage	185	301.06	20401.2	2	3
	4842	Specialized Freight Trucking	89	387.46	15391.3	2	4
	4921	Couriers and Express Delivery Services	190	280.48	15230.0	5	5
Wholesale and Retail Trade	4244	Grocery and Related Product Merchant Wholesalers	198	329.89	19507.7	1	1
	4413	Automotive Parts, Accessories, and Tire Stores	154	198.84	10316.2	2	2
	4441	Building Material and Supplies Dealers	158	152.82	6479.3	3	7
	4421	Furniture Stores	43	209.96	8580.4	4	4
	4451	Grocery Stores	526	118.7	3876.1	4	10

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Table S7
Top 5 Industry groups under each major NORA industry sector ranked by prevention index (PI) for young workers, Oregon workers' compensation accepted **non-disabling** claims, 2013–2018.

NORA sector	4-digit NAICS	Industry group (4-digit NAICS Description)	Claim Count	Claim Rate/ 10,000 Workers	Cost Rate/ 100 Workers	Basic PI	Expanded PI
Agriculture, Forestry & Fishing (except Wildland Firefighting and including seafood processing)	1133	Logging	312	1259.08	16702.5	1	1
	1153	Support Activities for Forestry	415	1160.19	13135.7	2	2
	1119	Other Crop Farming	257	698.75	6815.7	3	4
	1131	Timber Tract Operations	41	2645.16	23922.5	4	3
	1129	Other Animal Production	35	1174.5	13167.1	5	5
Construction	2383	Building Finishing Contractors	778	1373.59	11955.9	1	1
	2381	Foundation, Structure, and Building Exterior Contractors	349	710.22	5645.7	2	3
	2382	Building Equipment Contractors	546	631.07	4927.8	2	5
	2389	Other Specialty Trade Contractors	263	782.04	5920.4	4	3
	2379	Other Heavy and Civil Engineering Construction	74	1541.67	25863.0	5	2
Healthcare & Social Assistance (including Veterinary Medicine/Animal Care)	6239	Other Residential Care Facilities	643	8712.74	71249.1	1	1
	6231	Nursing Care Facilities (Skilled Nursing Facilities)	1377	2356.67	26040.7	2	2
	5419	Other Professional, Scientific, and Technical Services	335	1182.07	6542.0	3	3
	6221	General Medical and Surgical Hospitals	451	527.3	4172.1	4	7
	6222	Psychiatric and Substance Abuse Hospitals	100	3921.57	27482.1	5	4
Manufacturing (except seafood processing)	3331	Agriculture, Construction, and Mining Machinery Manufacturing	178	5562.5	49842.6	1	1
	3211	Sawmills and Wood Preservation	322	1816.13	18314.5	2	2
	3219	Other Wood Product Manufacturing	327	1474.3	12078.0	3	3
	3323	Architectural and Structural Metals Manufacturing	160	1515.15	12244.3	4	4
	3339	Other General Purpose Machinery Manufacturing	125	2055.92	11970.9	4	6
Services (except Public Safety and Veterinary Medicine/Animal Care)	9241	Administration of Environmental Quality Programs	144	3348.84	21636.7	1	1
	6113	Colleges, Universities, and Professional Schools	565	714.74	5114.9	2	7
	5413	Architectural, Engineering, and Related Services	146	989.16	8652.7	3	4
	5617	Services to Buildings and Dwellings	477	634.65	5775.9	4	6
	7212	RV (Recreational Vehicle) Parks and Recreational Camps	106	1606.06	16850.3	5	3
Transportation, Warehousing & Utilities	4859	Other Transit and Ground Passenger Transportation	52	4727.27	40569.0	1	1
	4841	General Freight Trucking	177	1614.96	17650.8	2	2
	2211	Electric Power Generation, Transmission and Distribution	19	2878.79	19363.0	3	2
	4911	Postal Service	12	4000	40691.7	4	2
	4921	Couriers and Express Delivery Services	19	81.9	587.4	5	5
Wholesale and Retail Trade	4233	Lumber and Other Construction Materials Merchant Wholesalers	121	2180.18	26269.0	1	1
	4441	Building Material and Supplies Dealers	343	943.6	8127.8	2	6
	4411	Automobile Dealers	349	938.68	7019.3	2	7
	4235	Metal and Mineral (except Petroleum) Merchant Wholesalers	85	2656.25	28355.7	4	2
	4239	Miscellaneous Durable Goods Merchant Wholesalers	105	1539.59	10735.5	5	4

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Table S8
Top 3 NAICS Industry groups ranked by prevention index (PI) for four major injury types among young workers, Oregon workers' compensation accepted disabling and non-disabling claims, 2013–2018.

Injury Type	NORA sector	4-digit NAICS	Industry group (4-digit NAICS Description)	Claim Count	Claim Rate/ 10,000 Workers	Cost Rate/ 100 Workers	Basic PI	Expanded PI
Disabling Claims								
Work-related Musculoskeletal Disorders	Healthcare	6231	Nursing Care Facilities (Skilled Nursing Facilities)	197	209.8	6984.4	1	1
	Healthcare	6221	General Medical and Surgical Hospitals	239	173.8	6136.2	2	2
	Transportation	4931	Warehousing and Storage	94	153.0	7553.1	3	3
Struck by/against	Agriculture	1133	Logging	90	327.2	45906.5	1	1
	Construction	2381	Foundation, Structure, and Building Exterior Contractors	91	143.1	8365.9	2	3
	Agriculture	1153	Support Activities for Forestry	61	153.7	13077.3	3	2
Fall on same level	Agriculture	1133	Logging	42	162.5	7491.4	1	1
	Agriculture	1153	Support Activities for Forestry	41	117.1	7271.5	2	2
	Construction	2381	Foundation, Structure, and Building Exterior Contractors	22	38.6	1827.5	3	3
Violence	Healthcare	6232	Residential Intellectual and Developmental Disability, Mental Health, and Substance Abuse Facilities	145	144.6	4932.8	1	2
	Healthcare	6222	Psychiatric and Substance Abuse Hospitals	33	804.9	15067.5	2	1
	Healthcare	8129	Other Personal Services	30	73.8	3238.8	3	3
Non-disabling Claims								
Work-related Musculoskeletal Disorders	Healthcare	6231	Nursing Care Facilities (Skilled Nursing Facilities)	516	883.1	13915.8	1	1
	Healthcare	6239	Other Residential Care Facilities	92	1246.6	16438.9	2	1
	Manufacturing	3211	Sawmills and Wood Preservation	50	282.0	4591.6	3	3
Struck by/against	Construction	2383	Building Finishing Contractors	459	939.6	7174.0	1	2
	Manufacturing	3331	Agriculture, Construction, and Mining Machinery Manufacturing	80	2941.2	22160.9	2	1
	Manufacturing	3219	Other Wood Product Manufacturing	178	953.4	6605.6	3	4
Fall on same level	Healthcare	6239	Other Residential Care Facilities	42	569.1	4449.7	1	1
	Healthcare	6231	Nursing Care Facilities (Skilled Nursing Facilities)	103	176.3	2092.0	2	2
	Agriculture	1133	Logging	41	165.5	1339.4	3	3
Violence	Healthcare	6239	Other Residential Care Facilities	237	3211.4	29056.6	1	1
	Healthcare	5419	Other Professional, Scientific, and Technical Services	275	970.4	4288.3	2	2
	Healthcare	6222	Psychiatric and Substance Abuse Hospitals	54	2117.7	15440.9	3	3

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Journal of Safety Research 77 (2021) 229–240

Contents lists available at ScienceDirect

Journal of Safety Research

journal homepage: www.elsevier.com/locate/jsr

Behavioral pathways in bicycle-motor vehicle crashes: From contributing factors, pre-crash actions, to injury severities

Jun Liu [a,*], Steven Jones [a], Emmanuel Kofi Adanu [b], Xiaobing Li [b]

[a] Department of Civil, Construction and Environmental Engineering, The University of Alabama, Tuscaloosa, AL 35487, United States
[b] Alabama Transportation Institute, The University of Alabama, Tuscaloosa, AL 35487, United States

ARTICLE INFO

Article history:
Received 2 September 2019
Received in revised form 18 August 2020
Accepted 26 February 2021
Available online 18 March 2021

Keywords:
Bicycle-motor vehicle crash
Behavioral pathway
Pre-crash action
Path analysis
Marginal effects

ABSTRACT

Introduction: This study performed a path analysis to uncover the behavioral pathways (from contributing factors, pre-crash actions to injury severities) in bicycle-motor vehicle crashes. *Method:* The analysis investigated more than 7,000 bicycle-motor vehicle crashes in North Carolina between 2007 and 2014. Pre-crash actions discussed in this study are actions of cyclists and motorists prior to the event of a crash, including "bicyclist failed to yield," "motorist failed to yield," "bicyclist overtaking motorist," and "motorist overtaking bicyclist." *Results:* Model results show significant correlates of pre-crash actions and bicyclist injury severity. For example, young bicyclists (18 years old or younger) are 23.5% more likely to fail to yield to motor traffic prior to the event of a crash than elder bicyclists. The "bicyclist failed to yield" action is associated with increased bicyclist injury severity than other actions, as this behavior is associated with an increase of 5.88 percentage points in probability of a bicyclist being at least evidently injured. The path analysis can highlight contributing factors related to risky pre-crash actions that lead to severe injuries. For example, bicyclists traveling on regular vehicle travel lanes are found to be more likely to involve the "bicyclist failed to yield" action, which resulted in a total 44.38% (7.04% direct effect + 37.34% indirect effect) higher likelihood of evident or severe injuries. The path analysis can also identify factors (e.g., intersection) that are not directly but indirectly correlated with injury severity through pre-crash actions. *Practical Applications:* This study offers a methodological framework to quantify the behavioral pathways in bicycle-motor vehicle crashes. The findings are useful for cycling safety improvements from the perspective of bicyclist behavior, such as the educational program for cyclists.

1. Introduction

Cycling is an important mode of transportation around the world. In many societies, it serves daily transport needs such as commuting or accessing social and economic opportunities (Ogilvie et al., 2004). Cycling is also an important recreational activity around the world (De Hartog et al., 2010). In either case, cycling presents many potential benefits including reduced traffic congestion, fuel consumption, and air pollution (Hamilton & Wichman, 2018). In addition, cycling, as an active transportation mode, brings health benefits to cyclists. For example, regular cycling under good air-quality conditions was found to reduce the risk of obesity, cancer, and diabetes (Khreis et al., 2019).

The potential benefits of cycling, however, must be weighed against the risks of potential injuries and deaths attributable to crashes, especially those involving motor vehicles (Ogilvie et al., 2004). Indeed, bicyclists are categorized as vulnerable road users (VRUs) along with motorcyclists, pedestrians, and other forms of non-motorized transportation (e.g., animal-powered) due to their inherent mass difference (and exposure or protection) when compared to motor vehicles. As such, bicyclists and other VRUs are at greater risk of injury, especially severe ones (Ogilvie et al., 2004).

Recent data indicate that there were 840 bicyclist fatalities in the United States in 2016 comprising 2.2% of total road deaths over this period (NHTSA, 2018). The nationwide data revealed that 71% of bicyclist fatalities occurred in urbanized areas and that males were considerably more likely (5.6 times) to be killed as a bicyclist than were females. The data also showed that alcohol was a factor in 35% of all fatal bicyclist crashes, where either a motor-vehicle driver and/or the bicyclist was under the influence of alcohol.

Many researchers have undertaken studies into the nature of bicycle-involved crashes and their outcomes. The majority of previous studies on the subject have focused on the identification of relationships among factors contributing to crashes between

* Corresponding author.
E-mail addresses: jliu@eng.ua.edu (J. Liu), sjones@eng.ua.edu (S. Jones), ekadanu@crimson.ua.edu (E.K. Adanu), xli158@ua.edu (X. Li).

https://doi.org/10.1016/j.jsr.2021.02.015
0022-4375/

bicyclists and motor vehicles and the resulting injury severities. These studies have primarily focused on modeling direct relationships among contributing factors and injury outcomes (Hu et al., 2014; Kaplan et al., 2014; Behnood & Mannering, 2017; Chen et al., 2017; Robartes & Chen, 2017; Salon & McIntyre, 2018). In doing so, these studies treat the actions of bicyclist and motorists immediately prior to the crash in parallel with other contextual contributing factors reported in the crash data (crash type, bicyclist and motorist demographics, location, facility type, etc.).

We explore a path analysis approach to uncover underlying relationships between contextual factors contributing to the occurrence and severity of bicycle crashes and the actions (i.e., behaviors) contributing immediately preceding a crash event. In doing so, we are able to draw indirect linkages among key bicyclist and motorist actions and the behavioral pathways leading up to them prior to a crash. The indirect linkages are particularly important when they reveal factors that may not be directly related to the crash outcome, but they have a significant relationship with dangerous pre-crash actions, which eventually lead to a severe crash.

2. Literature review

2.1. Contextual crash contributing factors

There have been numerous studies documenting direct relationships between injury severities and factors contributing to bicycle crashes involving motor vehicles. These studies have been based on different sets of contributing factors as best served the research purpose and data availability of the individual analysis. Table 1 summarizes contributing factors analyzed in a sample of key previous bicycle crash studies.

Demographics are often included in the injury severity discussions. Most studies reported that bicyclist age is significantly related to bicyclist injury severity (Kim et al., 2007; Yan et al., 2011; Kaplan et al., 2014; Behnood & Mannering, 2017; Salon & McIntyre, 2018) and age is positively correlated with injury severity (Kim et al., 2007; Yan et al., 2011; Kaplan et al., 2014; Behnood & Mannering, 2017; Salon & McIntyre, 2018); older cyclists are more likely to be severely injured than younger cyclists. The involvement of alcohol and drugs typically increases the injury severity of bicycle crashes, especially with bicyclists (Kim et al., 2007; Kaplan et al., 2014; Behnood & Mannering, 2017; Robartes et al., 2017). Several studies documented the positive role of the use of protective equipment (e.g., helmet, or reflective suit) in reducing injury severities among bicyclists (Kim et al., 2007; Kaplan et al., 2014; Behnood & Mannering, 2017; Chen & Shen (2016); Salon & McIntyre, 2018. Some studies have reported increased severity of crashes involving larger vehicles (Kim et al., 2007; Yan et al., 2011; Behnood & Mannering, 2017; Chen & Shen (2016); Salon & McIntyre, 2018; Robartes et al., 2017.

Due to the unavailable data about bike facility, most studies failed to include bike lane-related factors in their discussions. Kaplan et al. (2014) showed that bike lanes are associated with a decreased likelihood of severe injury. However, Chen et al. (2017) observed an opposite relationship; they found that bike lanes are often provided at higher classes of roads with higher traffic speeds. Rather obviously, injury severities were shown to increase with the speed of motor vehicles at the time of a crash (Robartes et al., 2017; Salon & McIntyre, 2018), whereas, no significant effect was attributed to the bicycle speed. Kim et al. (2007) found that if a bicyclist was facing the traffic (opposite direction) when a crash occurred, the crash typically resulted in severer injuries than

Table 1
Summary of previous bicyclist injury severity studies.

Factors	Contributing Factor	Selected Studies							
		Kim et. al., 2007	Yan et. al., 2011	Kaplan et. al., 2014	Chen & Shen (2016)	Behnood & Mannering, 2017	Robartes et. al., 2017	Chen et. al., 2017	Salon et. al., 2018
Bicyclist-related	Age	**	***	***	*	***			***
	Gender					***			***
	Alcohol or drug	***		***		***	**		***
	Protective equipment	***		***	**	***			**
Motorist related	Age			***		*			
	Gender			***		**			
	Alcohol or drug	***				**	***		#
	Vehicle type	***	***	***	***	***	***		**
Roadway related	Land use	***		***	***				
	Bike facility			***				***	
	Road characteristics	***	***	**		*	***	***	
	Traffic control					**		#	**
	Traffic volume							*	
Environment related	Season								***
	Weekday	***							
	Time of day	*	***					**	
	Weather	**				#	***		
	Road condition			***			**		
	Lighting	***	***	***	*	***			***
Crash related	Bicycle speed						*		#
	Motor vehicle speed	***	***	***	*		***	*	
	Traffic direction	***							
	Collision type	*	***			***			
	Crash location		***	**		***		*	**
	Pre-crash action	***		***	***	***			***

Notes: Empty cell means not reported in final models; # not significant at 90% confidence level; * significant at 90% confidence level; ** significant at 95% confidence level; *** significant at 99% confidence level.

crashes where the bicycle and car were traveling in the same direction. More injury severity correlates are summarized in Table 1. Crashes that occurred at different locations may cause uneven injury severities. Kaplan et al. (2014); Behnood & Mannering, 2017 both reported that intersection crashes were associated with less severe injury to bicyclists than crashes occurring at mid-block or along sections of open road – likely further substantiating the effect of vehicle speed. And finally, with regard to pre-crash actions, the behavior of bicyclist and/or motor-vehicle driver prior to the crash event was found to be a significant contributing factor determining bicyclist injury severity independently from the other contextual factors in some studies (Kim et al., 2007; Kaplan et al., 2014; Behnood & Mannering, 2017; Salon & McIntyre, 2018; Chen & Shen (2016).

2.2. Pre-crash action

Road users, both bicyclists and drivers, interact with the immediate context of the road and its environment based on their perception and judgment, as well as their motives for traveling (commuting, leisure, etc.). Therefore, it is reasonable to investigate the independent relationship between pre-crash actions and other contextual contributing factors. Indeed, some previous researchers have offered insights into how pre-crash actions affect bicycle-vehicle crashes (Schramm et al., 2008; Yan et al., 2011). These studies found that pre-crash actions significantly relate to the demographics of bicyclists and motorists. Generally, given a bicycle-motor vehicle crash, males and younger bicyclists are more likely to violate traffic rules or fail to give way to other road users. In addition, pre-crash actions are found to relate to the environment, such as the presence of median, night with or without streetlights, and so forth. Table 2 summarizes some of the key findings related to pre-crash actions of both bicyclists and motorists documented in key previous studies.

However, limited discussions have focused on the complete behavior pathway, from contributing factors, pre-crash actions to injury severity. Giving the modeling insights from previous studies, this study uses a new database and re-develops models for pre-crash actions (associations between contributing factors and pre-crash actions) and injury severity (relationships between pre-crash actions along with other factors and injury severities) in bicycle-motor vehicle crashes. Through a path analysis, this study connects two models and highlights contributing factors that are likely related to risky pre-crash actions that lead to bicyclist injuries in bicycle-motor vehicle crashes.

3. Approach

3.1. Conceptual framework

As synthesized above, previous studies have addressed the explicit role of pre-crash actions in bicycle-vehicle crash severities. These studies offered insights into the direct relationships between them. In addition to revisiting such direct relationships, this study examines indirect relationships among contextual contributing factors and pre-crash actions via the conceptual framework to model behavioral pathways illustrated in Fig. 1. The behavioral pathway contains two parts: correlations between contributing factors and pre-crash action, and relationships between pre-crash action and bicyclist injury severity.

3.2. Data

In order to test the proposed behavioral pathway framework, we used data from a bicycle and pedestrian crash database maintained by the North Carolina Department of Transportation (NCDOT, 2018). The database contained crash records from North Carolina over the period 2007 to 2014. This is the primary database in which inputs of crash records by all traffic safety law enforcement officers in North Carolina are maintained. All bicyclist-involved crashes were extracted from the database and then crashes involving motorcycles and pedestrians were removed leaving only bicycle-vehicle crashes. The data were error-checked and observations with missing or clearly invalid information were

Table 2
Summary of previous studies addressing pre-crash actions and bicyclist injury severity.

Author, Year	Bicyclist pre-crash actions	Motorist pre-crash actions	Selected findings
Relationships between contributing factors and pre-crash actions			
Schramm et al., 2008	• Disregard for road rules	N/A	• Young bicyclist → Being at-fault (right-of-way conflict) prior to a crash
Yan et al., 2011	• Disobeying traffic signals • Failing to give way when turning • Non-compliant roadway-crossing	• Disobeying traffic signals • Failing to give way • Turning without due care • Following too close • Failing to give wayNon-compliant occupation of bikeway	• Young and male bicyclists → Disobey traffic signals • Higher speed limits → Bicyclists failing to give way when turning • Male and senior bicyclists → Non-compliant roadway-crossing • Presence of median → Bicyclists non-compliant roadway-crossing • Night with streetlight → Motorists disobeying signals • Peak hour → Motorists failing to give way, or following too close. • Night without streetlight → Motorists driving in wrong way
Relationship between pre-crash actions and injury severity			
Kim et al., 2007	• Turning/merging • Bicyclist at fault	• Turning/merging • Overtaking • Backing • Speeding • Driver at fault	• Speeding involved → Greater likelihood of bicyclist fatality • Either bicyclist or motorist at fault → Greater likelihood of non-fatal injuries
Kaplan et al., 2014	• Left or right turns • straight movements	• Left or right turns • Straight movements	• Bicycle going straight + motor vehicle going straight → Increased bicyclist-injury severity • Bicycle turning left → Increased bicyclist-injury severity
Salon & McIntyre, 2018	• Unsafe speed • Disregard for traffic signal	• Unsafe speed • Disregard for traffic signal • Driver right turn	• Cyclist Unsafe speed → Increased bicyclist injury severity for bicyclist-at-fault crashes • Cyclist disregard for traffic signal → Severer bicyclist injuries for driver-at-fault crashes
Behnood & Mannering, 2017	• Wrong side of road • Changing lanes • Right movement • Straight movement	• Wrong side of road • Straight movement • Opposite lane crossing • Left movement	• Bicyclist changing lanes → Increased bicyclist-injury severity • Motorist opposite lane crossing, Straight movement or left turn → Increased bicyclist-injury severity

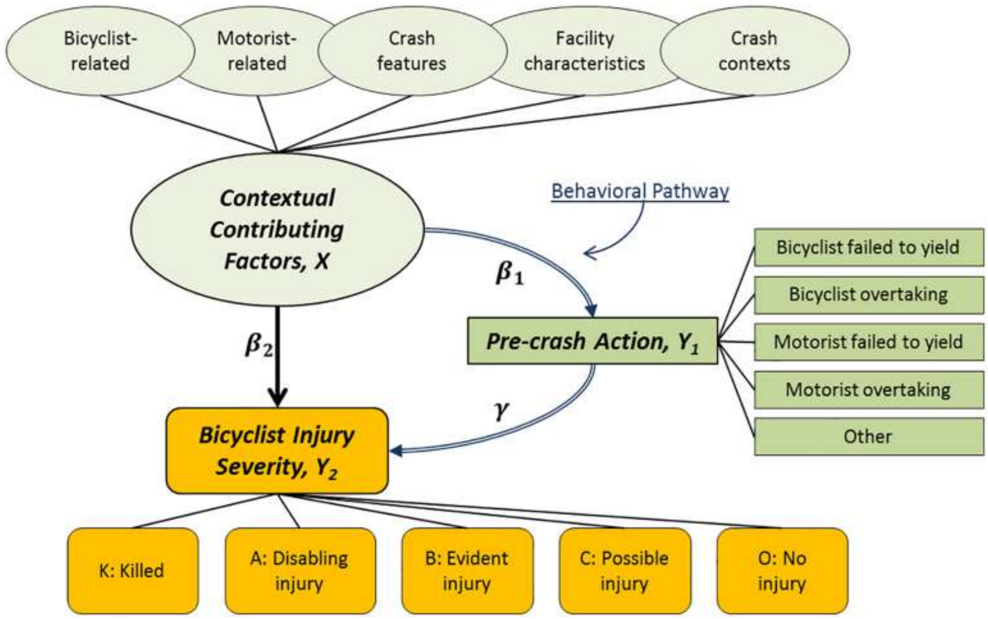

Fig. 1. Conceptual framework of modeling behavioral pathways in bicycle-motor vehicle crashes.

excluded from the final dataset for modeling. A total of 7,082 bicycle-motor vehicle crashes are sampled for this study. Table 3 presents the descriptive statistics of the pre-crash action and bicyclist injury severity variables.

This is a pre-processed database, rather than raw crash reports. This study identified pre-crash actions based on two variables in the database that briefly describe the behavior or movement of bicyclists and motorists prior to a crash. These descriptions often contain the information about pre-crash behavior and crash locations or some other critical information that is worth being noted here. These descriptions are pre-formulated into more than 20 categories, such as "bicyclist failed to yield – midblock," "bicyclist failed to yield – intersection," "motorist overtaking bicyclist," "motorist failed to yield – midblock," and "parallel paths – other circumstances." This study re-grouped crashes to highlight causal actions of bicyclists and motorists, as shown in Table 3. The information about crash location is captured by another newly created variable. This study models five categories of pre-crash actions and employs the KABCO Injury Classification Scale (AASHTO, 2010).

Table 4 also presents the summary statistics of other key variables that are available in the database. This study builds models to examine what variables are significantly related to pre-crash action and bicyclist injury severity. Noticeably, teenagers (11~18 years old) and mid-aged (35~50 years old) bicyclists were involved in the majority of the crashes. Over 85% of bicyclists involved were males. Nearly 6% of bicyclists were intoxicated by either alcohol or drugs at the time of the crash. Most bicycle-motor vehicle crashes (65%) occurred on travel lanes where bicycles and motor vehicles share the road, and 61% of crashes occurred when the bicyclists and motorists were traveling in the same direction. More findings can be found in Table 4.

Table 3
Descriptive statistics of pre-crash action and injury severity among sampled crash records variable.

		Frequency	Percent
Pre-crash action	Bicyclist failed to yield	1282	18.1%
	Bicyclist overtaking motorist	145	2.0%
	Motorist failed to yield	1395	19.7%
	Motorist overtaking bicyclist	1328	18.8%
	Other	2932	41.4%
Bicyclist Injury severity	O: No injury – 1	664	9.4%
	C: Possible injury – 2	2861	40.4%
	B: Evident injury – 3	3036	42.9%
	A: Disabling injury – 4	361	5.1%
	K: Killed – 5	160	2.3%

4. Methodology

Pre-crash action, as the response variable, may be regarded as a discrete choice that a bicyclist or motorist made prior to a crash. To model the discrete-choice response variable, we employ a multinomial logistic (MNL) model to estimate the correlates of pre-crash action (Yan et. al., 2011; Liu et. al., 2015). To account for the potential unobserved heterogeneity across observations, a random-parameter model is applied to allow estimates to vary across observations. The random-parameter MNL model is estimated by predicting the probability of one possible pre-crash action given a set of contributing factors:

$$\Pr(Y_1 = i) = \frac{\exp\left(\alpha_1^{(i)} + \beta_1^{(i)}X + Z_1^{(i)}U\right)}{\sum_1^n \exp\left(\alpha_1^{(i)} + \beta_1^{(i)}X + Z_1^{(i)}U\right)} \tag{1}$$

where Y_1 is the response variable (i.e., pre-crash action); i is one of five possible pre-crash actions; $\alpha_1^{(i)}$ is the constant term in estimates corresponding to pre-crash action i, X is a vector of explanatory variables (i.e., contributing factors); $\beta_1^{(i)}$ is a set of fixed coefficients of X corresponding to the pre-crash action$i$; U is a vector of variables with corresponding random parameters; and $Z_1^{(i)}$ is a set of random-parameters of U corresponding to the pre-crash action$i$; $Z_{1j}^{(i)} = \overline{Z}_{1j}^{(i)} + \Delta z_j + \Gamma v_j$, where j is the index for observations, $\overline{Z}_{1j}^{(i)}$ is the fixed means of the distributions for the random parameters, z_j is a set of M observed variables entering the means, Δ is the coefficient matrix forming the observations specific terms in the mean, v_j is the unobservable latent random term in jth observation following distributions (e.g., normal, uniform, triangular) with zero mean and

Table 4
Descriptive statistics of pre-crash action, bicyclist injury severity and contextual variables.

Variable		Freq.	Percent	Variable			Freq.	Percent
Bicyclist age	< = 10 yrs old	590	8.30%	Bicycle direction	Facing the traffic		1645	23.20%
	11∼18 yrs old	1503	21.20%		With the traffic		4318	61.00%
	19∼24 yrs old	1041	14.70%		Other or unknown		1119	15.80%
	25∼35 yrs old	946	13.40%	Crash location	Non-intersection		3572	50.40%
	35∼50 yrs old	1539	21.70%		Intersection	with signal	679	9.60%
	50∼65 yrs old	1149	16.20%			with sign	1266	17.90%
	>65 yrs old	314	4.40%			Other	1565	22.10%
Bicyclist gender	Female	1024	14.50%	Land use	Other		1108	15.60%
	Male	6058	85.50%		Commercial		2962	41.80%
Bicyclist intoxicated	No	5830	82.30%		Residential		3012	42.50%
	Yes	414	5.80%	Lighting	Daylight		5215	73.60%
	Missing info	838	11.80%		Dark with streetlights		834	11.80%
Bicycle	Travel lane	4626	65.30%		Dark without streetlights		667	9.40%
position	Bike lane	388	5.50%		Other		366	5.20%
	Sidewalk	1149	16.20%	Locality	Rural		1093	15.40%
	Driveway	185	2.60%		Mixed		973	13.70%
	Other	734	10.40%		Urban		5016	70.80%
Motorist age	Unknown	929	13.10%	Traffic volume (AADT)	<4400		1062	15.00%
	<= 20 yrs old	594	8.40%		4401∼9000		1083	15.30%
	21∼30 yrs old	1412	19.90%		9001∼15,000		1032	14.60%
	31∼45 yrs old	1634	23.10%		15,001∼23,000		1031	14.60%
	45∼65 yrs old	1785	25.20%		> 23,000		1166	16.50%
	>65 yrs old	728	10.30%		Unknown		1708	24.10%
Motorist gender	Female	2803	39.60%	Lane number	< = 2 lanes		4201	59.30%
	Male	3355	47.40%		3∼4 lanes		1526	21.50%
	Unknown	924	13.00%		> 4 lanes		1020	14.40%
Motorist intoxicated	No	5477	77.30%		Unknown		335	4.70%
	Yes	107	1.50%	Curve road	Yes		382	5.40%
	Missing info	1498	21.20%	Level road	Yes		5519	77.90%
Motor vehicle speed	<= 10 mph	2464	34.80%	Weather	Clear or cloudy		6760	95.50%
	11∼20 mph	1050	14.80%		Inclement weather		322	4.50%
	21∼30 mph	858	12.10%	Time of day	Early morning		403	5.70%
	31∼45 mph	1703	24.00%		Morning peak		709	10.00%
	>45 mph	504	7.10%		Mid-day		2376	33.50%
	Unknown	503	7.10%		Afternoon peak		2624	37.10%
Motor vehicle type	Auto	3772	53.30%		Night		970	13.70%
	Pickup	939	13.30%	Weekend	Yes		1707	24.10%
	SUV	1109	15.70%	Time of year	Spring		1418	20.00%
	Van	460	6.50%		Summer		3801	53.70%
	Truck or Bus	205	2.90%		Fall		1200	16.90%
	Other/unknown	597	8.40%		Winter		663	9.40%

variance one, and Γ is the lower triangular or diagonal matrix, which produces the covariance matrix of the random parameters.

Given the ordinal nature of injury severity, this study builds an ordered logistic model to show how contributing factors (plus pre-crash behavior) are associated with bicyclist injury severity. Again, with the consideration of unobserved heterogeneity crashes, a random-parameter multinomial logit model is estimated:

$$\Pr(Y_2 = c) = \frac{1}{1 + \exp\left(-k_c + \beta_2 X + \gamma Y_1 + Z_2 U\right)} - \frac{1}{1 + \exp\left(-k_{c-1} + \beta_2 X + \gamma Y_1 + Z_2 U\right)} \tag{2}$$

where Y_2 is the response variable, bicyclist injury severity; c is the specific level of injury severity level, $c = 1\sim5$ possible levels of injury severity; k_c is the threshold value for injury severity level$c$,$k_0 = -\infty$ and$k_5 = +\infty$; X is a vector of contributing factors excluding pre-crash action; β_2 is a set of coefficients corresponding to X; Y_1 is the pre-crash action, treated as an explanatory variable; γ is coefficient of Y_1; U is a vector of variables with a random parameter; and Z_2 is a set of random-parameters of U. $Z_{2j} = \overline{Z}_{2j} + \Delta h_j + \Gamma w_j$, where j is the index for observations, $\overline{Z}_{2j}$ is the fixed means of the distributions for the random parameters, z_j is a set of M observed variables entering the means, Δ is the coefficient matrix forming the observations specific terms in the mean, Γ is the diagonal matrix of standard deviations, and w_{jk_c} $N[0,1]$ is the unobservable latent random term in jth observation.

The model parameters are estimated by simulated maximizing likelihood. This method has been proved to be effective in generating accurate and quick approximations of the estimations, because the Monte Carlo integration method in the maximization process can perform risk analysis by building models of possible results by substituting a range of values based on various probability distribution functions (i.e., normal, log-normal, log-logistic and triangular) for random parameters that have inherent uncertainty. The default 1,000 Halton draws were used in this study, which is often done by other researchers (Behnood & Mannering, 2017; McFadden & Train, 2000). Monte Carlo Method then calculates results over and over based on the predefined number of Halton draws using a different set of random values from the probability functions each time and produces improved outcomes. A likelihood ratio test is performed to compare the random-parameter model with the regular logistic model that does not account for the unobserved heterogeneity. The test is done by calculating the ratio of log likelihoods of two models (Vuong, 1989):

$$LR = -2Ln\frac{LL_{regular}}{LL_{random-parameter}} \tag{3}$$

where $LL_{regular}$ is the estimated log likelihood of the regular model and $LL_{random-parameter}$ is the log likelihood of random-parameter model. The ratio is assumed to have an approximate χ^2 distribution with k degrees of freedom. k is the number of model parameters. If the χ^2 is larger than the 95-percentile value in the χ^2 distribution for the same degrees of freedom. A p-value is given to indicate whether the random-parameter model outperforms the regular model.

The unit of coefficients in both multinomial and ordered logistic models is log of the odds, showing the change of log of the odds of one response with one unit change in one explanatory variable if other variables are held constant. To quantify the behavioral pathway (i.e., combining β_1 and γ), this study calculates the marginal effects of explanatory variables based on the model coefficients. Marginal effects show the probability change of one response with one unit change in one explanatory variable if other variables held constant. For multinomial logistic models, marginal effects can be calculated by using the following equation:

$$\frac{\partial \Pr(Y_1 = i)}{\partial X} = \frac{\exp\left(f^{(i)}(X,U)\right)\left(\beta_1^{(i)}\right)' + \exp\left(f^{(i)}(X,U)\right)\left(\sum_{j=1}^{n}\exp\left(f^{(j)}(X,U)\right)\left(\left(\beta_1^{(i)}\right)' - \left(\beta_1^{(j)}\right)'\right)\right)}{\left[1+\sum_{j=1}^{n}\exp\left(f^{(j)}(X,U)\right)\right]^2} \tag{4}$$

where $f^{(i)}(X,U) = \alpha_1^{(i)} + \beta_1^{(i)}X + Z_1^{(i)}U$, and $f^{(j)}(X,U) = \alpha_1^{(j)} + \beta_1^{(j)}X + Z_1^{(j)}U$. For ordered logistic models, marginal effects can be estimated by using the following method:

$$\frac{\partial \Pr(Y_2 \le c)}{\partial X} = \frac{\exp\left(-k_c + \beta_2 X + \gamma Y_1 + Z_2 U\right)}{\left[1 + \exp\left(-k_c + \beta_2 X + \gamma Y_1 + Z_2 U\right)\right]^2}\beta_2{}' \tag{5}$$

Finally, we apply path analysis to quantify the behavioral pathways (Liu et al., 2015; Liu et al., 2016; Liu & Khattak, 2018) and quantitatively combine direct and indirect relationships among contextual contributing factors (X), pre-crash actions (Y_1), and bicyclist injury severity (Y_2). We illustrate the path analysis concept using the following simplified equations (6) and (7):

$$Y_1 = \alpha_1 + \beta_1 X \tag{6}$$

$$Y_2 = \alpha_2 + \beta_2 X_2 + \gamma Y_1 \tag{7}$$

Both equations represent linear form models to: (6) estimate the relationships β_1 between contributing factors$X$ and pre-crash actionY_1; and (7) express direct relationshipsβ_2 between bicyclist injury severity $Y_2$and contributing factorsX_2 plus pre-crash actionY_1. As such, the direct effects of the contextual contributing factors on injury severity are captured in addition to their influence on pre-crash actions. The two are then connected by γ.

Equation (6) models the relationships among contributing factors and pre-crash action, and Equation (7) models the correlates of bicyclist injury severity, similar to most previous studies. With marginal effects of two models, the correlates of pre-crash actions and their relationship with bicyclist injury severity can be combined as the indirect relationships between contributing factors and injury severity through pre-crash actions as written by equation (8):

$$IndirectMEofXonY_2 = \left(\mu_X + MEofXonY_1\right) * \left(\mu_{Y_1} + MEofY_1onY_2\right) - \mu_X * \mu_{Y_1} \tag{8}$$

where ME represents marginal effects; μ_X is the probability of the outcomes of Y_1 (i.e., pre-crash actions) when X is at its base; μ_{Y_1} is the probability of the outcomes of Y_2 (i.e., bicyclist injury severity) when Y_1 is at its base. The calculation example is shown in Results section. Direct marginal effects of contributing factors are calculated based on Equation (5) from the injury severity model. The total marginal effects of contributing factors on bicyclist injury severity are then given by equation (9) as:

$$TotalMEonY_2 = DirectMEofX_2onY_2 + IndirectMEofXonY_2 \tag{9}$$

where X_2 and X should be the same variable when their direct and indirect marginal effects are added.

5. Results

5.1. Pre-crash action model

Table 5 shows the results of random-parameter multinomial logistic model for correlates of pre-crash actions. The likelihood ratio test indicates that the random-parameter model outperformed the regular multinomial parameter model. As expected, some estimates are not statistically significant. Only variables with at least one level of attributes that is marginally significant (p-value <0.1) are kept in the final model. The results show the relationships between contributing factors and pre-crash actions. The model's goodness-of-fit seems reasonable (e.g., likelihood ratio test results in p-value 0.000, Pseudo-R^2 = 0.335). Marginal effects are also shown to help interpret modeling results. Marginal effect indicates the increase or decrease in percentage point of the probability of one response outcome (i.e., one pre-crash action) compared to the probability of this outcome when a variable of interest is at its base (e.g., female for bicyclist gender).

Compared to mid-aged bicyclists (36∼50 years old), young bicyclists seemed to be more likely to have engaged in the pre-crash action – "failed to yield." Given a bicycle-motor vehicle crash, bicyclists (10 years old or younger) appeared to associate with the greatest likelihood of failing to yield to the traffic prior to the crash. The marginal effect shows that these bicyclists were associated with an increase of 9.66 percentage points in the probability of engaging in pre-crash action – "failed to yield," relative to mid-aged bicyclists. For teenagers (11∼18 years old), the marginal effect is even higher – a 25.9% point increase. The results strongly suggest that educational programs focusing on traffic rules and riding behavior for students in school can help in preventing dangerous pre-crash behavior that may lead to bicycle crashes.

Operating a bicycle under the influence of alcohol or drugs has been consistently found to be dangerous on the road. The results in this study show that intoxicated bicyclists were more likely to be engaged in the pre-crash action – "bicyclists failed to yield," by 4.18 percentage point, compared to those who were not intoxicated. According to the scale parameter for this variable, there seems to be a relatively stable relationship between the bicyclist intoxication and the "bicyclists failed to yield" pre-crash action. In addition, the bicycling direction and location also have significant relationships with pre-crash actions across observations. In some cases, bicyclists may overtake a car if: (a) the car is slowing to make turn or stop due to traffic control, or (b) vehicle traffic is queued or otherwise traveling at a speed slower than the bicycle. Bicyclists were less likely to fail to yield to the traffic or overtake motorists when they were cycling on bike lanes or sidewalk, compared to those cycling in travel lanes with motor vehicles. The presence of a bike-lane or sidewalk seems to help prevent bicyclists from behaving inappropriately. Intersection is associated with a greater likelihood of "bicyclist failed to yield." But this variable holds a significant varying negative correlation with "bicyclist overtaking motorist," indicating that at other road locations (e.g., flat road segments with driveway), bicyclists might overtake motorists. "Bicyclist failed to yield" pre-crash behavior is also more likely to happen on multilane highways than two-lane roads. Other significant correlates of bicyclist pre-crash actions can be found in Table 5.

In terms of motorists' pre-crash actions, the results in Table 5 additionally show that motorists were more likely to fail to yield at speeds slower than 10 mph. Similarly, if motorists were driving through commercial or residential areas (vs. other land use), at

Table 5
Pre-crash Action Model Estimates and Marginal Effects.

Y_1 = Pre-crash action (base: other actions)		Bicyclist failed to yield		Bicyclist overtaking motorist		Motorist failed to yield		Motorist overtaking bicyclist	
Variable		β	ME	β	ME	Β	ME	β	ME
Constant		−4.705***	-	−7.941***	-	−1.204***	-	−5.397***	-
Bicyclist age (base: 36~50 yrs old)	<= 10 yrs old	3.193***	10.79%						
	11~18 yrs old	2.265***	25.90%						
	19~24 yrs old	0.978***	9.95%						
	25~35 yrs old	0.512**	4.80%						
	50~65 yrs old	0.727***	8.52%						
	>65 yrs old	0.631*	1.88%						
Bicyclist gender	Male								
Bicyclist intoxicated	Yes (base: no)	1.077***	4.18%						
Bicycle direction	With traffic (base: facing traffic)	−1.949***	−83.85%	4.869***	270.18%	−1.040***	−55.17%	4.020***	166.32%
Bicycle location	**Travel lane (vs. sidewalk or bike lane)**	1.298***	64.79%	**0.919***	**212.75%**				
Intersection	**Yes**	**0.391****	**59.67%**	−1.768***	−83.46%	0.905***	31.39%	−2.015***	−93.35%
Land use (base: other)	Commercial	0.496**	13.35%			0.893***	26.07%		
	Residential	0.173	4.41%			0.546***	19.01%		
Motorist intoxicated	Yes							0.580*	0.57%
Motorist age (base: 31~45 yrs old)	Unknown							0.788***	6.62%
	<= 20 yrs old							−0.067	−0.48%
	21~30 yrs old							0.014	0.24%
	45~65 yrs old							0.088	1.88%
	> 65 yrs old							0.740***	5.63%
Motor vehicle speed (base: <=10 mph)	**11~20 mph**	1.316***	10.17%	−1.125***	−15.67%	−1.391***	−17.68%	**0.827*****	**19.66%**
	21~30 mph	2.146***	12.02%	−2.882***	−34.30%	−1.966***	−22.08%	1.898***	18.62%
	31~45 mph	1.803***	29.26%	−2.840***	−67.04%	−2.553***	−59.39%	2.219***	32.32%
	> 45 mph	1.509***	9.29%	−2.761***	−19.22%	−3.999***	−28.33%	2.171***	6.54%
	Unknown	0.411	2.16%	1.948***	11.33%	−0.225*	−1.11%	1.418***	8.41%
Motor vehicle type (base: auto)	Pickup	−0.061	−0.57%	−1.118**	−14.44%			0.258**	2.48%
	SUV	0.042	0.42%	−0.094	−1.39%			0.147	1.92%
	Van	0.302	1.22%	0.898**	5.33%			−0.171	−0.93%
	Truck or Bus	−0.109	−0.22%	1.126**	2.82%			0.375	0.82%
	Other/unknown	−1.213***	−8.08%	−2.568***	−21.17%			0.579***	3.00%
Visibility and lighting (base: daylight)	Dark with streetlights	−0.112	−0.81%	−0.182	−2.02%	0.033	0.31%	0.378**	3.53%
	Dark without streetlights	−0.950***	−7.52%	−1.779**	−16.54%	0.483**	4.16%	0.695***	3.13%
Locality (base: mixed)	Rural					0.461**	6.56%	0.099	0.82%
	Urban					−0.015	−0.80%	−0.378***	−23.49%
Lane number (base: 2 lanes)	3~4 lanes	0.470***	6.16%			0.128	2.06%		
	> 4 lanes	0.602***	4.97%			0.135	1.38%		
	Unknown	−2.033***	−8.66%			−0.274*	−0.86%		
Curve or straight	Curve	−0.679***	−2.75%						
Level or grade	Level			0.508*	37.32%				
Inclement weather	Yes	−0.510*	−1.60%			−0.463***	−1.73%		
Time of day (base: other)	**Morning peak**					**0.491****	**7.19%**	−0.123	−0.96%
	Mid-day					0.558***	13.73%	−0.473***	−13.73%
	Afternoon peak					0.225	6.77%	−0.290**	−8.85%
Standard Deviations for Random Parameters (with normal distribution)	**Intersection**	2.788***							
	Travel lane (vs. sidewalk or bike lane)			1.556***					
	Morning peak					0.963***			
	Motor vehicle speed 11~20 mph (base: <=10 mph)							0.944*	
Summary Statistics	Number of observations	7082							
	Log likelihood at empty model	−9829.921							
	Log likelihood at convergence	−6540.905							
	Pseudo-R^2	0.335							
	Likelihood-Ratio Test (vs. Regular Multinomial Logit)	Prob = 0.000							

Notes: *** = significant at 99% level; ** = significant at 95% level; and * = significant at 90% level. Shaded cells = variables removed from the model if not significant at the 90% level. The bold variables and numbers indicate the random parameters with respect to each individual utility function.

night without streetlights (vs. daylight), in rural areas, under inclement weather conditions, during morning peak or mid-day (vs. other time in a day), they were also more likely to fail to yield.

As for the overtaking bicyclist pre-crash action, motorists were more likely to engage in this behavior when they were intoxicated, over 65 years old (vs. 31 to 45 years old), driving with speed over

10 mph (vs. 10 mph and under), driving with pick-up trucks (vs. passenger cars), or driving in the dark.

5.2. Bicyclist injury severity model

Table 6 presents estimates of bicyclist injury severity model and associated marginal effects. Model's goodness-of-fit seems reasonable (i.e., the Chi-square test results in p-value of 0.000), and signs of estimates are as expected compared to findings in a previous study by Kim et al. (2007). In general, modeling results are consistent with findings in previous studies (Kim et al., 2007; Martínez-Ruiz et al., 2013; Hu et al., 2014; Kaplan et al., 2014; Behnood & Mannering, 2017; Chen et al., 2017; Robartes & Chen, 2017; Salon & McIntyre, 2018).

Pre-crash actions are found to be significantly associated with bicyclist injury severity. Crashes that involved pre-crash actions of "bicyclist failed to yield" were more likely to result in severe injury than other crashes. Marginal effects show that pre-crash action of "bicyclist failed to yield" was associated with an increase of 6.11 percentage points (5.1%+0.77%+0.24%) in probability of having an evident injury or more severe injury. The estimated random parameters (with normal distribution) that this pre-crash action has a substantially varying relationship with the bicyclist injury severity across observations, indicating significant unobserved heterogeneity in this relationship. Regarding the other three pre-crash actions, estimates of "bicyclist overtaking motorist" and "motorist failed to yield" are not statistically significant, but estimates of "motorist overtaking bicyclist" are statistically significant. According to the negative estimate signs of these three pre-crash actions, bicyclists themselves may be partially responsible for their own injuries owing to their improper behaviors on road.

Factors relating to bicyclist age and gender are also significantly related to injury severity. As expected, younger bicyclists were less likely to be severely injured than seniors, and females are more likely to be injured than males. Operating a vehicle or a bicycle under influence of alcohol or drugs is dangerous, as confirmed by

Table 6
Bicyclist Injury Severity Model Estimates and Marginal Effects.

Y_2 = Bicyclist injury severity		Model		Marginal Effects				
Variable		β		O	C	B	A	K
Constant		2.356	***					
Pre-crash action (base: other actions)	**Bicyclist failed to yield**	0.246	***	−1.29%	−4.83%	5.10%	0.77%	0.24%
	Bicyclist overtaking motorist	−0.031		0.18%	0.61%	−0.67%	−0.09%	−0.03%
	Motorist failed to yield	−0.024		0.13%	0.46%	−0.50%	−0.07%	−0.02%
	Motorist overtaking bicyclist	−0.169	**	0.99%	3.23%	−3.60%	−0.47%	−0.15%
Bicyclist age (base: 36~50 yrs old)	<= 10 yrs old	−0.254	**	1.56%	4.78%	−5.46%	−0.68%	−0.21%
	11~18 yrs old	−0.192	***	1.12%	3.66%	−4.09%	−0.53%	−0.16%
	19~24 yrs old	−0.082		0.47%	1.59%	−1.75%	−0.23%	−0.07%
	25~35 yrs old	−0.234	***	1.41%	4.43%	−5.01%	−0.63%	−0.19%
	50~65 yrs old	0.101		−0.55%	−1.97%	2.12%	0.31%	0.09%
	> 65 yrs old	0.258	**	−1.30%	−5.08%	5.27%	0.84%	0.26%
Bicyclist gender	Male	−0.242	***	1.25%	4.75%	−5.00%	−0.77%	−0.24%
Bicyclist intoxicated	**Yes (base: no)**	0.285	***	−1.42%	−5.61%	5.81%	0.93%	0.29%
Bicycle direction	With traffic (base: facing traffic)	0.269	***	−1.54%	−5.17%	5.71%	0.77%	0.24%
Bicycle location	**Travel lane (vs. sidewalk or bike lane)**	0.282	***	−1.69%	−5.35%	6.03%	0.77%	0.24%
Motorist intoxicated	**Yes (base: no)**	1.133	***	−4.00%	−21.19%	17.87%	5.49%	1.83%
Motor vehicle speed (base: <=10 mph)	11~20 mph	0.278	***	−1.43%	−5.46%	5.72%	0.89%	0.28%
	21~30 mph	0.600	***	−2.76%	−11.78%	11.69%	2.17%	0.69%
	31~45 mph	0.922	***	−4.26%	−17.84%	17.61%	3.41%	1.09%
	> 45 mph	1.734	***	−5.41%	−30.07%	21.83%	10.06%	3.59%
	Unknown	0.042		−0.23%	−0.81%	0.88%	0.12%	0.04%
Motor vehicle type (base: auto)	Pickup	0.170	**	−0.90%	−3.32%	3.53%	0.53%	0.16%
	SUV	0.099		−0.54%	−1.93%	2.08%	0.30%	0.09%
	Van	0.244	**	−1.24%	−4.80%	5.01%	0.79%	0.25%
	Truck or Bus	−0.033		0.18%	0.63%	−0.69%	−0.09%	−0.03%
	Other/unknown	−0.102		0.59%	1.96%	−2.18%	−0.29%	−0.09%
Visibility and lighting (base: daylight)	Dark with streetlights	0.167	**	−0.88%	−3.28%	3.48%	0.52%	0.16%
	Dark without streetlights	0.368	***	−1.81%	−7.25%	7.43%	1.23%	0.39%
Curve or straight	**Curve**	0.495	***	−2.28%	−9.74%	9.70%	1.77%	0.56%
Level or grade	Level	−0.412	***	2.09%	8.08%	−8.41%	−1.34%	−0.42%
Standard Deviations for Random Parameters (with normal distributions)	Bicyclist failed to yield (base: other actions)	0.942	***					
	Motorist overtaking bicyclist (base: other actions)	0.830	***					
	Bicyclist intoxicated	1.238	***					
	Travel lane (vs. side walk or bike lane)	0.781	***					
	Motorist intoxicated	0.885	***					
	Dark without streetlights	1.206	***					
	Curve road	0.884	***					
Mu (01)		2.681	***					
Mu (02)		5.947	***					
Mu (03)		7.454	***					
Summary Statistics	Number of observations	7082						
	Log likelihood at empty model	−8417.329						
	Log likelihood at convergence	−8029.38						
	Pseudo-R^2	0.046						
	Likelihood-Ratio Test (vs. Regular Ordered Logit)	Prob. = 0.000						

Notes: *** = significant at 99% level; ** = significant at 95% level; and * = significant at 90% level. Variables are removed from the model if not significant at the 90% level. The bold variables are estimated with random parameters.

the severity model. Increased bicyclist injury severity is associated with crashes that involved an intoxicated bicyclist or motorist. Marginal effects show an increase of 7.03 percentage points in probability of a bicyclist having an injury at B or more severe levels, if the bicyclist was intoxicated. The marginal effect can, unfortunately, be as high as a 25.19 percentage point increase if the intoxicated one is the motorist.

In addition, the model shows that bicyclist injury severity could be increased in a crash when the bicyclist was traveling the same direction with traffic as opposed to facing the traffic (i.e., opposite direction). There are several possible reasons. When traveling the same direction, either the bicyclist or motorist may not notice each other; under this situation, there is minimal time for the bicyclist or motorist to respond promptly and properly, and the collision may happen at relatively higher speeds. Additionally, the reasons may be related to other contextual factors such as visibility. For example, Table 5 shows that motorists were more likely to overtake a cyclist in the dark with no streetlights. Many factors that could affect model estimation remain unobserved. For concrete reasons, a deeper investigation specifically focused on this type of bicycle-motor vehicle crashes might be needed.

Bicycle location is another significant contributing factor with random parameters (normally distributed). The findings show that where a bicyclist was at a sidewalk or in a bike lane, he or she was less likely to have severe injuries in a crash, relative to one cycling in motor vehicle travel lane. As expected, motor-vehicle speed is strongly related to bicyclist injury. Severer injuries were associated with higher speeds. Relative to the base speed (<=10 mph), speeds higher than 45 mph can result in an increase of 35.48 percentage point in probability of a bicyclist having an injury at B or higher level. Among vehicle types involved, vans were found to be associated with an increased bicyclist injury severity in a bicycle-motor vehicle crash. Crashes that occurred in darkness without streetlights and at curved roads were also associate with severe injuries to bicyclists. More correlates of bicyclist injury severity can be found in Table 6.

5.3. Path analysis

The path analysis is a quantitative process of combining marginal effects from the two models above. The injury severity model provides direct marginal effects of contributing factors on injury severity, including the marginal effects of pre-crash actions. The pre-crash action model delivers marginal effects of contributing factors on pre-crash actions. Given that pre-crash action has a marginal effect on injury severity, the indirect marginal effects of contributing factors through pre-crash actions can be quantified. Marginal effect (ME) of a variable (e.g., bicyclist gender) indicates the increase or decrease in percentage point of the probability of one response outcome (e.g., one pre-crash action, or fatal injury) compared to the probability of this outcome when this variable is at its base (e.g., female for bicyclist gender).

Table 7 synthesizes the process of quantifying behavioral pathways to obtain the total MEs of contributing factors on bicyclist injury severity. MEs from insignificant model estimations (p-value >0.05) are omitted, assuming zero MEs. In the severity model, among pre-crash actions, the estimates of "bicyclist failed to yield" and "motorist overtaking bicyclist" are statistically significant. We select "bicyclist failed to yield" to show an example of qualifying the behavioral pathways, and also this study is focused on the bicyclists. Therefore, in Table 7, Y_1 refers to the pre-crash action of "bicyclist failed to yield." As shown in Table 5, one contributing factor has one ME on each level of bicyclist injury severity, and clearly, MEs on "O: No injury" and "C: Possible injury" have different signs from those on other three higher levels of injury severity including "B: Evident injury," "A: Disabling injury," and "K: Killed." This study summarizes the MEs for three higher injury severity levels, referring to MEs of contributing factors on probability of having evident injury or severer. This is noted as Direct ME on Y_2 in Table 7. Other notations are also given in Table 7.

Equations (8) and (9) show the calculation of how to quantitatively combine direct and indirect MEs of contributing factors. For example, the total ME of the random parameter X_{BLTL} – "bicycle location – travel lane" is an increase of 44.38 percentage points in probability of "evident injury or severer," relative to the base – "non-intoxicated." The calculation procedure is shown below:

- Direct ME of X_{BLTL} on Y_2 = 7.04%, from injury severity model;
- ME of X_{BLTL} on Y_1 = 64.79%, from pre-crash action model;
- ME of Y_1 on Y_2 = 6.11%, from injury severity model;
- μ_X = 10.28%, from observed statistics, referring to the share of pre-crash action (Y_1 = "Bicyclist failed to yield") among all observations when X_{BLTL} is at its base – "non-intoxicated";
- μ_{Y_1} = 50.55%, from observed statistics, referring to the share of crashes causing evident injuries or severe among all crashes when Y_1 is at its base – "other actions";
- Indirect ME of X_{BLTL} on Y_1 = (10.28% + 64.79%) × (50.55% + 6.11%) – 10.28% × 50.55% = 37.34%;
- Total ME of X_{BLTL} on Y_1 = 7.04% + 37.34% = 44.38%.

The path analysis shows that bicyclists traveling on regular travel lanes are more likely to be injured in crashes (by 7.04 percentage points) regardless of their pre-crash behavior. In addition, bicyclists traveling on regular travel lanes are associated with a greater likelihood of failure to yield to traffic, which would further aggravate the injury severity (by 37.34 percentage points) if colliding with a motor vehicle. For the factor of bicycle location on regular travel lanes, both direct and indirect MEs are positive, which applies to some other contributing factors including bicyclist intoxication, motor vehicle speed, motor vehicle type (e.g. pickup and van), and lane number (e.g., 3∼4 lanes).

Some factors are associated with negative MEs, meaning an association with decreased injury severity. However, their indirect MEs are positive. For example, young bicyclists seem to relate to decreased injury severity (e.g., <=10 years old), perhaps due to their physical strengths relative to seniors. However, young bicyclists are more likely to fail to yield to traffic prior to a crash, which would cause them more likely to be injured in a crash. Therefore, education programs regarding the riding rules and behavior are strongly needed for young bicyclists. Noticeably, some variables, such as intersection, are not statistically significantly correlated to injury severity, but they are significantly associated with dangerous pre-crash actions. Therefore, quantifying behavioral pathway can highlight these contributing factors that are indirectly correlated to bicyclist injury severity.

6. Limitations

The data used in this study were a pre-processed database, released by NC DOT, rather than raw crash reports. Besides, the database spans from 2007 to 2014. The data reporting procedures may vary across time. Considering that the data used for the study ranged from 2007 to 2014, it is possible that the models could suffer from temporal instability in some of the variables (Behnood & Mannering, 2015). The extent and consistency of data accuracy remain unknown, though the descriptive statistics (i.e., the percentage of fatal bicyclists is only 2.3%, male is the predominant bike users 85.5%) look reasonable compared with previous studies (i.e., 3.5% of the bicyclists were dead, 86.1% of the bicyclists were male studied by Kim et al., 2007). This study has a focus on pre-crash actions. It is possible that crash reporters or investigators

Table 7
Path Analysis-Quantifying Direct and Indirect Marginal Effects.

Variable (X)		DirectMEonY_2	μ_X forY_1	ME onY_1	μ_{Y_1} forY_2	MEofY_1 onY_2	IndirectME onY_2	TotalMEonY_2
Bicyclist age (base: 36~50 yrs old)	<= 10 yrs old	−6.34%	8.25%	10.79%	50.55%	6.11%	6.62%	0.28%
	11~18 yrs old	−4.78%	8.25%	25.90%	50.55%	6.11%	15.18%	10.40%
	19~24 yrs old		8.25%	9.95%	50.55%	6.11%	6.14%	6.14%
	25~35 yrs old	−5.84%	8.25%	4.80%	50.55%	6.11%	3.22%	−2.61%
	50~65 yrs old		8.25%	8.52%	50.55%	6.11%	5.33%	5.33%
	> 65 yrs old		8.25%	1.88%	50.55%	6.11%	1.57%	1.57%
Bicyclist gender	Male	−6.00%	17.97%		50.55%	6.11%	1.10%	−4.90%
Bicyclist intoxicated	Yes (base: no)	7.03%	17.95%	4.18%	50.55%	6.11%	3.47%	10.50%
Bicycle direction	With traffic (base: facing traffic)	6.71%	26.81%	−83.85%	50.55%	6.11%	−45.87%	−39.16%
Bicycle location	Travel lane (vs. side walk or bike lane)	7.04%	10.28%	64.79%	50.55%	6.11%	37.34%	44.38%
Intersection	Yes		13.21%	59.67%	50.55%	6.11%	34.62%	34.62%
Land use (base: other)	Commercial		8.94%	13.35%	50.55%	6.11%	8.11%	8.11%
	Residential		8.94%		50.55%	6.11%	0.55%	0.55%
Motorist age (base: 31~45 yrs old)	<= 20 yrs old		19.46%		50.55%	6.11%	1.19%	1.19%
	21~30 yrs old		19.46%		50.55%	6.11%	1.19%	1.19%
	45~65 yrs old		19.46%		50.55%	6.11%	1.19%	1.19%
	> 65 yrs old		19.46%		50.55%	6.11%	1.19%	1.19%
	Unknown		19.46%		50.55%	6.11%	1.19%	1.19%
Motorist intoxicated	Yes	25.19%	18.19%		50.55%	6.11%	1.11%	26.30%
Motor vehicle speed (base: <=10 mph)	11~20 mph	6.88%	9.33%	10.17%	50.55%	6.11%	6.33%	13.21%
	21~30 mph	14.54%	9.33%	12.02%	50.55%	6.11%	7.38%	21.92%
	31~45 mph	22.10%	9.33%	29.26%	50.55%	6.11%	17.15%	39.25%
	> 45 mph	35.48%	9.33%	9.29%	50.55%	6.11%	5.83%	41.31%
	Unknown		9.33%		50.55%	6.11%	0.57%	0.57%
Motor vehicle type (base: auto)	Pickup	4.22%	19.49%		50.55%	6.11%	1.19%	5.41%
	SUV		19.49%		50.55%	6.11%	1.19%	1.19%
	Van	6.04%	19.49%		50.55%	6.11%	1.19%	7.23%
	Truck or Bus		19.49%		50.55%	6.11%	1.19%	1.19%
	Other/unknown		19.49%	−8.08%	50.55%	6.11%	−3.39%	−3.39%
Visibility and lighting (base: daylight)	Dark with streetlights	4.16%	19.57%		50.55%	6.11%	1.20%	5.36%
	Dark without streetlights	9.05%	19.57%	−7.52%	50.55%	6.11%	−3.06%	5.99%
Lane number (base: 2 lanes)	3~4 lanes		18.33%	6.16%	50.55%	6.11%	4.61%	4.61%
	> 4 lanes		18.33%	4.97%	50.55%	6.11%	3.94%	3.94%
	Unknown		18.33%	−8.66%	50.55%	6.11%	−3.79%	−3.79%
Curve or straight	Curve	12.03%	18.39%	−2.75%	50.55%	6.11%	−0.43%	11.59%
Level or grade	Level	−10.17%	20.22%		50.55%	6.11%	1.24%	−8.93%

Notes: Y_2 is "evident injury or severer"; Y_1 is "bicyclist failed to yield"; μ_X is probability of "bicyclist failed to yield" when contributing factor X is at base; μ_{Y_1} is probability of "evident injury or severer" when pre-crash action Y_1 is at base (i.e., "other actions"); $IndirectMEofXonY_2 = (\mu_X + MEofXonY_1) * \left(\mu_{Y_1} + MEofY_1onY_2\right) - \mu_X * \mu_{Y_1}$; $TotalMEonY_2 = DirectMEofXonY_2 + IndirectofXonY_2$; Some cells are empty due to the insignificant estimates (*p*-value >0.05) from models.

instead of expert crash analysts, who were not at the scene at the moment of a crash, were given limited or inaccurate descriptions of the true bicyclist and motorist behavior prior to a crash. It is possible to validate them with data such as naturalistic driving data, videos, or kinematic data; however, such data are not often available in a crash database.

Further, this study only examined contributing factors or variables that are available in the database. The correlates of pre-crash action and bicyclist injury severity may also involve other factors. Models with different sets of variables may give dissimilar implications about pre-crash action and bicyclist injury severity in bicycle-motor crashes.

7. Conclusion

This study extends the understanding of bicycle-motor vehicle crashes, which could cause severe injuries to bicyclists as vulnerable road users. This study explicitly revealed the roles of behavioral pathways in bicycle-motor vehicle crashes, which were under-discussed by previous studies. Specifically, this study built two models to disentangle correlates of pre-crash actions and bicyclist injury severity, respectively.

The model results are useful in identifying contributing factors that are associated with dangerous pre-crash actions that lead to severe injuries. Then a path analysis was performed to quantitatively evaluate the behavioral pathways in bicycle-motor vehicle crashes, from contributing factors, pre-crash actions, to bicyclist injury severities. The path analysis quantified an indirect relationship between contributing factors and bicyclist injury severity through the correlates of pre-crash action. The results highlight contributing factors associated with dangerous pre-crash actions that lead to severe bicyclist injuries in crashes.

Through building a multinomial logistic model, this study revealed a number of factors that are significantly associated with pre-crash actions. An ordered logistic model developed in this study covered contributing factors that directly relate to bicyclist injury severity. The results are consistent with findings in previous studies (Martínez-Ruiz et al., 2013; Hu et al., 2014; Kaplan et al., 2014; Behnood & Mannering, 2017; Chen et al., 2017; Robartes & Chen, 2017; Salon & McIntyre, 2018). Significant factors include pre-crash action, bicyclist age and gender, intoxication, bicycling direction and location, and so forth. Among all pre-crash actions, "bicyclist failed to yield" seems to be most dangerous; because such actions are more likely to lead to severe injuries than other actions. Besides, the severity model in this study again confirmed that driving or riding under the influence or impairment is dangerous, causing increased bicyclist injury severity in a bicycle-motor vehicle crash. Results from the path analysis show that some contributing factors (e.g., bicyclist intoxication) are found to be positively associated with both severe injuries and dangerous pre-crash actions that lead to severe bicyclist injuries in crashes. Some other factors (e.g., young bicyclists) are negatively associated with severe injuries, but they are strongly related to dangerous pre-crash actions. These factors are also likely to connect with severe injuries due to the dangerous behavioral pathway. Further, some factors (e.g., intersection) are not significantly correlated to injury severity, but they are significantly associated with dangerous pre-crash actions. Through path analysis, marginal effects of contributing factors on pre-crash actions and bicyclist injury severity are integrated together to quantitatively show which behavioral pathway leads to severe injuries. These findings are new insights into bicycle-motor vehicle crashes.

This study contributes by revealing the behavioral pathways in bicycle-motor vehicle crashes. Behavioral pathways may exist in other traffic crashes that involve human behaviors. For researchers and practitioners who are concerned with bicycling safety, this study offers a method to quantify the behavioral pathways in bicycle-motor vehicle crashes. The methodology helps clarify the roles of pre-crash actions in the relationships between contributing factors and bicyclist injury severity. Further, the findings offer insights for bicycling safety improvements from the perspective of bicyclist and motorist behavior, such as the educational program for students.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

The authors are very thankful for support received from the Department of Civil, Construction and Environmental Engineering at the University of Alabama, University Transportation Center for Alabama and Alabama Transportation Institute. The data used in this study was provided by the North Carolina Department of Transportation. The views presented are in this paper are those of the authors, who are responsible for the facts and accuracy of information.

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Jun Liu, Ph.D. is an Assistant Professor of Civil, Construction and Environmental Engineering at the University of Alabama. His primary areas of research interests are innovations related to traffic safety, transportation planning, intelligent transportation systems, connected and automated vehicles. He has published more than 100 journal articles, book chapters, technical reports, and conference papers or presentations. He is a member of TRB Standing Committee on Transportation Safety Management (ANB10) and a National Cooperative Highway Research Program (NCHRP) Panel Member for NCHRP 20-102(22) State and Local Impacts of Automated Freight Transportation Systems. Dr. Liu also serves on the Inaugural Editorial Board of Transportation Research Record: Journal of Transportation Research Board. He is also an Editorial Board member of Journal of Intelligent Transportation Systems: Technology, Planning, and Operations. He has worked on projects sponsored by NSF, US DOT, US DOE, TDOT, TxDOT, VDOT, and ALDOT. Prior to joining the University of Alabama, Dr. Liu worked as a transportation planner at Virginia Department of Transportation and as a post-doc researcher at the University of Texas at Austin.

Steven Jones, Ph.D., is a Full Professor of Civil, Construction and Environmental Engineering at the University of Alabama. He has led numerous safety-related projects for the Alabama Department of Transportation (ALDOT). Most recently he oversaw the development of the 3rd Edition of the statewide Strategic Highway Safety Plan. Additionally, Steven has been involved in projects to develop Safety Performance Functions (SPFs) for two lane roads, multilane highways, bridges and railroad grade crossings throughout the state. He has been involved in several commercial vehicle related safety studies. In addition to safety-oriented research, Steven has led the development of design guidance and standards for traffic signal systems, roundabouts, access management, and red-light running enforcement cameras to enhance the safety and consistency of transportation projects in Alabama. His current research into traffic safety in Alabama is focused on identifying the primary human behaviors and underlying cultural aspects that influence the frequency and severity of crashes in different geographical regions and socioeconomic groups.

Emmanuel Kofi Adanu, Ph.D., is a postdoctoral research associate at the Alabama Transportation Institute (ATI). He has conducted extensive analysis of road safety data in Alabama, as well as for Namibia and Ghana. He is passionate about identifying ways to address various forms of disparities in transport. He has published in top transportation safety journals and has been involved in both federal and state Department of Transportation (DOT) funded projects. He has also presented at many regional, national, and international conferences. He is currently part of a team of researchers at ATI who are working to document and forecast the extent, conditions, performance, and economic impacts of the Alabama transportation

infrastructure by 2040. Dr. Adanu recently won the 2018 best dissertation award by the Department of Civil, Construction and Environmental Engineering.

Xiaobing Li, Ph.D. is a postdoctoral research associate with the Alabama Transportation Institute (ATI). His research interest primarily focuses on big data analytics and simulations for traffic safety and operations. He received his Ph.D. degree from the University of Tennessee, Knoxville. He has published more than 10 peer reviewed journal articles and conference proceedings. He is a member of Institute for Transportation Engineers, and Institute of Industrial and Systems Engineers. He has worked on projects sponsored by TDOT and NSF. His is currently working on a project evaluating CAV mobility benefits for commercial vehicles. Prior to joining ATI, he worked as an ITS traffic engineer intern at Tennessee Department of Transportation.

Journal of Safety Research 77 (2021) 263–267

Contents lists available at ScienceDirect

Journal of Safety Research

journal homepage: www.elsevier.com/locate/jsr

Characteristics of vehicles driven by teens and adults killed in crashes, 2013–2017

Rebecca A. Weast, Samuel S. Monfort

Insurance Institute for Highway Safety, 98 Dairy Road, Ruckersville, VA 22986, United States

ARTICLE INFO

Article history:
Received 25 September 2020
Received in revised form 18 December 2020
Accepted 11 March 2021
Available online 5 April 2021

Keywords:
Vehicle characteristics
Fatality statistics
Teen drivers

ABSTRACT

Introduction: Teen drivers experience higher crash risk than their experienced adult counterparts. Legislative and community outreach methods have attempted to reduce this risk; results have been mixed. The increasing presence of vehicle safety features across the fleet has driven fatality numbers down in the past decades, but the disparity between young drivers and others remains. *Method:* We merged Fatality Analysis Reporting System (FARS) data on fatal crashes with vehicle characteristic data from the Highway Loss Data Institute (HLDI). The analysis compared the vehicle type, size, age, and the presence of select safety features in vehicles driven by teens (ages 15–17 years) and adult drivers (ages 35–50 years) who were killed in crashes from 2013 to 2017. Results were compared with a similar analysis conducted on data from 2007 to 2012. *Results:* Teen drivers were more likely than their adult counterparts to be killed while driving older, smaller vehicles that were less likely to have the option to be equipped with side airbags. *Discussion:* Teenage drivers remain more likely to be killed while driving older, smaller vehicles than adult drivers. Parents and guardians are mainly responsible for teen vehicle choice, and should keep vehicle size, weight, and safety features in mind when placing their teen in a vehicle. *Practical Application:* These findings can help guide safer vehicle choice for new teen drivers.

1. Introduction

Despite driving less than almost every other age group, teen drivers are associated with a fatal crash rate per miles driven that is about three times that for drivers ages 20 years old and older (Insurance Institute for Highway Safety, 2019). Legislative efforts targeted at new teen drivers have corresponded with a drop in teen crashes and deaths over the past 20 years, as have improvements in vehicle design and safety (McCartt, Teoh, Fields, Braitman, & Hellinga, 2010; Farmer & Lund, 2015). However, past research has found that vehicles driven by fatally injured teens were older and smaller compared with those driven by fatally injured adults (McCartt & Teoh, 2015). Thus, although innovations in design and technology have resulted in increasingly safer motor vehicles year after year, teen drivers lag behind adult drivers in their adoption of these technologies.

Vehicle safety technologies that were once new are now standard or at least very common among the fleet on the road today. Frontal airbags became standard on new passenger vehicles by 1999, electronic stability control (ESC) became standard on all passenger vehicles and light trucks beginning with 2012 models, rearview cameras became standard on all new U.S. vehicles in May 2018, and side airbags continue to be offered as standard equipment on more new models, although they are not required to be so. One analysis estimates that most or all reductions in crash fatalities from the mid-90s through about 2007 were due to the increased safety of the vehicles on roadways (Farmer & Lund, 2015). Continuing design advances also reduce vehicle incompatibility, or the energy mismanagement that occurs during a crash that results in an uneven distribution of injury risk. Although incompatibility remains high between vehicles of very different weights, reductions in incompatibility between vehicles of the same class have contributed to reduced crash risk among newer vehicles (Monfort & Nolan, 2019).

Advancements in safety technology notwithstanding, vehicle technology takes longer to reach the teen driver population. Parents tend to put their teens in smaller, older, and less expensive vehicles (Eichelberger, Teoh, & McCartt, 2015). Teens driving relatively older cars combined with their tendency to engage in riskier driving behaviors (Oviedo-Trespalacios & Scott-Parker, 2018) places them at a greater risk of collision and injury. The persistent disparity between teen and adult crash outcomes necessitates ongoing research on the various sources of risk for teen drivers. The current analysis was therefore conducted to update an analysis published in 2015 comparing the characteristics of the vehicles

E-mail address: rweast@iihs.org (R.A. Weast)

https://doi.org/10.1016/j.jsr.2021.03.010
0022-4375/

driven in fatal crashes by teen drivers with those driven by adult drivers (McCartt & Teoh, 2015). An up-to-date understanding of the vehicles driven by fatally injured teens can help guide efforts to improve vehicle safety for teenage drivers.

2. Method

The current study analyzed Fatality Analysis Reporting System (FARS) data from 2008 through 2017 merged with vehicle information and features data from the Highway Loss Data Institute (HLDI). These data were used to examine vehicle characteristics-like the availability of front and side airbags, ESC, curb weight, and vehicle age-in vehicles driven by fatally injured drivers. We focused on the differences in vehicle characteristics for driver deaths in two age groups: 15 to 17- and 35 to 50-year-olds. The data were also split into two 5-year time periods to make an explicit comparison with the time period studied by McCartt and Teoh (2015), that is, to determine if teen driver vehicle characteristics have changed over time. Rate ratios (relative proportion, computed as the percent of driver deaths in 2013–2017 / the percent of driver deaths in 2008–2012) were used to make comparisons across age groups and time periods. Confidence intervals for the rate ratios (RR) were computed using a normal distribution approximation given by the following:

$$95\%CI = e^{\ln(RR)\pm 1.96\sqrt{\frac{1}{a}-\frac{1}{a+b}+\frac{1}{c}-\frac{1}{c+d}}}$$

where a, b, c, and d are the frequencies in a 2 by 2 contingency table (Morris & Gardner, 1988).

3. Results

3.1. Vehicle type and size

The 2013–2017 crash data showed that the majority of teenage drivers killed in crashes were in a car (63%); the remainder were split between pickups (18%) and SUVs (17%), with a small number in minivans (2%). By comparison, fewer fatally injured adult drivers were in cars (50%), but the remainder were again split between pickups (23%) and SUVs (23%), with a small number in minivans (4%).

Fatally injured teenage drivers tended to drive smaller vehicles compared with their adult counterparts. In particular, teenage drivers were significantly more likely to be killed in a micro, mini, or small car (28% vs. 19%) or in a midsize car (25% vs. 20%) compared with adult drivers (Fig. 1). Teen drivers were significantly less likely to have been killed in pickups and in SUVs. Consistent with these differences, the vehicles in which teenage drivers were killed were 250 pounds lighter on average than those in which adult drivers were killed (overall: 3460 lbs vs. 3710 lbs).

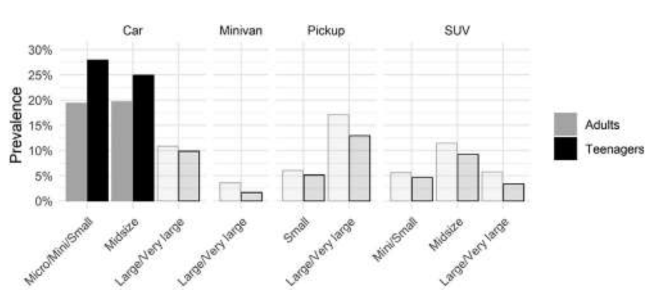

Fig. 1. Comparison between fatally injured adult and teenage drivers in 2013–2017 by vehicle type and size; statistically significant differences between age groups are denoted by opaque bars.

The tendency for teenage drivers to be killed in smaller vehicles than adults is consistent with the effects observed in the 2008–2012 crash data (Table 1). In both 2008–2012 and 2013–2017, teenagers were more likely to have been killed in midsize or smaller cars, while adults were more likely to be killed in pickups and SUVs. The prevalence of teenage drivers killed in large or very large pickup trucks significantly increased in the latest dataset, however (10.4% to 12.9%), while the prevalence of adult drivers in these vehicles remained the same (17.0% to 17.2%).

3.2. Vehicle age and type

From 2013–2017, teenage drivers killed in a crash were significantly less likely to be driving a new vehicle (<3 years old) compared with adult drivers (3.7% vs. 8.6%). Conversely, fatally injured teenage drivers were significantly more likely to be driving an older vehicle (11–15 years old) compared with adult drivers (38.0% vs. 31.6%). The differences between other vehicle age groups were not statistically significant by driver age group (Fig. 2), but these differences were consistent with teenagers driving older vehicles, on average, than adults.

The fact that fatally injured teenagers tended to drive older vehicles than fatally injured adults in 2013–2017 is broadly consistent with the trends observed in 2008–2012 (Table 2). However, the latest crash data show that all drivers (i.e., both teenagers and adults) have moved toward older vehicles—overall vehicle age increased from 10.4 years to 12.0 years between the two study periods. Compared with 2008–2012, significantly fewer teenagers and adults crashed in vehicles that were 3–5 years old and significantly more crashed in vehicles older than 5 years old. The only exception to this pattern occurred among new vehicles (<3 years old). The proportion of adults driving new vehicles in 2013–2017 was unchanged since 2008–2012 (8.3% to 8.6%).

In sum, teenagers remain disproportionately likely to be fatally injured in older vehicles. Although the average vehicle age increased for both driver age groups between 2008–2012 and 2013–2017, this increase was somewhat larger for teenage drivers.

Compared with fatally injured teenagers in 2008–2012, teenagers in 2013–2017 were less likely to drive cars, pickups, and SUVs that were under 11 years old and more likely to drive cars, pickups, and SUVs that were at least 11 years old (Table 3). Of these vehicles, the highest increase was observed for SUVs that were 16+ years old (an increase of 156%, compared with an increase of 62% for cars and 63% for pickups). A similar pattern was observed for adults.

3.3. Safety features

In addition to driving older vehicles, fatally injured teenage drivers tended to drive vehicles with fewer advanced safety features than their adult counterparts. Teenage drivers in the current sample were significantly less likely than adults to have vehicles equipped with side airbags (both for the head and for the chest) and ESC as standard equipment. Conversely, teenage drivers were significantly more likely to be driving vehicles where head-protecting side airbags and ESC were not available, or in the case of chest-protecting side airbags, merely optional (Fig. 3).

Although the latest fatal crash data show that teenage drivers remain disadvantaged with respect to the presence of standard safety systems, the degree to which they were disadvantaged has decreased since 2008–2012 (Table 4). In 2008–2012, fatally injured adult drivers were nearly twice as likely than fatally injured teen drivers to have been killed in a vehicle equipped standard with ESC (6.5% vs. 3.3%; 2.0 times as likely). In 2013–2017, this discrepancy was somewhat smaller (24.0% vs. 15.0%; 1.6 times as likely).

Table 1
Distribution (percent) of the type and size of vehicles driven by fatally injured passenger vehicle drivers ages 15–17 and 35–50 years, comparison between 2008–2012 and 2013–2017.

	Teenagers				Adults			
Vehicle type and size	2008–12 (N = 2394)	2013–17 (N = 1911)	Rate ratio [95% CI]		2008–12 (N = 18,273)	2013–17 (N = 17,253)	Rate ratio [95% CI]	
Car	**64.2**	**63.0**	**0.98 [0.94, 1.03]**		**48.3**	**50.2**	**1.04 [1.02, 1.06]**	*
Micro/mini/small	28.8	28.0	0.97 [0.88, 1.07]		20.2	19.4	0.96 [0.92, 1.00]	
Midsize	23.6	24.9	1.06 [0.95, 1.17]		16.8	19.7	1.17 [1.12, 1.22]	*
Large/very large	11.8	9.9	0.84 [0.70, 1.00]	*	11.0	10.9	0.99 [0.93, 1.05]	
Minivan	**1.9**	**1.7**	**0.89 [0.57, 1.39]**		**4.6**	**3.6**	**0.77 [0.70, 0.86]**	*
Pickup	**17.1**	**18.1**	**1.06 [0.93, 1.21]**		**25.7**	**23.4**	**0.91 [0.88, 0.94]**	*
Small	6.6	5.1	0.77 [0.60, 0.98]	*	8.4	6.1	0.72 [0.67, 0.77]	*
Large/very large	10.4	12.9	1.25 [1.06, 1.47]	*	17.0	17.2	1.01 [0.96, 1.05]	
SUV	**16.8**	**17.2**	**1.02 [0.90, 1.21]**		**21.5**	**22.9**	**1.07 [1.03, 1.11]**	*
Mini/Small	4.7	4.6	0.99 [0.76, 1.30]		5.4	5.6	1.04 [0.96, 1.14]	
Midsize	9.3	9.2	1.00 [0.83, 1.20]		11.2	11.5	1.02 [0.96, 1.08]	
Large/very large	2.9	3.3	1.16 [0.83, 1.62]		4.8	5.8	1.20 [1.13, 1.27]	*

Note. Percentages may not add up to the overall category value due to vehicles of unknown size; * = difference between study periods statistically significant at $\alpha = 0.05$; Bold values indicate total values for the given vehicle category. Non-bold values are for specific sizes of vehicle within each category.

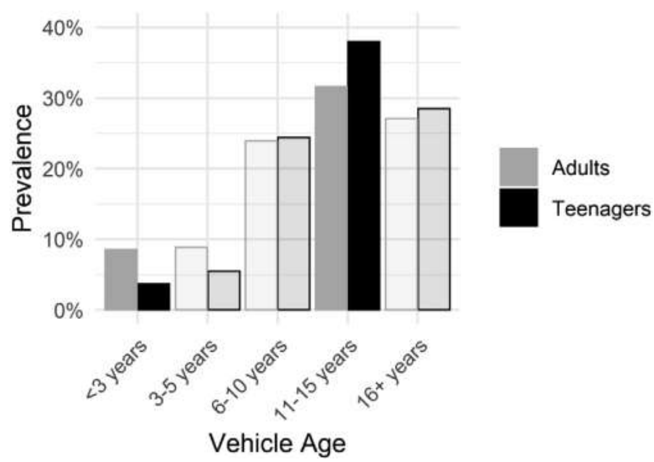

Fig. 2. Comparison between fatally injured adult and teenage drivers in 2013–2017 by vehicle age; statistically significant differences between teenagers and adults are denoted by opaque bars.

4. Conclusion

Teenage drivers remain more likely to be killed while driving older, smaller vehicles than adult drivers. Compared with adults, teenagers were more likely to be killed driving micro, mini, small, and midsize cars, and were less likely to be killed driving pickups and SUVs.

This pattern is largely consistent with the differences observed in 2008–2012 with a few notable exceptions. Teenage drivers killed in crashes in 2013–2017 were driving even older vehicles than teenage drivers killed in 2008–2012. Even so, adult drivers were also driving older vehicles in 2013–2017 than they were in the 2008–2012 interval. While this shift to older vehicles has had a bigger impact on teen drivers, it could be the result of broader market trends towards vehicles remaining on the roads longer. However, a 5-year-old vehicle in 2017 likely was more advanced than a 5-year-old vehicle in 2012, with improvements in crashworthiness and safety technology (Highway Loss Data Institute, 2019).

The availability of advanced safety systems—particularly ESC—has increased for all drivers since 2008–2012. However, fatally injured teen drivers are still less likely to have been driving vehicles equipped with ESC and side airbags than their adult counterparts. Regulations and improving technology have had a delayed impact on teen driving safety, relative to that of adult drivers.

Graduated driver licensing laws (GDL) have targeted teen driving risk, and laws have been implemented and strengthened across the country since the national effort began in 1996. Several studies have found that some components of GDL (passenger and nighttime restrictions, and minimum licensing age) have had a greater impact on teen driving safety than others (the number of required supervised practice driving hours), but overall the presence of GDL provisions has significantly reduced crash risk among teen drivers (McCartt, Teoh, Fields, Braitman, & Hellinga, 2010; Williams, 2017). Unfortunately, no state has implemented all of the strongest provisions available, and efforts to pass new GDL legislation have essentially stopped since 2015. Public health communication efforts targeted at teen drivers have had minimal positive impact on teen drivers to date, and evaluations of driver education programs show minimal or neutral effects of such programs on teen driving safety (Curry, Peek-Asa, Hamann, & Mirman, 2015; Mayhew et al., 2017). A key to improving teen driving safety lies in increased vehicle safety.

Ongoing research is needed to address the potential safety benefit of new and existing safety features for all age groups as they are released and pervade the fleet. The choices that parents make

Table 2
Distribution (percent) of age of vehicles driven by fatally injured passenger vehicle drivers ages 15–17 and 35–50 years, comparison between 2008–2012 and 2013–2017.

	Teenagers				Adults			
Vehicle age	2008–12 (N = 2394)	2013–17 (N = 1911)	Rate ratio [95% CI]		2008–12 (N = 18,273)	2013–17 (N = 17,253)	Rate ratio [95% CI]	
<3 years	6.1	3.7	0.60 [0.46, 0.80]	*	8.3	8.6	1.03 [0.96, 1.10]	
3–5 years	12.1	5.5	0.45 [0.37, 0.56]	*	14.2	8.8	0.62 [0.59, 0.66]	*
6–10 years	34.3	24.4	0.71 [0.65, 0.78]	*	31.6	23.9	0.76 [0.73, 0.78]	*
11–15 years	30.8	38.0	1.23 [1.14, 1.34]	*	26.8	31.6	1.18 [1.14, 1.22]	*
16+ years	16.7	28.5	1.70 [1.52, 1.91]	*	19.1	27.1	1.42 [1.36, 1.47]	*

Note. * = difference between study periods statistically significant at $\alpha = 0.05$.

Table 3
Distribution (percent) of the type and age of vehicles driven by fatally injured passenger vehicle drivers ages 15–17 and 35–50 years, comparison between 2008–2012 and 2013–2017.

Vehicle type/age		Teenagers				Adults			
		2008–12 (*N* = 2394)	2013–17 (*N* = 1911)	Rate ratio [95% CI]		2008–12 (*N* = 18,273)	2013–17 (*N* = 17,253)	Rate ratio [95% CI]	
Car									
	<3 years	4.8	2.7	0.56 [0.40, 0.77]	*	4.9	5.4	1.11 [1.01, 1.21]	*
	3–5 years	7.8	3.7	0.47 [0.36, 0.62]	*	6.9	5.5	0.79 [0.72, 0.85]	*
	6–10 years	21.3	17.2	0.81 [0.71, 0.91]	*	13.7	12.6	0.92 [0.87, 0.97]	*
	11–15 years	20.2	23.0	1.14 [1.02, 1.28]	*	12.8	13.9	1.09 [1.03, 1.15]	*
	16+ years	10.1	16.4	1.62 [1.39, 1.90]	*	9.9	12.8	1.29 [1.21, 1.37]	*
Minivan									
	<3 years	0.0	0.1	2.50 [0.23, 27.6]		0.2	0.1	0.88 [0.52, 1.50]	
	3–5 years	0.1	0.2	1.25 [0.25, 6.19]		0.7	0.2	0.33 [0.23, 0.47]	*
	6–10 years	0.8	0.5	0.69 [0.32, 1.50]		1.6	0.9	0.56 [0.46, 0.68]	*
	11–15 years	0.6	0.7	1.08 [0.52, 2.27]		1.5	1.6	1.01 [0.86, 1.20]	
	16+ years	0.3	0.2	0.63 [0.19, 2.07]		0.7	0.8	1.13 [0.88, 1.44]	
Pickup									
	<3 years	0.8	0.1	0.14 [0.03, 0.60]	*	1.9	1.4	0.74 [0.63, 0.87]	*
	3–5 years	2.0	0.5	0.23 [0.12, 0.48]	*	3.8	1.3	0.36 [0.31, 0.41]	*
	6–10 years	5.4	3.6	0.67 [0.50, 0.89]	*	7.8	5.4	0.39 [0.64, 0.75]	*
	11–15 years	4.4	6.6	1.49 [1.16, 1.91]	*	6.2	7.2	1.16 [1.08, 1.26]	*
	16+ years	4.5	7.4	1.63 [1.28, 2.08]	*	6.0	8.0	1.33 [1.23, 1.44]	*
SUV									
	<3 years	0.5	0.8	1.71 [0.79, 3.70]		1.4	1.6	1.16 [0.98, 1.37]	
	3–5 years	2.2	1.1	0.53 [0.32, 0.87]	*	2.8	1.8	0.65 [0.57, 0.75]	*
	6–10 years	6.9	3.1	0.45 [0.34, 0.60]	*	8.5	5.1	0.59 [0.55, 0.64]	*
	11–15 years	5.5	7.7	1.39 [1.11, 1.75]	*	6.3	8.9	1.42 [1.32, 1.53]	*
	16+ years	1.8	4.5	2.56 [1.78, 3.69]	*	2.5	5.5	2.23 [1.99, 2.48]	*

Note. * = difference between study periods statistically significant at $\alpha = 0.05$.

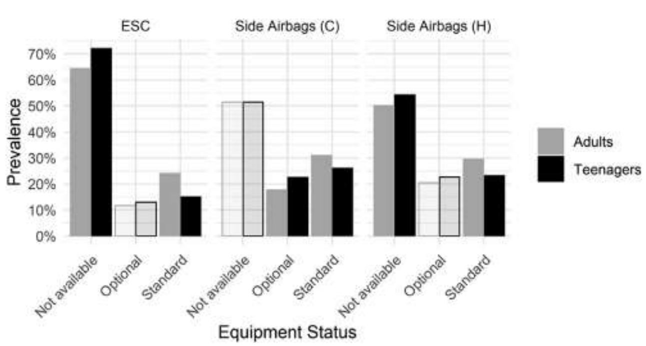

Fig. 3. Comparison between fatally injured adult and teenage drivers in 2013–2017 by vehicle safety equipment status; significant differences between teenagers and adults are denoted by opaque bars. C = chest; H = head.

when placing their teen in a vehicle can substantially affect the safety of their teen as well as the safety of other road users; up-to-date information about available vehicle technology will continue to be a vital component of informed decision-making for these parents. The current analysis suggests that trends in vehicle choices for teens and adults have held relatively consistent over the past 10 years, and that greater efforts to shift how parents think about and choose the vehicle they let their teen drive will be necessary moving forward.

As time passes and improved vehicle technology continues to spread throughout the fleet, safety features like ESC and side airbags will become standard, while more advanced driver assistance features, such as automatic emergency braking, will become increasingly common. As a result, we expect that vehicles and roadways will become safer for both teenage and adult drivers in

Table 4
Distribution (percent) of vehicle safety features for fatally injured passenger vehicle drivers ages 15–17 and 35–50 years, comparison between 2008–2012 and 2013–2017.

	Teenagers				Adults			
	2008–12 (*N* = 2,394)	2013–17 (*N* = 1,911)	Rate ratio [95% CI]		2008–12 (*N* = 18,273)	2013–17 (*N* = 17,253)	Rate ratio [95% CI]	
Side airbags (chest)								
Not available	70.3	51.4	0.73 [0.70, 0.77]	*	70.9	51.4	0.73 [0.71, 0.74]	*
Optional	18.7	22.5	1.20 [1.07, 1.35]	*	16.2	17.6	1.09 [1.04, 1.14]	*
Standard	11.0	26.1	2.37 [2.07, 2.72]	*	13.0	30.9	2.39 [2.28, 2.49]	*
Side airbags (head)								
Not available	72.5	54.3	0.75 [0.71, 0.79]	*	70.2	50.0	0.71 [0.70, 0.73]	*
Optional	18.9	22.6	1.19 [1.06, 1.34]	*	18.7	20.4	1.09 [1.05, 1.14]	*
Standard	8.6	23.2	2.68 [2.30, 3.13]	*	11.1	29.5	2.66 [2.53, 2.78]	*
ESC								
Not available	88.1	72.0	0.82 [0.79, 0.84]	*	84.6	64.3	0.76 [0.75, 0.77]	*
Optional	8.5	13.0	1.52 [1.28, 1.81]	*	8.9	11.7	1.32 [1.24, 1.40]	*
Standard	3.3	15.0	4.49 [3.53, 5.72]	*	6.5	24.0	3.67 [3.51, 3.83]	*

Note. * = difference between study periods statistically significant at $\alpha = 0.05$.

the future. However, it is disappointing that, 5 years after the problem was recognized by McCartt and Teoh (2015), teenage drivers still are driving less safe vehicles. Changing this trend for the riskiest driving population requires more informed decision-making by parents and the acceleration of vehicle technology by automakers. Parents need to be educated on the safety benefits of placing their teen driver in the newest vehicle with the most advanced safety features. At the same time, automakers need to more rapidly expand vehicle safety features across their fleets to ensure that teens are driving vehicles with the latest technology.

5. Practical application

The disparity highlighted by these results can guide improvements in vehicle selection for teen drivers by both teens and, more often, their parents. A shift towards placing teens in larger vehicles could boost teen safety as time progresses and ESC becomes ubiquitous in the available vehicle fleet.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Rebecca A. Weast is a Research Scientist at the Insurance Institute for Highway safety. Dr. Weast joined the Institute in 2016 and conducts research on a range of topics including issues related to young drivers and drowsy driving. She received her bachelor's degree in psychology from Franklin and Marshall College in 2009, and her M.A (2014) and Ph.D. (2016) in Psychology with a focus on human cognition and visual perception from the University of Virginia.

Journal of Safety Research 77 (2021) 139–150

Contents lists available at ScienceDirect

Journal of Safety Research

journal homepage: www.elsevier.com/locate/jsr

Coercive pressure as a moderator of organizational structure and risk management: Empirical evidence from Malaysian construction industry

Manal Tagod *, A.Q. Adeleke, Taofeeq D. Moshood

Faculty of Industrial Management. University Malaysia Pahang, Lebuhraya Tun Razak, 26300 Gambang, Darul Makmur Kuantan, Pahang, Malaysia

ARTICLE INFO

Article history:
Received 29 October 2019
Received in revised form 30 November 2020
Accepted 19 February 2021
Available online 20 March 2021

Keywords:
Coercive Pressure
Organizational Structure
Construction Risk Management
PLS-SEM
Partial Least Squire
Malaysia

ABSTRACT

Introduction: The construction industry in Malaysia has been bedevilled by myriads of risk issues that have hampered its smooth operations in recent times. This paper is an empirical assessment that aims to examine the effect of coercive pressure on the relationship between organizational structure and construction risk management among construction industry in Malaysia. *Method:* Based on the proposed model, a quantitative method was employed to obtain data from G7 construction industry operating within the peninsular Malaysia. Out of the 180 copies of questionnaire, 165 copies were properly filled, returned, and used for the analysis. PLS-SEM was used to analyze the obtained data. *Results:* The findings of the study affirmed that specialization, centralization, and management of risk by the construction industry had positive correlation. *Conclusions*: As anticipated, coercive pressure had positive moderating correlation with both formalization and the management of risk by the construction industry. Similarly, it was also found that in the course of carrying out construction activities, coercive pressure made significant interactive influence on formalization, specialization, and centralization. *Practical Applications*: Coercive pressure reduced the frequency of accidents among workers in the process of carrying out construction works.

1. Introduction

The construction industry is a fast-growing sector with significant contributions to the economic growth of any country (Farooq et al., 2018). It also helps in improving the quality of life of citizens by providing the necessary socio-economic infrastructure such as roads, hospitals, schools, and other basic facilities. Despite the global economic downfall, the construction industry contributes significantly to the Gross Domestic Product (GDP) of Malaysia's economy. As reported by CIDB (2020), the construction sector has been consistently contributing an average of 3.8% over the last 30 years. Furthermore, the Malaysian construction industry is rapidly growing and improving significantly (Bamgbade et al., 2018). This sector has registered a strong growth of 4.7% in 2019 and 5.9% for the first quarter of 2020, as against the overall GDP growth of 6.7% during the first quarter of the year. Hence, a lot of money is invested to sustain the growth of the construction industry (World Bank, 2020).

According to Muhammad (2017), 28 major construction risks factors that lead to delay due to improper effective construction risk management with their effects on the construction projects in Malaysia are identified. The leading factors are inadequate finance and payments for completed project; lack of materials; labor supply; failure in the availability of equipment; poor communication between parties; and misapprehension during construction works. Risk management is one of the most important procedures in project management (Artto & Wikstro, 2005; Adeleke et al., 2019).

Risk management is the term designated to the formalized process involved in the control of risk occurrences with a view to quickly make proper decisions and take actions that will produce effective results (Omer and Adeleke 2019). The way this process is frequently carried out is by individual's level of experience and intuition (Hassan et al., 2012). Because each construction project is dynamic and unique, construction operations comprise several uncertainties, various techniques, multiple intricacies, and divergent environments. Thus, identifying and managing the possible risk factors that are different from one project to another is contingent on playing a vital role in improving the performance, so as to attain the successful delivery of the project (Haupt, 2018).

Risk in construction projects is the occurrence of uncertain situations that have the possibility of having either negative or positive consequences on scope, cost, time, and quality of a project as specified (Project Management Institute, 2008). As far as this study is

* Corresponding author.
E-mail address: manaltagot@gmail.com (M. Tagod).

https://doi.org/10.1016/j.jsr.2021.02.011
0022-4375/

concerned, the management of risk can be defined as the procedures involved in risk identification and risk analysis with a view to achieving positive outcomes in administration, designing of project, funding, manual labor, and the utilization of equipment. It further means that it is the ability to properly analyze and evaluate risk so as to prevent or reduce any negative influence it may have on financial status of a project (Abdul-Rahman et al., 2015).

Furthermore, in construction projects, the management of risk embraces an orderly manner of detecting, analyzing, and reacting to risk prone situations so as to achieve a project's goals (Adeleke et al., 2020). As stated by Assaf (2015), risk management in construction projects has been recognized as one of the most important processes for achieving project objectives with reference to quality, time, and cost. The advantages of the process include being able to identify and analyze risk prone situations, with a view to improving the processes involved in the construction of project so as to effectively utilize resources (Abu Bakar et al., 2012). Nevertheless, this process involves both cost and time overrun in projects (Adeleke et al., 2019).

Adnan and Morledge (2003) state that risk can be absolutely avoided during the construction of projects. Hence, it is important to establish suitable management with the responsibility of managing different types and levels of risks for the duration of the project. Most of the definitions proposed by authors regarding risk management focus on the fact that risk is "the probability of occurrence of any unexpected or ignored event that can hinder the achievement of project objectives which may be in the form of management, materials, design, finance, Labor, and equipment risks" (Adeleke et al., 2018). Previous studies have established that because many industry in Malaysian that usually handle most of the construction projects only intermittently adopt risk management practices, there have not been constant and consistent practices of risk management, thereby leading to countless negative outcomes on construction sites (Kang et al., 2015; Omer, 2019).

Similarly, a study carried out by Shunmugam and Rwelamila (2014) revealed that the prevalence of ill examined and poorly incorporated risk management among the clients, contractors, and consultants have been instrumental to the regular disputes concerning claims and contracts during the construction of projects. Therefore, risk management is an inevitable role for every project manager. In view of this, it becomes very imperative to implement, from the start to the end of a project, effective management policies (Kang et al., 2015). This will enable the project manager to systematically put into practice the appropriate risk management approaches based on their knowledge and experiential level.

A particular study conducted by Goh and Hamzah (2013) unveiled that many construction industry owners, contractors, and consultants in Malaysia do haphazardly apply the risk management process, thereby leading to the undesirable outcomes of many projects. In the same vein, Adnan et al. (2008) revealed that many in the construction industry do not emphasize the importance of risk management during the execution of project, thus leading to project failures. It was added that they usually adopted practices of risk management that do not produce the anticipated outcome regarding the quick distribution of project materials. Hence, it becomes very imperative to adopt and apply methodical style, knowledge, and experience of previous workable risk management approaches. For instance, having good knowledge and experience of previous issues relating to a situation while executing a project will help facilitate the adoption of the right method while considering the possibility of risk (Assaf, 2015).

Studies conducted by Moa et al. (2017) and Anumba and Khalfan (1997) revealed that there are some particular organizational structures that are linked to management of risks in the construction industry. A significant one is the coercive pressure that has not been focused on. This study considers this significant variable. Considering coercive pressure in this study will throw more light on the dynamics of coercive pressure in relation to organizational structure or makeup and management of risks among the construction industry in the Malaysia peninsular.

Since there hasn't been much attention on the influence of organizational structure on effective risk management in the Malaysia peninsular construction industry (Goh & Hamzah, 2013), this study focusses on this investigation. To elucidate the inconclusive assertions on the relationship between the organizational structure on the effective construction risks management, a comprehensive framework that will integrate these factors via the moderating roles of coercive pressure from the Malaysian construction point of view is needed.

2. Objective

In line with the abovementioned issues and arguments from the extant literature, this article seeks to examine the effect of formalization, specialization, and centralization of construction risk management. It also intends to examine the moderating effects of coercive pressure on the influence of formalization, specialization, and centralization on construction risk management.

3. Literature review

3.1. Organizational structure

According to Katsikea et al. (2011), organizational structure is used by various firms as a control mechanism to influence employees' work outcomes so as to ensure that the required tasks are performed effectively and efficiently, and to assist the attainment of organizational goals and objectives. Moreover, organizational structure describes the internal characteristics of an organization. These internal characteristics receive attention since they are critical to organizational failure and success (Ahmady et al., 2016; Nasidi et al., 2016).

Organizational structure as indicated by Daft (2007) is viewed as "social entities that are goal-oriented and deliberately designed to coordinate activities so as to link system to the external environment." "The key element of an organization is not the building of a set of policies and procedures; organizations are made up of individuals and their relationship with one another. An organization exists when individuals interact with one another to perform important functions that help in attaining goals" (Mao et al., 2017). The current study's organizational structure is conceptualized as formalization, specialization, and centralization (Subramanian & Nilakanta, 1996); it seeks to examine the moderating effect of the coercive pressure on the relationship between organizational structure and construction risk management among construction industry in Malaysia.

3.1.1. Formalization and construction risk management

According to Martin, formalization is the degree to which rules and procedures are followed in an organization. Across various organizations the element varies greatly. For instance, the arrival and departure times to and from work are specified in any organization in order to control the workers' conducts. In some other organizations it is expected that employees will spend sufficient time on the job to accomplish the work. In a few organizations, rules and procedures cover most activities while in others, people are permitted to use their discretion. Yusuf et al. (2016) describe formalization as the extent to which rules, penalty, authority, relations, roles, line of communications, norms, and procedures are described within the organization.

Fundamentally, it can be seen as a way of maintaining the standards and rules that are guiding the employees while accomplishing the organization's goals. This study asserts that formalization is the extent to which decision and working relationships are controlled by formal rules, standard policies, and procedures in construction risk management organizations. Furthermore, the organization of the construction risk management with a formal structure will require the establishment of specific rules and procedures that indicate what needs to be done by the staff members (Katsikea et al., 2011). In addition, the organizational setup of this nature prevents staff members in the construction risk management organization from carrying out different activities in the performance of their daily work (Mao et al., 2017).

Among the dimensions of organizational structure is the formalization, which provides direction to employees and reduces ambiguity (Fredrickson, 1986; Sartipi, 2020). A high degree of formalization actually reduces innovativeness because the environment does not promote the freedom of creativity and introduction of new ideas among the construction risk management in Malaysian construction industry (Mao et al., 2017). The fact is that the frequent occurrence of strategic decision making in the construction industry is only when a crisis has erupted. A formalized structure of the construction risk management in the construction industry in Malaysia is likely associated with reduced motivation and job satisfaction as well as a slowing the pace of decision making. Morozenko (2020) emphasized that the service industry is particularly susceptible to problems associated with high levels of formalization. Therefore, lower level employees have limited power to resolve a service problem and are constrained by stringent rules that outline a limited number of acceptable responses.

H1: There is a positive correlation between formalization and construction risk management.

3.1.2. Centralization and construction risk management

Altinay and Altinay (2004) define centralization as the organizational process by which different tasks are given optimum priority most importantly in the area of planning and decision making. It is regarded as the overlapping of the spans of control, decision making, and communication within a formal organizational structure. In this context, the high-ranking executives and managers make decisions based on the set-down rules and organizations' policies. This is usually seen at the point of making decisions on tasks performed from different small groups by the top executives (Katsikea et al., 2011). In regard to risk management, the concept of centralization restricts the executive power to the directors or chief executive officers alone, thereby enabling the workers and the management a wide range of flexibility in carrying out their functions as maintained by Mao et al. (2017).

As stated by Ahmady et al. (2016), centralization is the procedure in which organizations' activities such as planning and decision-making are being focused on by a group in a particular location. Centralization is the extent at which control, decision-making, and communication within an organization is being connected. The top executive makes the decision for a centralized organization. Therefore, the enforcement of the policies is through various organizational levels after progressively expanding the control until its base level is achieved (Holagh et al., 2014).

However, the communication flow is usually required in centralized organizations through a central person or location. In centralized organizations, individual leaders play a major part and have a great deal of power in decision-making. Leaders in centralized organizations have more prominent access to information and, along these lines, they can exercise more influence over group members by controlling the flow of Critical Information and Knowledge Communication (Yusuf et al., 2016).

In addition, the broad purpose of this centralization as a composition in an organization is to produce uniform rules and actions so as to mitigate the propensity for making mistakes by a member of staff because of lack of information and skills. Also, it empowers the employees for significant utilization of skills and specialized expertise so that an organization can have a tighter control of operations (Katsikea et al., 2011; Kanimoli et al., 2020).

In this study, the construction risk management organization's centralized structure confines the manager's authority regarding decision-making, where the Chief Executive Officers (CEO) or the directors have the power to control and make decision. Therefore, centralization keeps the managers and members of the staff flexible and makes them take the initiative when performing their duties (Katsikea et al., 2011).

H2: There is positive correlation between centralization and construction risk management.

3.1.3. Specialization and construction risk management

Specialization is described as the division of labor or the procedure of dividing most of the activities required for the organization into individual tasks (Holagh et al., 2014). The entire philosophy of an organization is concentrated on the concept of the division of work and specialization. Therefore, the division of work is regarded as an assigned obligation to a particular person or a group of staff. Nevertheless, when the responsibility for a particular job is assigned to a designated expert in a field, it is called specialization. To ensure coordination, some of the workers occupy management positions at the different phases in the process (Altinay & Altinay, 2004).

Also, the perception of specialization plays a key role in the development of the management operations. The large-scale operations caused by the Industrial Revolution require that, as suggested by Frederick Taylor, the means of simplifying the complex processes be categorized into the breaking down of tasks, which will enhance the component steps so that workers will be encouraged to focus on repetitive task (Katsikea et al., 2011). Quick completion of the main tasks by workers is achieved through specialization (Fredrickson, 2013).

In relation to an individual worker, there is a great benefit in specialization because where individual staff remains in the same task over time, knowledge related to or gained on the job can help improve his or her performance (Shirazi et al., 2010). Nevertheless, there will be a motivational benefit as workers change tasks; the benefit is positioned so that it will likely be offset by the gains of specialization.

In this study, specialization is defined as a division of work. The division of work is the act of assigning responsibility to each organizational component or, specifically, to a specific individual or group. It becomes specialization when the responsibility for a specific task lies with a designated expert in that field. The efforts of the operatives are coordinated to allow the process at hand to function correctly. Certain operatives occupy positions of management at various points in the process to ensure coordination in the construction industry.

H3: There is positive correlation between specialization and construction risk management.

3.2. Moderating role of coercive pressure

Coercive pressure is one of the three fundamentals of institutional isomorphism reflecting the three analytically distinct processes of an institution (DiMaggio & Powell, 1983**).** It is argued that institutional pressures can originate from both formal rules (regulations and mandates) and informal constraints (norms, conventions, and beliefs), and the way in which organizations respond to these pressures will determine their institutional legitimacy (Toinpre et al., 2018).

Accordingly, Toinpre et al. (2018) revealed that imperfect institutional forces that surround the construction procurement environment lead to more legitimacy and/or use of risk-averse safeguarding approaches in procurement. In examining the coercive pressure of a construction industry's competency, Cao et al. (2014) claims that mandatory regulations that necessitate industry to comply to risk management rules to meet specific performance standards for some products or health with safety surroundings for the workers are forcing them to improve their implemented approaches for achieving the goals involved in promoting risk management regulations in the construction process. These pressures are often associated with legal requirements, health and safety regulations, but may also stem out of contractual obligations with other actors, which constrain organizational variety. The importance of the coercive forces in institutional theory highlights the impact of political rather than technical influences on organizational change. Scott comments that "an institutional perspective gives special emphasis to authority relations: the ability of organizations, especially public organizations, to rely on legitimate coercion (He et al., 2016). The Malaysian government has recently created a set of challenging construction targets for 2020 (CIDB, 2015). Moreover, in emerging economies (such as Malaysia) that are undergoing sustainable growth, infrastructure should support economic expansion and a citizen-centric public service with high productivity. Government agencies and affiliated associations still frequently interfere with daily design and construction activities (Bamgbade et al., 2019). It is realistic that the following forms of regulation and legislation could make a considerable contribution to solving construction issues.

In addition to being directly related to construction risk, this study proposes that coercive pressure moderates the relationship between organizational structure and construction risk management. Institutional theory presumes that risk occurrence can be minimized through the control introduced by an organization with the influence of coercive pressure, which would certainly encourage compliance to mandatory rules (He et al., 2016). Theoretically, coercive pressure might moderate the relationship among formalization, specialization, and centralization (organizational structure) with the management of risk in several ways (Fig. 1).

H4: Coercive pressure positively moderates the relationship between formalization and construction risk management.

H5: Coercive pressure positively moderates the relationship between specialization and construction risk management.

H6: Coercive pressure positively moderates the relationship between centralization and construction risk management.

3.3. Conceptual framework

The correlation between the different dimensions of organizational structure and risk management in construction industry with the moderating role of coercive pressure is presented in Fig. 1 Conceptual Framework.

4. Theory development

This study used the theory of organization control as a base of the theoretical framework. The theory of organizational control establishes some theoretical underpinnings to confirm the relationship between organizational structure and construction risk management. The organizational control theory (Kirsch, 1996) proposes that well established and implemented control by an organization must theoretically be able to curb risk occurrence on construction projects. This can be successfully achieved within the organization with the aid of proper monitoring, control, and compensation among the project managers, team members, and the organizations themselves. Similarly, this study is supported by institutional theory. The theory affirms that formation of high-quality institutional relations not only improves an organization's performance when it confronts intensive institutional pressures and expectations, but also mitigates the problems of competition for scarce resources that emerge from the organization's risk management. This study is the first attempt at evaluating the direct and indirect relationships among organizational structure, coercive pressure, and construction risk management among Malaysian peninsular construction industry.

5. Methodology

5.1. Method of collecting data and the sample size

Because the current study is cross sectional in nature, the gathering of data was done once from 165 contractors (i.e., contract managers, executive directors, marketing managers, project managers, and engineers) in the Malaysia peninsular, which consists

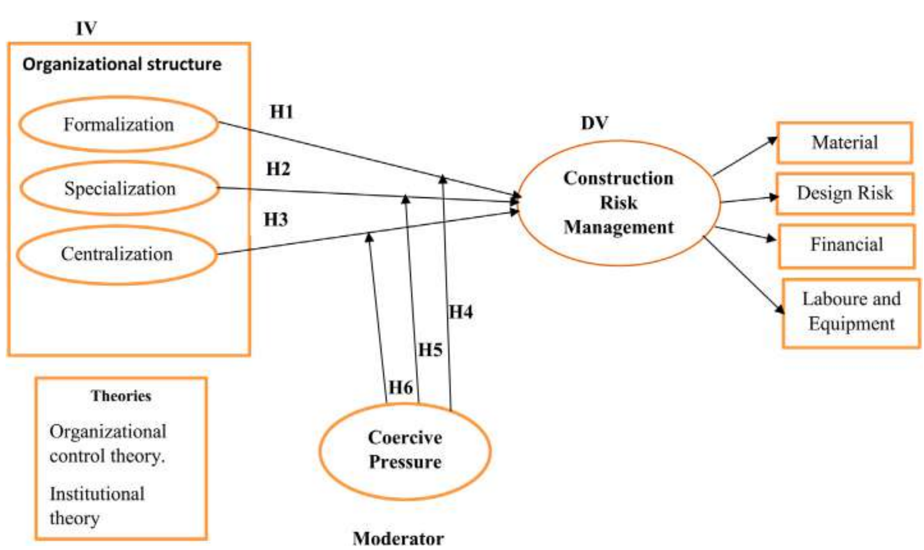

Fig. 1. Proposed Conceptual Framework.

of 12 states. The selection of the respondents was based on the fact that they had best knowledge and experience of risk management in the construction industry. The adopted sampling technique is proportionate stratified random sampling in which each member of the sample size was randomly selected from every layer. The percentages of the total 165 respondents were 13.9% (contract managers), 9.7% (executive directors), 8.5% (marketing managers), 35.2% (project managers), and 32.7% (engineers). The respondents' work experience was between 1 and 40 years.

The respondents consisted of both males and females (78.8% and 21.2%, respectively). The respondents were Grade 7 contractors specializing in building and civil engineering works in the Malaysia peninsular because there has been a great demand for building and civil engineering products so as to sustain the economy and to achieve the nation's social development goals (CIDB, 2007; Bamgbade et al., 2019). Grade 7 contractors were selected for this study as they have no limitation for tendering capacities and their net capital worth was the highest among the other grades (RM 750,000) (Lee & Azlan, 2012). In addition, the specialization of each industry were as follows: apartment buildings (59.4%), roads (24.6%), and bridges (16%). The various locations of the industry were as follows: local market areas (35%), within few states (20.6%), regional (13.9%), across Malaysia (21.8%), and international markets (7.9%).

Employees in each of the industries range between 10 and 7,000, thus showing reasonably representative coverage of the Malaysian construction industry. The study adopted the following rating scale in measuring responses from the questionnaire:1 "very low," 2 "low," 3 "medium," 4 "high," and 5 "very high " (Adeleke et al., 2019). Copies of the questionnaire were distributed to academics and practitioners in the construction industry to ensure its content validity, readability, and brevity, while the feedback on the instrument improvement was done.

6. Primary data analysis and results

This research method was grounded on Structural Equation Modelling (SEM), and the research model was ascertained through smart PLS 3.0 software (Ringle et al., 2015). SEM is considered a second- generation multivariate data analysis method (Hair et al., 2012) produced by two types of SEM applications being used in the social sciences research area (Covariance Variance-Based (CB-SEM) and variance-based SEM-PLS-SEM; Hair et al., 2017). Characteristically, the CB-SEM is used in theory confirmation, while the variance-based SEM is used to develop a theory. However, PLS-SEM seems to be an appropriate method to assess the results in this research. Therefore, a reflective model was employed in this study. This study also focused on Grade 7 contractors operating in the peninsular Malaysia construction industry that specialized in building and civil engineering projects.

6.1. Nonresponse bias and common method variance

A comparison of the initial responses (i.e., 70 respondents) and late responses (i.e., 95 respondents) was done so as to ensure their certainty (Hair et al., 2014; Bamgbade et al., 2015). The initial responses were those who answered the first request, while the late responses were the ones followed up through telephone calls and e-mails. All adopted variables in this study were assessed, and there were no notable variations (at $\alpha = 0.05$) between the initial and late responses. This result suggests that there was no response bias in this study. Also, the Common Method Variance (CMV) was sorted out since the gathered data (perceptual) were from the same sources of respondents (i.e., construction industry).

The Harman single-factor test was initially used to assess the CMV statistically (Ringle & Sinkovics, 2009; Adeleke et al., 2019). After the whole measures were loaded into an exploratory factor analysis, the result revealed the existence of multiple factors. This means that the probability of the CMV having biased measurement among the variables was impossible. Secondly, it means that CMV should be well anticipated in measuring the correlational levels of the variables (Mcarthur et al., 1997). Evidence of the correlation analysis indicated that there was no extreme correlation coefficient among the studied variables. Consequently, a considerable aggregate of CMV was no problem for this study.

7. Results

7.1. Response rate

In survey research, the response rate represents the number of people invited to participate in the study and the number of persons who actually completed the survey instrument. There are no standard expectations for response rates as they could vary across surveys (Adeleke et al., 2018; Taofeeq & Adeleke, 2019). In order to achieve the proper response rate for this study, a total of 180 questionnaires were randomly distributed to contractors and the team members of the construction industry in the Malaysia peninsular. Online and physical distribution of the questionnaire was done for targeted respondents. In order to show the importance of the survey, the researcher made personal contact with the respondents so as to inform them of the research objectives. This action helped to reduce the time spent in obtaining the posted responses and improved the response rate. Out of the 180 questionnaires distributed, 172 questionnaires were received, with a response rate of 95.5%. Conversely, eight questionnaires were found to be unusable due to missing data or providing the same responses to all the questions. Thus, overall, 91.6% of the total copies of the questionnaire were usable, making up an effective sample of 165.

A response rate of 91.6% was considered adequate for the analysis in this study because Sekaran suggested that a response rate of 30% is sufficient for surveys (Sekaran, 2010; Hair et al., 2014; Table 1). However, most importantly, the response rate was sufficient as a rule of thumb for the minimum number of data cases required to validate a study's research model. Using PLS-SEM, the number of predictors was calculated eight times (Chin & Wang, 2003; Omer, 2019).

7.2. Assessment of the measurement model (Outer model)

Smart PLS 3.2.8 statistical software was used for the data analysis in this study, primarily in the validity and reliability testing for measures of the construct. The PLS path modeling is seen as a statistical technique "required to evaluate a network of causal relationships, based on a theoretical model, connecting two or more latent composite concepts, in which each is measured through a number of observable indicators" (Hair et al., 2012).

The most suitable procedure adopted for the study is the PLS path modeling. The first reason is that it has the ability to estimate the link between the constructs (structural model) and correlation among indicators and corresponding latent constructs (measure-

Table 1
Summary of response rate of questionnaires.

Items	No. of questionnaire	Percentage
Total questionnaire distributed	180	100
Completed questionnaire received	172	95.5
Unusable questionnaire	8	4.6
Useable questionnaire	165	91.6

ment model), simultaneously. Second, PLS path modeling can accurately predict the endogenous latent variable, which is construction risk management. Thirdly, PLS path modeling could be seen as a technique that is most preferred in multivariate analysis as far as psychological and social research are concerned in technology management, accounting, operations management, information systems and marketing (Ringle & Schlittgen, 2015).

The model consists of formalization, specialization, centralization, construction risk management, and coercive pressure. Meaning that while the measurement model was mainly used to filter the data, it was also used to assess and confirm the constructs validity and reliability prior to the establishment of goodness, and these were used to examine the reliability of indicators. The acceptable loading is 0.5, and for internal consistency 0.7 level is accepted. According to Chin (1998), the composite reliability and the Cronbach's Alpha and Average Variance Explain (AVE) must be 0.5 and above, and for the convergent validity and factor loading discriminate validity used, the item (s) loading that is higher on the other construct than their construct should be deleted (Chin, 1998; Hairet al., 2012). Consequently, all the adapted instruments in this study were reliable, based on the fact that all the items were above 0.5. The items loaded on their individual construct ranged from 0.651 to 0886; they were acceptable since they were above the cut-off mark value of 0.5, which is in line with Chin's (1998) and Hair's (2011) recommendations. Similarly, the values of the composite reliability ranged from 0.847 to 0.939, and these were greater than the value of the benchmark 0.7 (Hair et al., 2011 Table 2).

The convergent validity was determined using AVE. The AVE ranged from 0.527 to 0.708, which was above the minimum cutoff value of 0.5 (Hair et al., 2011; Taofeeq & Adeleke, 2019). Lastly, in determining the discriminate validity, the Average Variance Extracted (AVE) was compared to the correlation squared of the interrelated variables of the constructs concerned, where it also indicated the adequate discriminate validity. Table 2 shows the factor loading, and Table 3 shows the discriminate validity. The authors deleted one of the 83 items because its loadings were below this threshold. The remaining 82 items represented loadings between 0.651 and 0.886.

Table 2
Construct reliability and validity.

Items	Loading	AVE	CR	Cronbach Alpha
MAT1	0.822	0.584	0.874	0.817
MAT2	0.843			
MAT3	0.658			
MAT4	0.663			
MAT5	0.812			
CEN1	0.781	0.527	0.847	0.784
CEN2	0.716			
CEN3	0.767			
CEN4	0.655			
CEN5	0.704			
COER1	0.728	0.573	0.903	0.876
COER2	0.707			
COER3	0.651			
COER4	0.809			
COER5	0.804			
COER6	0.770			
COER7	0.813			
DES1	0.703	0.595	0.898	0.862
DES2	0.755			
DES3	0.864			
DES4	0.751			
DES5	0.829			
DES6	0.712			
FIN1	0.830	0.708	0.924	0.896
FIN2	0.873			
FIN3	0.840			
FIN4	0.881			
FIN5	0.779			
FOR1	0.824	0.623	0.920	0.903
FOR2	0.798			
FOR3	0.853			
FOR4	0.828			
FOR5	0.715			
FOR6	0.828			
FOR7	0.663			
LAB1	0.818	0.689	0.939	0.924
LAB2	0.870			
LAB3	0.886			
LAB4	0.851			
LAB5	0.769			
LAB6	0.816			
LAB7	0.793			
MAN1	0.739	0.528	0.924	0.909
MAN10	0.555			
MAN11	0.693			
MAN2	0.763			
MAN3	0.808			
MAN4	0.675			
MAN5	0.761			
MAN6	0.709			
MAN7	0.719			
MAN8	0.761			
MAN9	0.777			
SPE1	0.827	0.673	0.924	0.879
SPE2	0.850			
SPE3	0.866			
SPE4	0.743			
SPE5	0.809			

Abbreviations: MAT, Materia risk; CEN, centralization; COER, coercive pressure; DES, design; FIN, Financial risk; FOR, formalization; LAB, labour and equipment risk; MAN, Management Risk; and SPE, specialization.

7.3. Discriminant validity

Discriminant validity is 'the extent to which a construct is truly distinct from other constructs by empirical standards (Hair et al., 2017). In this study, discriminant validity was evaluated using two criteria including cross-loadings, Forner–Lacker criterion, as suggested by Hair et al. (2017) and Hassan et al. (2019). In assessing the cross-loadings, the outer loading of an item should be greater on its respective latent variable than its cross-loadings of other latent variables. Table 2 summarizes that outer loading of each indicator was greater on its respective latent variable than its cross-loadings on any other latent variable.

The second approach of discriminant validity was evaluated using the criteria suggested by Fornell and Larcker (1981). The author suggested that discriminant validity is achieved when the square root of each construct's AVE is higher than the correlation of the construct to other latent variables.

Table 3 presents a list of the correlations between the variables and the values of the square root of the average variances extracted. This is an indication that all the diagonal values are greater than the correlation among the variables, meaning that there is sufficient discriminant validity (Fornell & Larcker, 1981).

7.4. Structural model results (Inner model)

To ascertain the significance of the coefficients for the actual model, the authors used a standard bootstrapping process with 5,000 bootstrap samples and 165 cases (Hair et al., 2012), Table 2 and Fig. 2 present the significant paths for this research model. Fig. 2 depicts the diagrammatical histrionics of the results for the structural modeling analysis proposed for checking the hypothesized relationship between the latent variables. Given that the author's hypotheses are specified in a directional form and the power of one tailed test is greater than for two-tailed test, the one-tailed test was chosen (Cho & Abe, 2013; Taofeeq & Adeleke, 2019). However, this study does not suggest ignoring the two-

Table 3
Discriminant validity results based on Fornell–Larcker criterion. (correlations among latent variables).

	CEN	COR	DES	FIN	FORM	LIB	MAN	MAT	SPE
CEN	**0.726**								
COR	−0.013	**0.757**							
DES	0.216	0.430	**0.771**						
FIN	0.279	0.338	0.564	**0.841**					
FORM	0.391	−0.139	0.138	0.312	**0.790**				
LIB	0.257	0.430	0.500	0.633	0.147	**0.830**			
MAN	0.323	0.391	0.637	0.534	0.178	0.628	**0.727**		
MAT	0.288	0.519	0.562	0.499	−0.018	0.659	0.715	**0.764**	
SPE	0.159	0.081	0.326	0.138	0.182	0.188	0.414	0.221	**0.820**

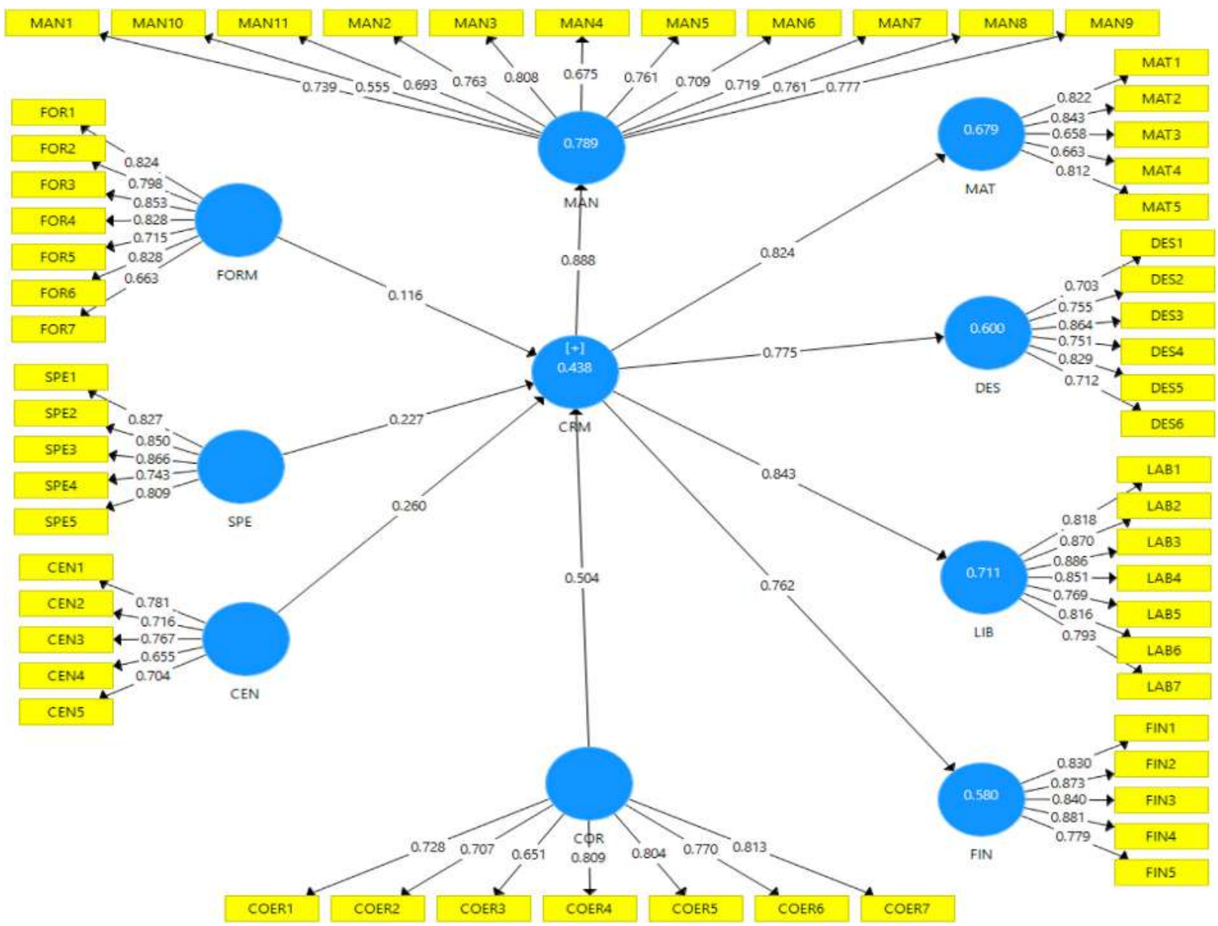

Fig. 2. The evaluation of measurement model through PLS algorithm.

Table 4
Path coefficient.

Items	Construct/variables	B	T-Values	P-Values	Findings
H1	FORM -> CRM	0.087	1.268	0.103	Not supported
H2	SPE -> CRM	0.236	3.426	0	Supported
H3	CEN -> CRM	0.195	3.227	0.001	supported
H4	COR*FOR -> CRM	0.137	1.948	0.026	supported
H5	COR*SPE -> CRM	0.03	0.317	0.376	Not supported
H6	COR*CEN -> CRM	0.15	1.671	0.048	supported

Note: p^*<0.05(1-tailed test).

Table 5
Variance explained in the endogenous latent variable.

Latent variables	Variance explained (R^2)
Construction risk management (CRM)	0.43

tailed test while testing a theory because we realize that there are some conditions in which a two-tailed test is suitable (Cho & Abe, 2013). Zikmund et al. (2009) for example, pointed out that two-tailed test is more suitable when the researcher is not sure about the directionality of the study's hypotheses.

Table 6
Effect sizes of the latent variables on Cohen's (1988) recommendation.

R^2	Included	ExcludedF^2	Effect size
FOR 0.438	0.438	0.019	None
SPE0.438	0.389	0.087	Small
CEN0.438	0.381	0.101	Small
COER0.438	0.192	0.437	Large

Abbreviations: FOR, formalization; SPE, specialization; CEN, centralization; COER, coercive pressure.

Hypothesis 1 anticipated that formalization would be positively related to construction risk management. The results (Table 4) confirmed that formalization had a negative relationship with construction risk management (β 0.087, $t = 1.268$ and $p < 0.01$). Therefore, Hypothesis 1 was not supported. Equally, it was predicted that specialization would positively correlate with Hypothesis 2, which is construction risk management. It was eventually confirmed that both had positive correlation (β 0.236, $t = 3.426$ and $p > 0.01$).

Hence, Hypothesis 2 supported the results. Hypothesis 3 stated that there is a positive correlation between centralization and construction risk management. The finding revealed that centralization had a positive influence on construction risk management (β 0.195, $t = 3.227$ and $p > 0.01$). Also, it was predicted that coercive pressure would positively moderate the relationship between formalization and construction risk management (Hypothesis 4). Findings revealed that coercive pressure had a positive moderation on the correlation between formalization and construction risk management, thus suggesting that Hypothesis 4 was supported (β 0.070, $t = 1.948$, and $p > 0.01$). Hypothesis 5 anticipated that coercive pressure would positively moderate the relationship between specialization and construction risk management. Going by the results, a negative relationship was affirmed (β 0.030, $t = 0.317$ and $p < 0.01$). Lastly, it was stated that coercive pressure positively moderate centralization and construction risk management (Hypothesis 6). The results showed that a positive correlation existed (β 0.150, $t = 1.671$ and $p > 0.01$) between the variables.

7.5. Coefficient of determination (R^2)

Having examined the significance and relevance of the path coefficients, the explanatory power of the structural model was determined. The explanatory power was examined by the coefficient of determination: R^2values (Hair et al., 2012; Taofeeq & Adeleke, 2019; Hassan et al., 2019). Another essential criterion for measuring structural model in the PLS-SEM is the use ofR^2 values or the coefficient of determination (Henseler et al., 2009; Hair et al., 2012). According to the literature, R^2 is the indicator that shows the amount of variance examined in the endogenous variable by its exogenous variable. R^2 reflects the quality of the variables included in the model (Hair et al., 2010). However, there are many criteria that can be employed as guidelines for assessing the level of the value ofR^2. For example, Cohen's (1988) criterion opines that R^2_0.26 is considered to be substantial, 0.13 is moderate, and 0.02 is weak. But Chin (1998) criterion states that R^2_0.67 is substantial, 0.33 is moderate, and 0.19 is weak.

Table 7
Construct Cross Validity Redundancy.

Total	SSO	SSE	Q^2 (=1-SSE/SSO)
Construction Risk Management	825	524.583	0.364

Table 5 presents the R^2 values of the endogenous (contraction risk management) latent variable. As summarized in Table 6, the research model explicates 0.43 of the total variances in contractual risk management. Therefore, following Falk and Miller's (1992) and Chin (1998) standards, the endogenous latent variable presented acceptable levels of R^2 values, which were regarded as substantial.

7.6. Effect size and predictive relevance

The determination of the significant path coefficient of the study's model was initially done. Thereafter, the evaluation of the level of theR^2values, effect size, and predictive relevance was carried out. It was revealed that the total construction risk management variance was 43% for all the four exogenous latent variables (i.e., formalization, specialization, centralization, and coercive pressure). The least satisfactory level suggested by Falk and Miller (1981) for R^2 is a value of 0.10.

$$\text{Effect size}: f^2 = \frac{R^{2\ included} - R^2\ excluded}{1 - R^{2\ included}}$$

The recommendation given by Fornell and Larcker (1981) emphasizes the possession of the threshold level of R^2 values by the endogenous latent variable. It further explains that the relative impact that the specific exogenous latent variable has on the endogenous latent variable(s) as a result of the changes in the R^2 values is revealed by effect size (Hair et al., 2012). The calculation is done by the increasedR^2 of the linked latent variable path, which is relative to the latent variable's equilibrium of unsolved variance. Thus, the calculation of the effect size can be done by using the following formula (Cohen 1988; Ringle & Schlittgen, 2007).

It was suggested by Cohen (1988) that f^2 values of 0.35, 0.15, and 0.02 should be measured as large, medium, and small effects, respectively. The current findings revealed that the effect size for formalization was 0.427, 0.389 for specialization, 0.381 for centralization, and 0.192 for coercive pressure. However, the predictive relevance of the model was ascertained by the use of Stone-Geisser test through the blindfolding processes (Stone, 1977). To be specific, a cross-validated redundancy measure (Q^2) was employed to check the predictive relevance of the whole research model (Hair et al., 2012). TheQ^2 is a touchstone to assess how good a model predicts the data for the omitted cases. According to Ringle and Sinkovics (2009), a study model that possessesQ^2 statistic(s) beyond zero is considered to have predictive relevance. Likewise, a study model with higher positive Q^2 values has more predictive relevance.

Results affirmed Q2 statistics of 0.364 for this study's endogenous latent variable as presented in Table 7, which is more than zero, indicating predictive relevance of the model (Hair et al., 2012).

7.7. Testing moderator effect of coercive pressure

A product-indicator method was adopted through the use of PLS structural equation modeling for observation and assessment of coercive pressure on the correlation between organizational structure and construction risk management.

In order to make use of the product-indicator method, the first step of evaluating direct effects was adopted. It involved integration of the exogenous latent variables and moderating variable as the independent latent variables in the model. The second required step involved the establishment of the latent interactive term through the procreation of the products of each indicator of the exogenous latent variables, as well as each indicator of the moderating variable (Ringle & Schlittgen, 2007). The third step was

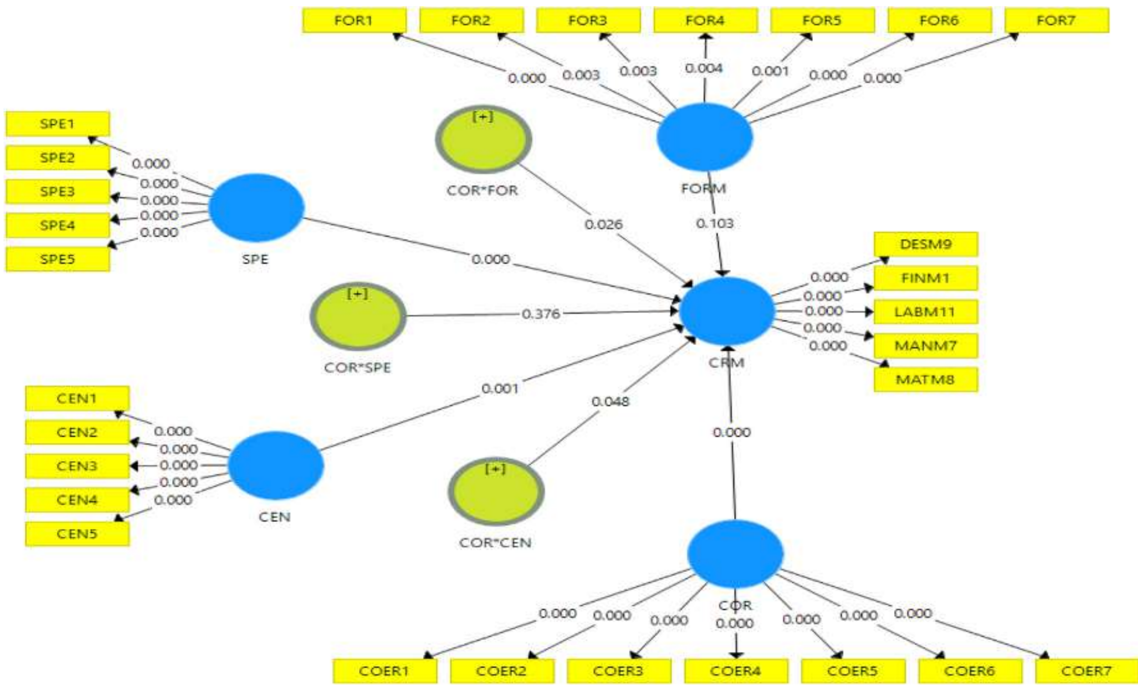

Fig. 3. Structural model. CRM, construction risk management; DESM, design risk; FINM, finance risk; LABM, labour and equipment risk; MATM, material risk or management risk; FOR, Formalization; SPE, Specialization; CEN, Centralization, COER, Coercive pressure.

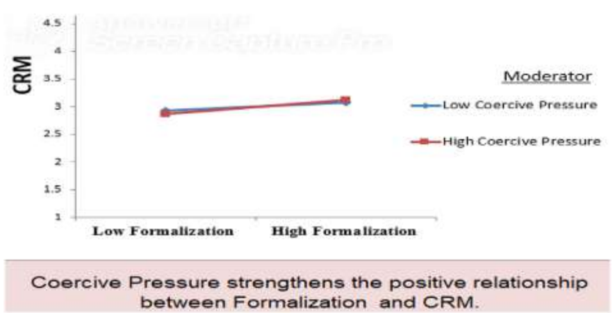

Fig. 4. The interaction between formalization and coercive pressure in predicting construction risk management (CRM).

involved in making a calculation of the standardized path coefficients so as to confirm that the interaction effects are significant for the model (0.023, 0.028, and 0.037 for the formalization, specialization, and centralization, respectively). Lastly, the determination of the moderating effects' strength was performed (Cohen, 1988).

Coercive pressure was predicted to have moderate correlation between formalization and construction risk management in order to strengthen their relationship (i.e., positively significant) (Hypothesis 4). It was revealed that formalization and coercive pressure had a significant interaction effect, meaning that it was supported (Fig. 3) (β 0.137, $t = 1.948$ and $p > 0.01$). Coercive pressure was predicted to have moderate correlation between specialization and construction risk management (Hypothesis 5). Nevertheless, it was not supported (β 0.030, $t = 0.317$ and $p > 0.01$). Lastly, coercive pressure was predicted to have moderate correlation between centralization and construction risk management (Hypothesis 6). Nevertheless, there was no support (β 0.150, $t = 1.671$ and $p > 0.01$).

The test of Hypothesis 1 showed that there was negative correlation between formalization and construction risk management. This suggests that the industry that adopted formalization structure experienced high risk during their construction activities. Also, it was predicted that specialization would have positive correlation with construction risk management (Hypothesis 2). The revealed result supported the hypothesis. The result therefore suggests that the proper division of task according to individual's or teams' knowledge within an organization would lead to reduction in the occurrence of risks on projects. That is to say, when an organization properly exercises control over activities within an organization, the organization would experience fewer problematic situations. In the same manner, it was predicted that centralization that is the control exerts on construction workers and construction risk management would have a positive relationship. The result showed a positive correlation, which suggests that the adoption of centralization in controlling construction workers leads to reduction in the occurrence of risks (Hypothesis 3). It was also anticipated that coercive pressure would moderate the correlation between formalization and construction risk management (Hypothesis 4). The result revealed a significant positive correlation between the two variables. This therefore suggests that every construction industry that ensures that its rules and regulations (government regulatory or regulation from other agencies) are properly assimilated within the system would definitely experience less risk in the process of carrying out construction projects.

Furthermore, it was predicted that coercive pressure would have a moderating effect on the correlation between specialization and construction risk management (Hypothesis 5). The two variables revealed a negative correlation.

Table 8
Strength of the moderating effects following Cohen's (1988) and Henseler and Fassott's (2010) guidelines.

Endogenous latent variables	R^2 Included Excluded	F^2	Effect size
Coercive pressure	0.438 0.192	0.437	Large

7.8. Determining the strength of the moderating effect

To ascertain the coercive moderating effect on the correlation between organizational structure and construction risk management, Cohen's (1988) effect sizes were computed. Similarly, the moderating effects strength can be measured by equating the coefficient of determination (R^2value) of the actual effect model together with the R^2 value of the full model that comprises both the exogenous latent variables with the moderating variable (Henseler & Fassett, 2010). Hence, the strength of the moderating effect could be determined with the use of the following formula (Cohen, 1988; Henseler & Fassett, 2010):

$$\text{Effect size}: f^2 = \frac{R^{2\ \text{model with modorator}} - R^2 \text{model without modorator}}{1 - R^{2\ \text{model with moderator}}}$$

Cohen (1988) and Henseler and Fassott (2010) suggested the moderating effect sizes $\left(f^2\right)$ values in Fig. 4. Interaction effect of coercive pressure on formalization and construction risk management were 0.35, 0.15, and 0.02, and can be considered as strong, moderate, and weak, respectively. However, according to Chin and Wang (2003), the effect sizes with low values do not essentially mean that the moderating effect is insignificant. 'Even a small interaction effect can be significant under utmost moderating conditions if the resulting b-changes are significant; then it is paramount to take these conditions into consideration' (Chin and Wang, 2003; Omer, 2019). The output of the strength of the moderating effects of rules and regulations is summarized in Table 8.

8. Discussion

The central focus of this study is to confirm the moderating effect of coercive pressure on the correlation between organizational structure and construction risk management. Findings confirm that coercive pressure plays a significant role in the relationship between formalization and construction risk management.

In terms of the research objective, Hypothesis 1 anticipated that formalization would be positively related to construction risk management. The results (Table 4) affirmed that formalization had a negative relationship with construction risk management (β 0.087, $t = 1.268$ and $p < 0.01$). Therefore, Hypothesis 1 was not supported. Similarly, Hypothesis 2 anticipated that specialization would be positively related to construction risk management. The result affirmed that specialization was positively related to construction risk management (β 0.236, $t = 3.426$ and $p > 0.01$). Hence, Hypothesis 2 supported the research findings.

Hypothesis 3 also predicted that centralization would positively relate to construction risk management. The result disclosed that centralization positively influenced construction risk management (β 0.195, $t = 3.227$ and $p > 0.01$). Likewise, Hypothesis 4 predicted that coercive pressure would positively moderate the relationship between formalization and construction risk management. The result showed that coercive pressure positively moderated the relationship between formalization and construction risk management, which means that the hypothesis was supported (β 0.070, $t = 1.948$, and $p > 0.01$).

Hypothesis 5 anticipated that coercive pressure would positively moderate the relationship between specialization and construction risk management. Going by the results, a negative relationship was affirmed (β 0.030, $t = 0.317$ and $p < 0.01$). Lastly, Hypothesis 6 proposed that coercive pressure would positively moderate centralization and construction risk management. The results showed that a positive relationship was affirmed (β 0.150, $t = 1.671$ and $p > 0.01$) between the variables. As summarized in Table 5, the t-values with each path coefficient have been determined by using the bootstrapping technique and p-values were subsequently generated.

This research has tested the moderating role of coercive pressure on the relationships between organizational structures and construction risk management by integrating coercive pressure as the moderating variable to identify the influence of formalization, specialization, and centralization on construction risk management. Thus, this study was able to fill in the theoretical gap in literature. The results suggest that an effective organizational structure motivates organizational members to achieve a common goal regarding risk on construction projects. It has been established that the numerous parts of organizational structure do have an influence on effectiveness (Mao et al., 2017). The negative moderating effect of coercive pressure on the relationship between construction risk management and organizational structures indicates the potential operation of other moderating variables.

8.1. Research implications

This study created awareness on useful and interesting information on organizational structure that affects construction risk management in the construction industry. Contractors should take into account that specific factors that are peculiar to the role can play into an individual's process of making decisions about risk management. As a result, top management should select a proper organizational structure that will improve the quality of the work and allow workers to know more about risks in construction.

Furthermore, team members should be persuaded to participate in training and courses on risk management. It is imperative that management has a clear understanding of the best way and strategy to encourage the workers to engage and to be committed to risk management issues. This is vital for the improvement of safety behavior. Although the organizational structure affecting construction risk management dimensions investigated in this study is easy to control during the selection of new structures, project managers should try to properly apply the result of this study in dealing with risk management in the construction industry. Our research also provides contractors, project managers, team members, and clients with some strategies on how to know and deal with risk management in the construction industry.

This study is not only essential to the academic world, but also to the contractors, project managers, and engineers who are required to control risk management in every construction industry. It is obligatory to all construction industries in Malaysia to register their industry under CIDB and other related legislation to ensure all safety aspects are strictly followed in the workplace. In the same vein, encouraging results toward improving construction risk management in the construction industry has become the most important part in recent years. In addition, it can help the industry to maximize their profit goals. The construction industry can use the information in this research in developing strategy on risk management.

8.2. Limitation of the study

This study needs to be replicated from another perspective and different samples to validate the research findings. Although this study has revealed some understanding of the influence of coercive pressure on the relationship between organizational structure and construction risk management, it is not without limitations. First, because this research adopted a cross-sectional design, underlying inferences cannot be made to the study population. Consequently, a longitudinal design can be used in future research to ascertain changes over time. Second, future studies can also increase or widen the study area within the Malaysian construction industry. Furthermore, future researchers should try to increase the study sample from the 165 being used in this study for a better result. As it was revealed in this research that the total variance in construction risk management as the endogenous variable is 43%, therefore, future studies can improve more on the variance. Regardless of its limitations, this study was able to portray the moderating effects of coercive pressure on the relationship between organizational structure and construction risk management.

8.3. Conclusion and recommendations

Findings from this study have uncovered the importance of formalization, specialization, and centralization in improving construction risk management within construction industry.

The findings also propose a scheme toward improving construction risk management through compensation and motivation at every stage of the construction process, which will enhance productivity within the construction industry. Furthermore, the results of this study will practically help stakeholders (i.e., agencies, both governmental and non-governmental organizations) in policy-making and appropriate decisions making with regard to the efficiency and effectiveness of the construction risk management practices.

Despite considerable research on construction risk management, the gap in knowledge is that there is no connection between specific structures affecting risk management and the moderating effect of coercive pressure. This gap, therefore, limits our understanding of the possible reasons for risk management in the construction industry. Hence, the aim of this study was to fill this gap by investigating the relationship of organizational structure on construction risk via the moderating effects of coercive pressure. The main concern of this study was to investigate the relationship between organizational structure and risk management with the help of coercive pressure as moderator in the construction industry. A quantitative method was used in this research to fulfil the objectives. The study is also cross-sectional in nature. Unit of analysis was individuals and they were G7 contractors, project managers, and engineers who were operating in the Malaysian peninsular construction industry. For the purpose of this research, the PLS-SEM was chosen. The software Smart PLS 3.2.8 was utilized to perform the analysis. The findings reveal that specific organizational structures are significantly related to construction risk management with the help of the coercive pressure moderating the relationship. From the objectives, it was found that specific organizational structures are more aligned with industrial goals. In addition, construction organizations that adopt formalization and centralization structure while imbibing coercive pressure will record less risk occurrence on projects.

Therefore, this study suggests that in industries, specialization and centralization of structure enhance productivity within the construction industry. This study has highlighted the underlying mechanism of how specific structure can affect construction risk in the construction industry, especially of G7 contractors. Importantly, this research provides construction industry with guidelines on how specific structures can relate to construction risk management positively.

Acknowledgements

The authors acknowledged the financial contribution of Research and Innovation Department University Malaysia Pahang (UMP), Malaysia through the grant PGRS-190377. Also, authors declare there is no conflicts of interest

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Manal Suliman Omer obtained his PhD degree in Faculty of Industrial Management, University Malaysia Pahang, Malaysia in 2019. He also obtained her master degree in (Management), from Open University Malaysia in 2017, Her current research is focused on the influencing of organizational internal factors and organizational structure on Malaysian construction industries. Her research interests include Risk Management in Construction Project, Issues in Construction Industry, Organizational Control, and institutional pressure in Construction Project. She has published in many international journals such as Safety Science (ISI), International Journal of Construction Management and so on. Currently working on 1 international grant in University Malaysia Pahang.

Adekunle Qudus Adeleke is a senior lecturer of Project Management at the Faculty of Industrial Management, University Malaysia Pahang since 2017. He was conferred a PhD degree from University Utara Malaysia, Malaysia in 2016. He badged his BSc. in Business Information System with First Class Honour from the University of East London in 2014. Presently, Adeleke is a professional member of the Malaysian Institute of Management (M.I.M) and Association of Construction Project Managers (ACPM), Malaysia. His primary research activities involve the area of Project Management (e.g., Risk Management in Construction Project, Issues in Construction Industry, Organizational Control, Sustainability in Construction Project, and Waste Management in Construction Project, Quantitative and Qualitative research experts). Adeleke has researched and published on Risk Management and Organizational Issues in the Construction Industry. Adeleke also anchored several guest speaker invitations from both local and international conferences. He is an author of a book with more than 40 publications and currently working on 2 international grants.

Taofeeq Durojaye Moshood obtained his Master degree in Faculty of Industrial Management, University Malaysia Pahang, Malaysia in 2019. He also obtained his higher national diploma (Electrical and Electronics Engineering), from Osun state polytechnic iree, Nigeria in 2015, His current research is focused on the influencing factor affecting contractor risk attitudes in Malaysia construction industries. His research interests include Risk Management in Construction Project, Issues in Construction Industry, Organizational Control, and Sustainability in Construction Project. He is has published in many international journals such as Safety Science (ISI), International Journal of Construction Management and so on. Currently working on 1 international grant in University Malaysia Pahang.

Journal of Safety Research 77 (2021) 217–228

Contents lists available at ScienceDirect

Journal of Safety Research

journal homepage: www.elsevier.com/locate/jsr

Comparison of motor vehicle-involved e-scooter and bicycle crashes using standardized crash typology

Nitesh R. Shah, Sameer Aryal, Yi Wen, Christopher R. Cherry *

Civil and Environmental Engineering, University of Tennessee, Knoxville, TN, United States

ARTICLE INFO

Article history:
Received 11 November 2020
Received in revised form 28 December 2020
Accepted 4 March 2021
Available online 26 March 2021

Keywords:
e-scooter
Bicycle
PBCAT crash typology
Micromobility
Safety

ABSTRACT

Introduction: The market share of e-scooters in the United States has proliferated in cities: 86 million trips were made on shared e-scooters in 2019, a more than 100% increase compared to 2018. However, the interaction of e-scooters with other road users and infrastructure remains uncertain. *Method:* This study scrutinized 52 e-scooter and 79 bicycle police-reported crashes in Nashville, Tennessee, from April 2018 to April 2020 from the Tennessee Integrated Traffic Analysis Network (TITAN) database. We used descriptive analysis and a recent prototype version of the Pedestrian and Bicycle Crash Analysis Tool (PBCAT) to classify crashes based on the locations of the crashes relative to roadway segments or intersections, as well as the maneuver of the motor vehicle and e-scooter/bicycle relative to the motor vehicle. *Results:* Two crash typologies can explain the majority of e-scooter crashes, while bicycle crashes are distributed over several crash typologies. Additionally, 1 in 10 e-scooter- and bicycle-motor vehicle crashes leads to the injury or fatality of the e-scooter rider or bicyclist. Furthermore, we noted statistically significant differences in spatial and temporal distribution, demographics, lighting conditions, and crash distance from home for e-scooter and bicycle crashes. *Conclusions:* The police crash report provides a comprehensive picture of e-scooter safety complementing existing literature. We found that e-scooter crash characteristics do not fully overlap with features of bicycle crashes. *Practical Implications:* A generalized engineering, education, and enforcement treatment to reduce and prevent e-scooter and bicycle crashes, injuries, and fatalities might not result in equal outcomes for each mode. More rigorous enforcement could be implemented to deter e-scooters riders under the age of 18 years and e-scooter safety campaigns could target female riders.

1. Introduction

Cities across the world face common transportation issues like traffic congestion, air pollution (Kennedy, Miller, Shalaby, Maclean, & Coleman, 2005), collisions (NHTSA, 2008), and negative impacts on equity and social development (Cao & Zhang, 2015). Micromobility systems have aimed to fill a niche for short trips in cities by providing alternative options to low occupancy travel modes, which aim to reduce the physical and environmental footprint required for moving people quickly over relatively short distances (Maiti, Vinayaga-Sureshkanth, Jadliwala, & Wijewickrama, 2019).

This novel category of transportation modes includes vehicles such as e-scooters, e-bikes, and docked-bikes. In this paper, "e-scooters" refers to the ultra-lightweight, standard width, low-speed electric standing scooters that carry one rider according to the SAE International J3194 standard (SAE International, 2019). The National Association of City Transportation Officials (NACTO) has tracked and published the most definitive aggregate scooter ridership estimates across the United States in the past two years. E-scooters have proliferated in many cities of the United States in the last decade: 86 million trips were made with shared e-scooters in 2019, a more than 100% increase in trips compared to 2018 (NACTO, 2020). With e-scooters' increasing popularity, one of the biggest challenges for decision-makers and transportation planners is to accommodate these emerging modes in the current transportation system.

The current literature lacks the understanding of e-scooter impacts, including safety. Most of the previous e-scooter safety studies have taken observational, survey-based, epidemiological, and news article mining approaches. However, these data sources and methods do not provide a comprehensive understanding of e-scooter safety and how it relates to other micromobility modes. This study contributes to the literature by applying standardized

* Corresponding author.
E-mail addresses: nshah12@vols.utk.edu (N.R. Shah), saryal2@vols.utk.edu (S. Aryal), ywen4@vols.utk.edu (Y. Wen), cherry@utk.edu (C.R. Cherry).

https://doi.org/10.1016/j.jsr.2021.03.005
0022-4375/

bicycle crash typology on both e-scooter and bicycle crashes in Nashville, Tennessee. The comparison of crash typology based on location and maneuver, as well as general characteristics and demographics of crashes, can inform targeted educational, design, and enforcement strategies to reduce e-scooter and bicycle crashes.

The remainder of this section is organized into three sub-sections. Relevant safety research approaches, including crash typology, is summarized in the first sub-section. The second sub-section provides an overview of prior e-scooter safety studies, while the last sub-section presents the research approach of this paper.

1.1. Relevant safety research approaches

Macro-level safety analysis evaluates the effect of traffic, roadway, and socio-demographic factors on crashes over a geographical space to provide countermeasures for a long-term perspective (Cai, Lee, Eluru, & Abdel-Aty, 2016). Micro-level crash analysis, on the other hand, can lead to better insights about the cause of the crash (Hertach, Uhr, Niemann, & Cavegn, 2018), and help to identify solutions that can be applied over a short period. Moreover, traffic safety problems can be related to microscopic factors such as a specific design of the road segment or intersection (Huang et al., 2016).

Crash typology analysis is one of the methods for the micro-level analysis of bicycle as well as pedestrian crashes. The National Highway Traffic Safety Administration (NHTSA) classified pedestrian (Snyder & Knoblauch, 1971) and bicycle crashes (Cross & Fisher, 1977), which was later refined for the development of the FHWA Pedestrian and Bicycle Crash Analysis Tool (PBCAT) (Harkey, Tsai, Thomas, & Hunter, 2006). This is the most common crash typology used in practice and contains 56 pedestrian crash types and 79 bicycle crash types based on a combination of the following factors: pedestrian, bicyclist, and motor-vehicle direction of travel; traffic control type; location; user behavior; and other circumstances such as school bus-related crashes.

Researchers have also developed other typologies to complement behavior- and circumstance-based PBCAT crash typology. Schneider and Stefanich (2016) developed the Location-Movement Classification Method (LMCM) crash typology that is based on location and movement characteristics of the crash. Other crash types consider the interaction between a bicycle and a motor vehicle (e.g., right hook, head-on, door; City of Cambridge, 2014; Lusk, Asgarzadeh, & Farvid, 2015), as well as crash characteristics that include the movement patterns of the bicyclist/pedestrian and motor vehicle, roadway attributes, lighting, and weather conditions (Jermakian & Zuby, 2011; MacAlister & Zuby, 2015).

These crash typologies can be used to identify design engineering and enforcement measures as well as educate people to reduce crashes. For example, "Motorists turned left into the path of bicyclist" crash type may be addressed by improving left turn infrastructure and operations, improving intersection lightning, and improving vehicle conspicuity. However, to the authors' knowledge, the crashes of emerging modes like e-scooters have not been scrutinized using any crash typologies. This paper uses the latest prototype version of PBCAT developed by Libby Thomas, Mike Vann, and UNC Highway Safety Research Center (2020) to evaluate the similarities and differences between e-scooter and bicycle crashes.

1.2. Prior e-scooter safety research

Unlike motor vehicle as well as bicycle crashes, e-scooter crashes lack national or statewide standardization, which has led researchers to adopt a wide range of data sources to assess e-scooter crashes. Emergency department and trauma center data is the most popular source to evaluate fatalities and the severity of injuries related to e-scooter crashes (Badeau et al., 2019; Beck, Barker, Chan, & Stanbridge, 2019; Sikka, Vila, Stratton, Ghassemi, & Pourmand, 2019; Trivedi et al., 2019). As a part of e-scooter pilot evaluation programs, city transportation agencies have adopted a combination of methods to assess e-scooter safety, which include surveys (Portland Bureau of Transportation, 2019) and hospital records (Austin Public Health, 2019; City of Chicago, 2020).

Several studies have evaluated e-scooter user behavior related to safety that is based on a survey or observation. Curl and Fitt (2019) surveyed 536 Lime e-scooter users in New Zealand and concluded that 90% of users used footpaths (sidewalks) to ride e-scooters, and safety was the primary concern among non-users. James, Swiderski, Hicks, Teoman, and Buehler (2019) surveyed 181 e-scooter riders and non-riders in Rosslyn, Virginia, and combined the results with observational parking behavior. The authors found that non-users perceived e-scooters as more dangerous than users perceived them.

Researchers have also used news reports and social media to understand e-scooter crash characteristics and user behavior. Yang et al. (2020) analyzed nationwide news reports to identify 169 e-scooter crashes in the United States between 2017 and 2019 and evaluated general crash characteristics, such as severity, demographics, and locations. Similarly, Allem and Majmundar (2019) evaluated 324 posts from Bird's official Instagram account and found that many depicted e-scooter users did not use protective gear like helmets.

However, the data sources used in the current e-scooter safety literature are not a comprehensive representation of e-scooter crashes. For example, hospital records are often limited to small sample sizes and can be biased towards severe injuries, and lack contextual transportation factors (Tin, Woodward, & Ameratunga, 2013), while news reports are biased in terms of crash severity, time and place of the crash, as well as the road user type and the victim's personal characteristics (De Ceunynck, De Smedt, Daniels, Wouters, & Baets, 2015). Furthermore, most crashes in those datasets include little information about the motor vehicle, which contributes to 80% of e-scooter rider fatalities (Santacreu, Yannis, de Saint Leon, & Crist, 2020). Therefore, there is a need to understand the interaction between e-scooters and motor vehicles and identify the most common crash typologies. To this end, we also hope to understand how e-scooter crashes differ from bicycle crashes to assess if e-scooter-specific safety strategies are warranted.

1.3. Research hypothesis

Most fatalities and severe injuries of e-scooter users involve a motor vehicle, while crash typologies focused on the interaction between micromobility and motor vehicles in the literature have only examined bicycle crashes. An evaluation of crash typology considering the location and maneuver of e-scooters and motor vehicles as well as a comparison with other micromobility modes, like bicycles, is lacking in the literature.

E-scooters are smaller than bicycles, which allows them to navigate pedestrian traffic, yet they are also fast enough to travel among cars on the roadway. This flexibility allows e-scooter riders to change when and where they ride, such as switching from riding on a sidewalk to using a traffic lane to avoid groups of pedestrians. Moreover, many policies require scooters ride on the road, but park on the sidewalk in the furniture zone, implicitly endorsing riding between the domains. Such navigation might be unpredictable, thereby increasing the risk of a collision between an e-scooter and a car, resulting in unique crash types. Therefore, the hypotheses of this study are as follows:

1. The general crash characteristics of bicycles or e-scooters colliding with a motor vehicle are different from each other.
2. The location as well as maneuver of bicyclists/e-scooter riders and motorists before the crash are different.

The remaining paper is organized as follows. The methods section describes the data and crash typology framework, with findings in the results section. A discussion of the findings along with limitations and further research provided in the discussion section. The conclusion section summarizes the paper.

2. Method

The research hypothesis was evaluated by analyzing e-scooter and bicycle crash records using descriptive analysis and PBCAT crash typology. The first sub-section describes the police crash reports, while the second sub-section provides an overview of the recent version of the PBCAT crash typology.

2.1. Crash report data

We accessed all the available e-scooter and bicycle crash reports between April 1, 2018 and April 30, 2020 in Nashville, Tennessee that were reported by the police and documented in Tennessee's Integrated Traffic Analysis Network (TITAN) (Tennessee Highway Safety Office, 2020). We relied on the tabulated crash data as well as narratives and crash diagrams to code specific information from the crashes. Although the TITAN dataset includes crash records throughout the state, we only analyzed crashes in Nashville, as e-scooter regulations differ between cities, which could influence riding behavior. Nashville additionally has the highest e-scooter deployment and usage amongst Tennessee cities, and crashes were consistently reported by two law enforcement agencies (Nashville Metro Police and Vanderbilt University Police). To legally ride a scooter in Nashville, a person must be 18 years or older, possess a valid driver's license, yield to pedestrians, and follow the rules of the road. A rider must not ride on sidewalks nor drink and ride.

This database includes crashes that involve a motor vehicle on public roadways, parking lots, and private driveways. The crash reports collect information on crash characteristics, general roadway characteristics, details of people and vehicles involved in a crash, as well as a narrative and a crash diagram describing the incident. Some crash reports include photographs. Incidents that do not involve motor vehicles, like e-scooter riders or bicyclists falling off or colliding with each other are not included in the TITAN database. This analysis only includes motor vehicle-involved crashes, which tend to be the most severe types of crashes. Although most reported injuries do not involve a motor vehicle, motor vehicle-involved crashes constitute about 80% of fatal crashes worldwide (Santacreu et al., 2020), emphasizing the importance of focusing on these conflicts to reduce severe injuries or death. The evaluation of such incidents is essential in developing countermeasures that reduce bicycle- and e-scooter-motor vehicle crashes.

We identified 33 unique e-scooter crashes in the TITAN database under the *Non-Motorized Personal Conveyance* category. E-scooter crashes were relatively consistently coded under this category several months after the launch of shared e-scooters in Nashville. In the early months of the launch, e-scooter crashes were reported as either bicycle or pedestrian crash types. Therefore, we used a text mining approach to identify these misclassified e-scooter crash reports by examining nine keywords (including company names) that may indicate an e-scooter involvement. The non-case sensitive search keywords are *scooter*, *sumd*, *bird*, *lime*, *lyft*, *spin*, *jump*, *gotcha*, and *bolt*. We used the *pdfminer* library in Python to read the narratives from the PDF format crash reports, which identified 9 e-scooter crashes in the bicycle crash records and 10 in the pedestrian crash records. With that, we identified a total of 52 unique e-scooter crashes in Nashville during this period.

While the e-scooter crashes were mostly located in the downtown area of Nashville (Fig. 1 (b)), the TITAN database also contains bicycle crashes in the suburban areas. However, the road infrastructure and bicycle riding behavior are likely different in the suburban area than the city center, which may not be comparable to e-scooter crashes. Therefore, we identified bicycle crashes in the urban area by visualizing the crash locations in ArcGIS, and selected bicycle crashes within 1 mile of the nearest e-scooter crash. We extracted 79 bicycle crashes for the analysis.

We consolidated a few variables that would allow a better comparison of the results. The redefined injury levels fall into three values: fatal, injury, and minor or no injury. *Incapacitating* and *Suspected serious injury* were classified as *Injury*, while *No injury*, *Non-incapacitating evident*, *Possible injury*, *Suspected minor injury*, and *Unknown* were classified as *Minor or no injury*. We also combined the *clear* and *cloudy* value of the weather condition field. Also, we extracted the home zip codes of the motorists as well as the bicyclists and e-scooter riders to calculate the distance of the crash location to their home to understand if they were Nashville residents or visitors.

2.2. Crash typology

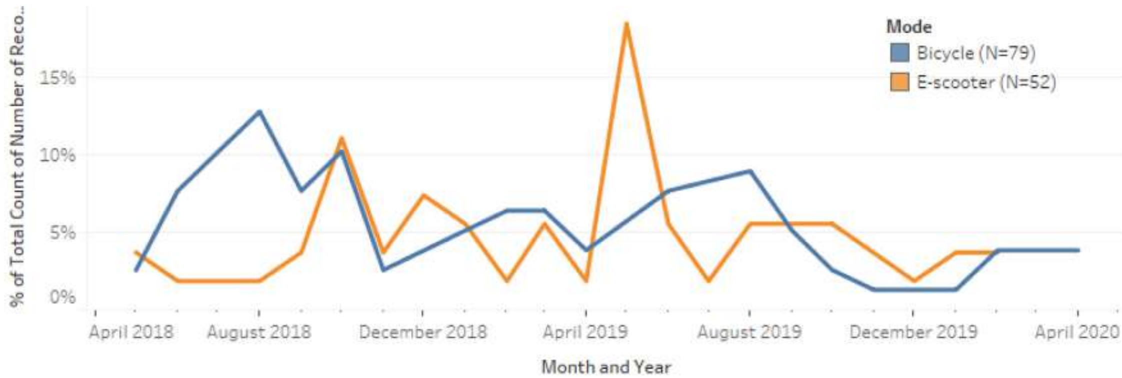
The Pedestrian and Bicycle Crash Analysis Tool (PBCAT) crash typology framework is undergoing significant redevelopment in Summer 2020 (Thomas et al., 2020). This analysis relies on version 3.0 of the framework that is expected for public release in Fall 2020. The PBCAT framework allows for consistent crash typology assignment and aims to understand factors that contribute to Vulnerable Road User (VRU) crashes. The framework classifies crashes based on the location of a crash (e.g., intersection) and the type of maneuver by the road users (e.g., left turn). Though relying on the most up-to-date version of the PBCAT framework, we also recorded other variables to compare e-scooter and bicycle crashes. The framework uses a series of codes that enable comparison between modes (Table 1). For example, the crash type "S-CR" means that motor vehicle is going straight, while the vulnerable road user is crossing from the right of the motorist.

2.3. Statistical test

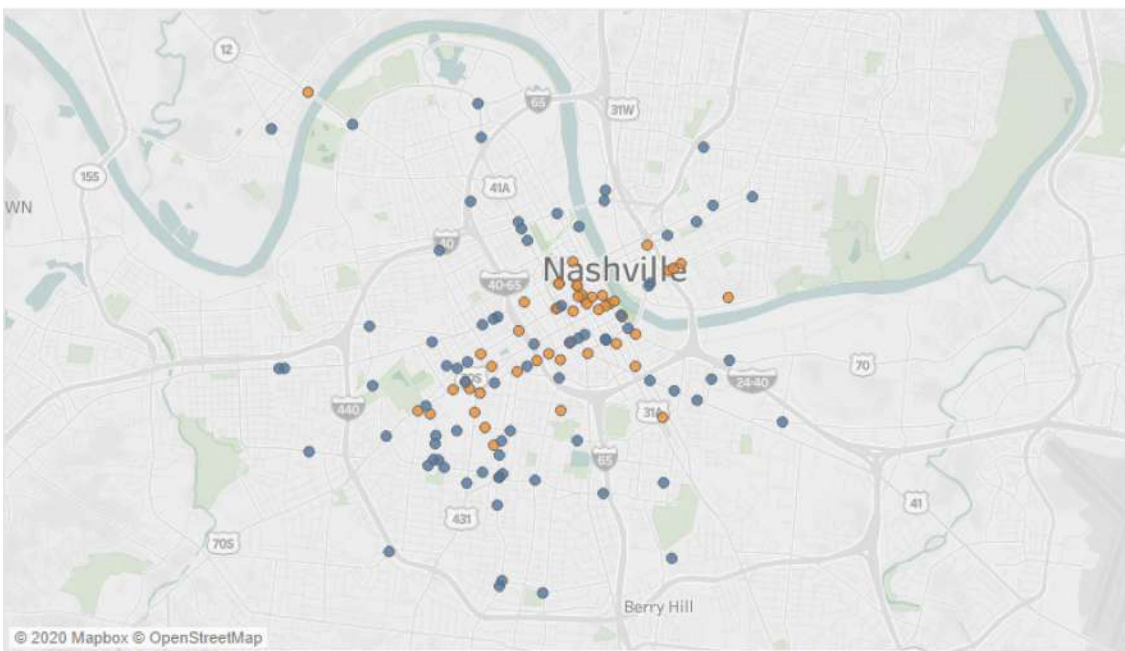
The relatively small sample size of observed motor vehicle-involved e-scooter and bicycle crash records restricted the crash comparison to univariate statistical analysis. Most variables, such as gender, weather condition, and PBCAT typology, are categorical variables. We also converted continuous variables, like age and crash distance from home, into bins to further examine the distribution. We used Fisher's Exact test of independence, which is more accurate than the chi-square test for small samples, to evaluate if the distribution of the e-scooter crash depends on the distribution of bicycle crashes. We also used a t-test for continuous variables to evaluate the difference in means for e-scooter and bicycle crashes.

3. Results

This section summarizes the key findings from the study, which are organized into two sub-section. The descriptive analysis of the crashes is presented in the first sub-section, followed by the crash typology in the next sub-section.



(a)



(b)

Fig. 1. Temporal and spatial distribution of bicycle and e-scooter crashes: (a) Temporal distribution, (b) spatial distribution.

Table 1
PBCAT crash typology.

Motorist Maneuver	VRU Maneuver						
	CR: Crossing from motorist's right	CL: Crossing from motorist's left	PS: Moving in same basic direction as the motorist	PO: Moving in opposite direction as the motorist	ND: Not moving or unknown direction	OV: Pushing, on, or clinging to a motor vehicle	UO: Unknown/ Other circumstances
S: Going straight	S-CR	S-CL	S-PS	S-PO	S-ND	S-OV	S-UO
R: Turning right (or preparing to turn right)	R-CR	R-CL	R-PS	R-PO	R-ND	R-OV	R-UO
L: Turning left (or preparing to turn left) or making a U-turn	L-CR	L-CL	L-PS	L-PO	L-ND	L-OV	L-UO
P: Parked (not in transport)	P-CR	P-CL	P-PS	P-PO	–	P-OV	P-UO
D: Slowing or stopped in traffic (in transport)	D-CR	D-CL	D-PS	D-PO	D-ND	D-OV	D-UO
E: Entering roadway or traffic lane	E-CR	E-CL	E-PS	E-PO	E-ND	E-OV	E-UO
B: Backing up	B-CR	B-CL	B-PS	B-PO	B-ND	B-OV	B-UO
O: Other/Unknown	O-C	O-C	O-P	O-P	O-ND	O-OV	O-UO

3.1. Descriptive analysis of crashes

We evaluated the differences in the characteristics of e-scooter and bicycle crashes that are not inherently included in the PBCAT crash typology. This sub-section summarizes the descriptive analysis of such characteristics.

3.1.1. Temporal and spatial distribution

Fig. 1 (a) presents the monthly crashes of bicycles and e-scooters (represented as a percentage of total crashes of each mode) from April 2018 to April 2020, whereas the locations of crashes for both modes are plotted in Fig. 1 (b). The first e-scooter crash was reported in May 2018, while the first peak of e-scooter crashes was observed in October 2018, and the crash rate peaked in May 2019. The peak of bicycle crashes during the study period was observed in August 2018 with smaller subsequent peaks. The number of crashes for both modes increased during the summer of 2019. Fig. 1 (b) illustrates that the e-scooter crashes were mostly concentrated in the city center of Nashville, whereas the bicycle crashes were more spatially dispersed.

3.1.2. Crash characteristics and demographics

Fig. 2 shows the general characteristics and demographics of the bicyclists and e-scooter riders involved in crashes. The weather and light conditions of crashes of both modes are illustrated in Fig. 2 (a) and (b), respectively. E-scooter and bicycle crashes have similar weather conditions (Fisher's Exact test p-value = 0.779) and lighting conditions (Fisher's Exact test p-value = 0.134). Most of the

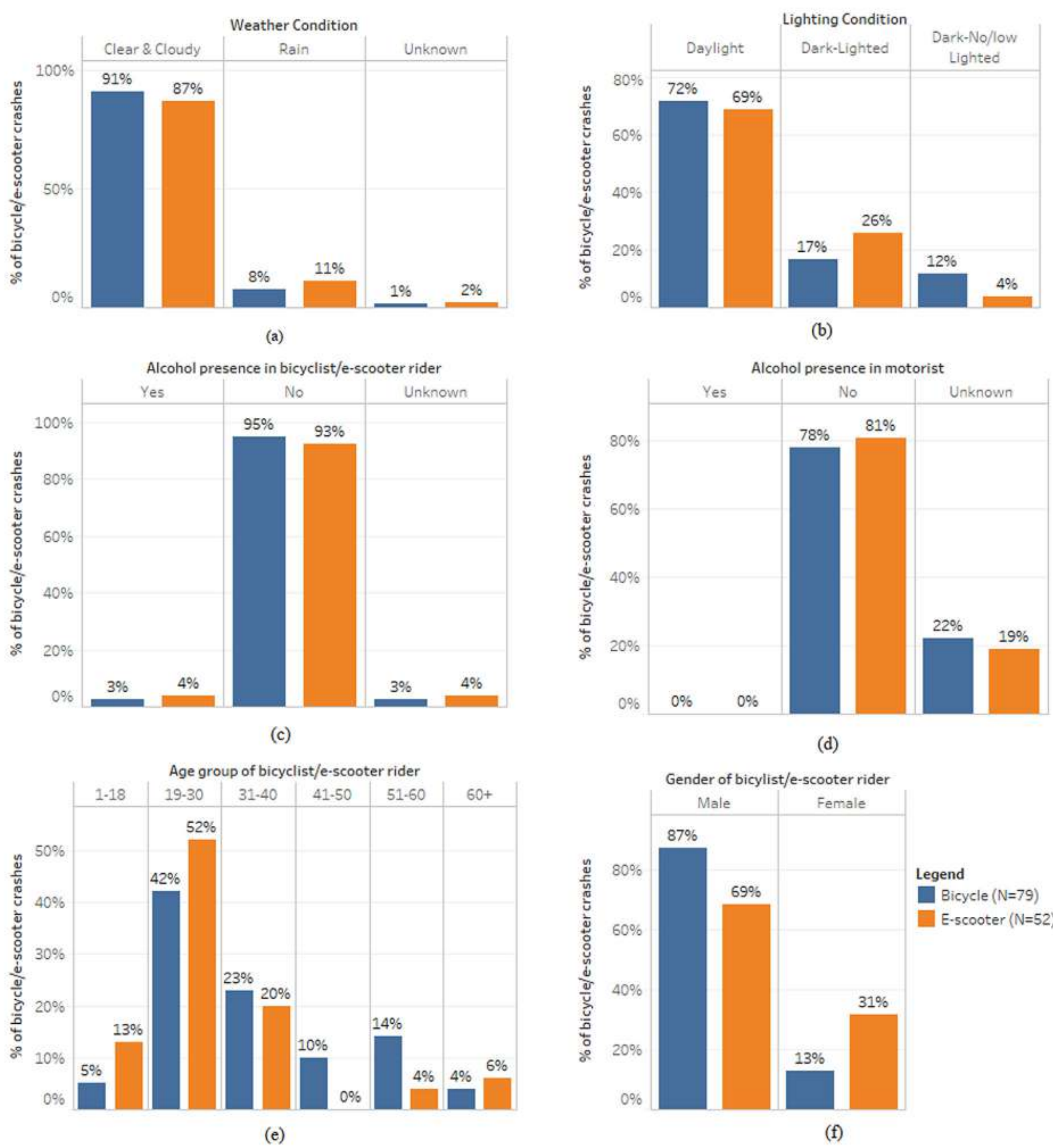


Fig. 2. General characteristics of bicycle and e-scooter crashes: (a) weather condition, (b) light condition, (c) bicycle/e-scooter rider intoxication, (d) motorist intoxication, (e) age distribution of bicyclist and e-scooter riders, (f) gender distribution of bicyclist/e-scooter rider.

e-scooter and bicycle crashes occur in clear or cloudy weather conditions and daylight. Although not statistically significant, it is worth noting that e-scooter crashes occurred more frequently in dark and lighted conditions than bicycles (26% vs. 17%) and less frequently in no light condition (4% vs. 12%). It is likely that Downtown Nashville, where most of the e-scooter crashes occurred, is better lit during the nighttime than bicycle crash locations, mostly outside the city center on potentially unlit roads.

Fig. 2 (c) and (d) reflect the intoxication level of the bicycle/e-scooter riders and the motorists, respectively. There is no significant difference in the intoxication level among e-scooter riders and bicyclists involved in the crash (Fisher's Exact test p-value = 1.000) and motorists colliding with e-scooter or bicycle (Fisher's Exact test p-value = 0.827). We found only two motor vehicle-involved e-scooter crashes (4% of e-scooter-related crash in the study) involved intoxicated e-scooter riders, including one fatal crash. On the other hand, most bicyclists, e-scooter riders, and motor-vehicle drivers were not reported to be intoxicated during other crashes. This contrasts findings that many injured scooter riders are intoxicated (Kobayashi et al., 2019). Most of the intoxication tests are based on observation of the police officer at a crash location, and they are not reliable unless the breath test is administered for both motor-vehicle driver and bicycle/e-scooter rider. In most of the police reports, tests were not administered and the responding officer relied on visual or behavioral cues to assess intoxication, limiting the definitive assessment that scooter riders or drivers were not impaired. However, 1 in 5 bicycle-motor vehicle and e-scooter-motor vehicle crashes involved a hit and run, where motor-vehicle drivers most often fled the crash scene. We found a few instances of bicyclists and e-scooter riders leaving the scene before police arrived for minor crashes. Thus, a significant number of motor driver intoxication data is not available, as the drivers fled in a hit-and-run event.

The age distribution of bicyclists and e-scooter riders recorded in police crash reports are plotted in Fig. 2 (e). E-scooter riders crashing with motor vehicles tend to be younger in age than bicyclists colliding with a motor vehicle (t-test p-value = 0.010 and Fisher's Exact test p-value = 0.021 for age group). Although the legal age to ride e-scooters in Nashville is 18 years, 13% of e-scooter riders crashing with motor vehicles were below 18 years old. 65% of e-scooter riders were below 30 years compared to only 47% of bicyclists in the same age group. Similarly, Fig. 2 (f) indicates the gender distribution of bicyclists/e-scooter riders involved in a crash, which is statistically different (Fisher's Exact test p = 0.015). Males riding bicycles or e-scooters were more represented in crashes with a motor vehicle. Amongst crashes involving female riders, the proportion of e-scooter crashes is higher: 31% of e-scooter riders were females, while only 13% of bicyclists were females. This potentially reflects the higher proportion of women using scooters (Sanders, Branion-Calles, & Nelson, 2020).

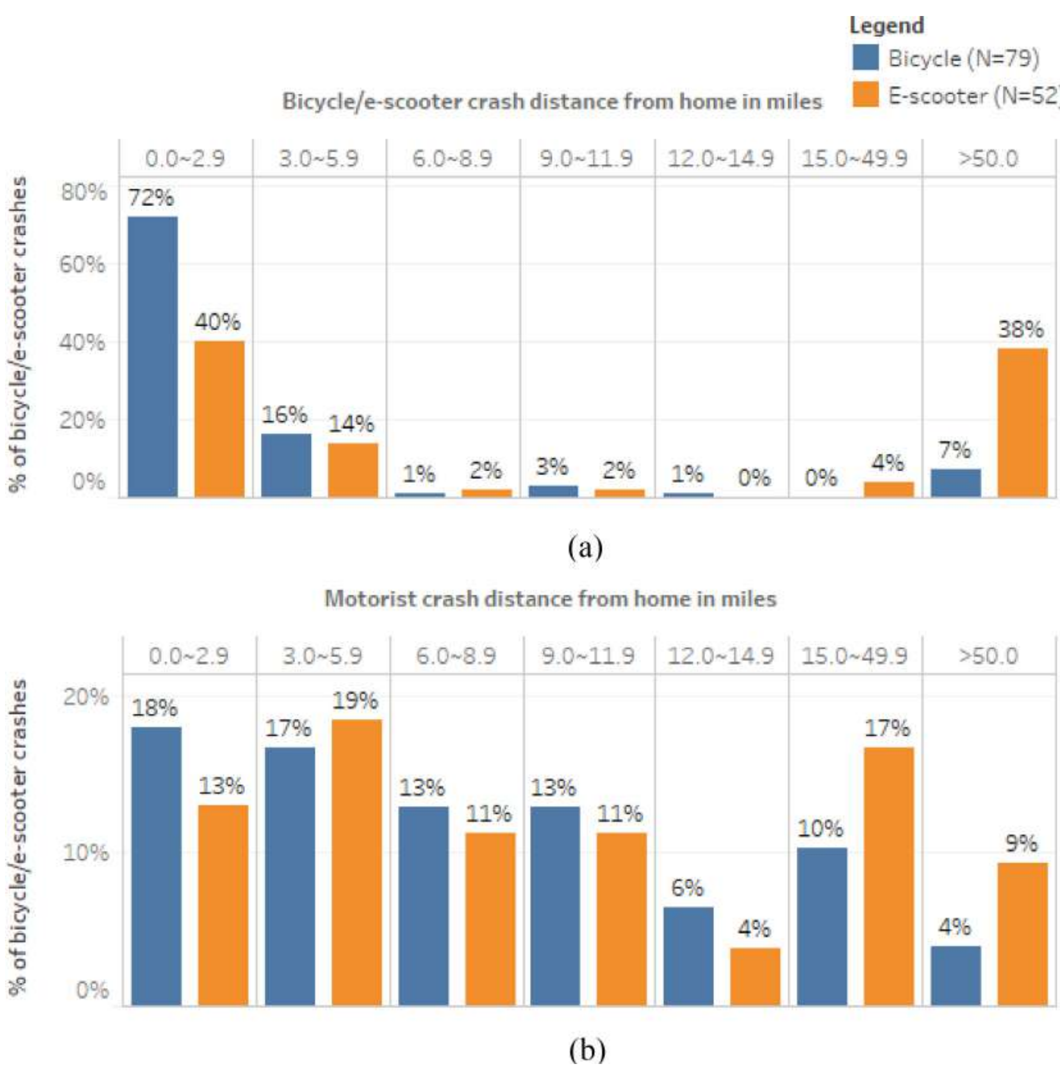


Fig. 3. Crash distance from home: (a) bicyclist/e-scooter riders; (b) motorists.

3.1.3. Crash distance from home

Fig. 3 summarizes the crash distance from home observed in the police crash report, estimated as the straight line distance of the centroid of the zip code of the driver or rider to the coordinates of the crash location. Fig. 3 (a) shows a histogram of crash distance away from home for bicyclist/e-scooter riders. E-scooter riders are farther from home than bicyclists (Fisher's Exact Test $p = 0.000$). More than 70% of the bicyclists lived within 3 miles of the crash location, while only 7% lived more than 50 miles away. On the other hand, only 40% of the e-scooter riders lived within 3 miles of the crash location, while approximately 38% of e-scooter riders lived more than 50 miles away. Though a substantial portion of e-scooter riders in the crash records appear to be visitors (e.g., tourists) in Nashville, a majority of scooter crash victims are local riders. In contrast, almost all bicyclists crashed within bicycling range of home.

Similarly, Fig. 3 (b) shows the histogram of crash site distance from home for the motorists involved in a crash with bicycles and e-scooters. This is important because drivers from suburban and rural areas outside the city might not be experienced driving around bicycle and scooter riders. We did not find a statistical difference in motorist's crash distance crashing with an e-scooter or bicycle (Fisher's Exact test p-value = 0.747). However, most vehicle drivers involved in crashes live outside the core area of Nashville compared to e-scooter and bicycle riders who tend to be more local.

3.2. PBCAT crash typology

We used the PBCAT tool to identify the locations and maneuver of bicycles and e-scooter crashes reported in Nashville. The general location of e-scooter and bicycle crashes (road type such as intersection and driveway) is similar (Fisher's Exact test p-value = 0.644). Fig. 4 summarizes the PBCAT typology on location factors. The vertical axis is a general crash location on vertical axes, and the horizontal axis is the bicycle or e-scooter rider's location during the crash.

As depicted in the diagram, most e-scooter and bicycle crashes occurred at an intersection (65% of e-scooter and 67% of bicycle crashes). Driveway-to-roadway junctions accounted for the second-largest number of crashes (17% of both e-scooter and bicycle crashes). Non-junctions along the roadway ranked third in the proportion of crash locations (13% of e-scooter and 14% of bicycle crashes). The distribution of bicycle crash locations is consistent with the national average (National Transportation Safety Board, 2019), and the locations of e-scooter crashes are similar to bicycle crash locations.

In contrast, the motor-vehicle maneuvers during a crash with an e-scooter are different than colliding with a bicycle (Fisher's Exact test p-value 0.087), as illustrated in Fig. 5. A motor vehicle turning left (L) contributed to 23% of e-scooter crashes and 9% of bicycle crashes, while the straight maneuver of the motor vehicle (S) accounted for 44% of e-scooter crashes and 31% of bicycle crashes. 33% of e-scooter and bicycle crashes occurred during the right maneuver of the motor vehicle (R). Other maneuvers of motor vehicles contributed to a fraction of crashes for both modes.

Maneuvers of e-scooter riders before a crash is also different than bicyclists (Fisher's Exact test p-value = 0.055), as illustrated in Fig. 5. The maneuver of e-scooter riders or bicyclists from the right side of the motor vehicle (CR) contributed to the most frequent crashes; however, the proportion is much higher for e-scooter crashes (59% of e-scooter crashes as compared to 33% of bicycle crashes). These were often e-scooters or bicyclists riding on sidewalks, approaching intersections from the driver's right side (opposite to drivers' expectations). E-scooters moving in the same direction as a motor vehicle (PS) accounted for 20% of e-scooter crashes, whereas 29% of bicycle crashes occurred for the same direction of maneuver. While other maneuver directions of e-scooters during crashes were not recorded in a substantial number, the maneuver of bicyclists from the opposite direction of the motor vehicle (PO) contributed to 17% of bicycle crashes, and maneuver from the left of a motor vehicle (CL) accounted for 12% of bicycle crashes. In summary, only two maneuvers (CR and PS) accounted for 80% of e-scooter crashes, whereas bicycle crashes were distributed among several maneuvers.

3.2.1. Intersection crashes

Since more than 60% of the bicycle and e-scooter crashes occurred at an intersection, we further scrutinized these crashes. There is a strong difference in the distributions of e-scooter and bicycle crashes among the PBCAT crash typology (Fisher's Exact test p-value = 0.033). Table 2 summarizes the maneuvers of the motorists, bicyclists, and e-scooter riders at different locations of

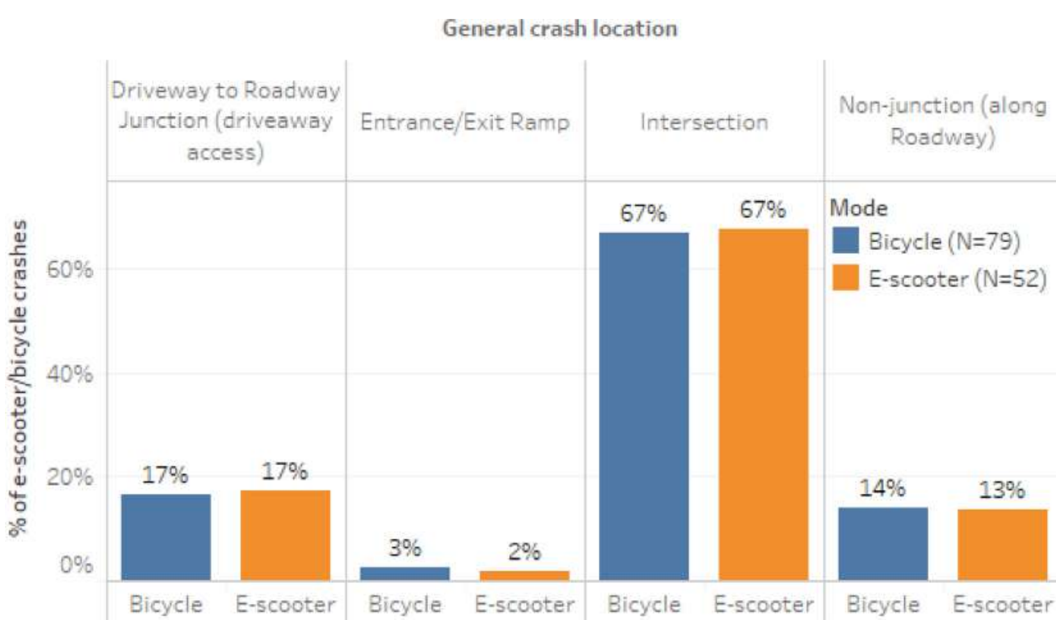


Fig. 4. PBCAT typology – location.

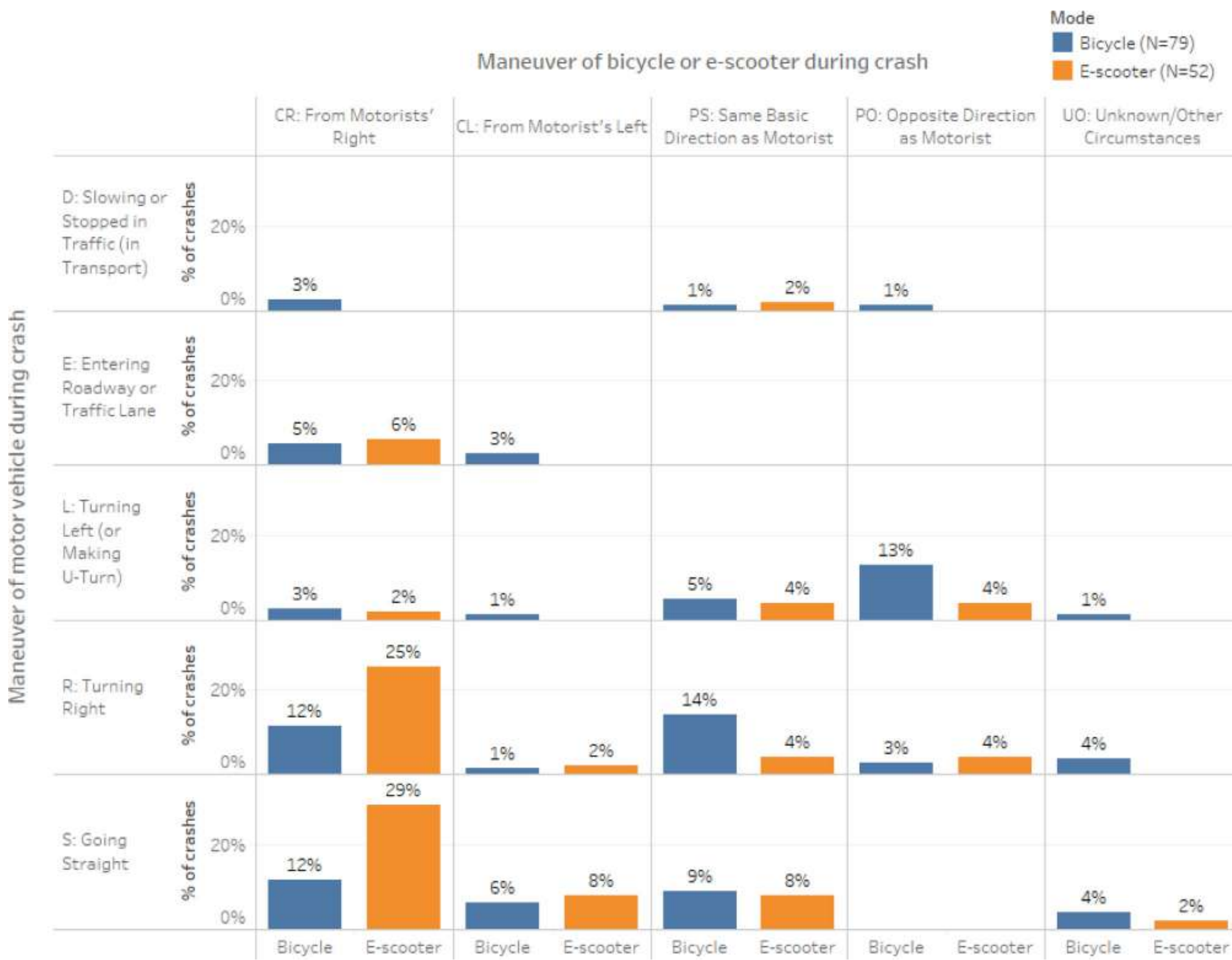


Fig. 5. PBCAT typology – maneuver.

an intersection. The motor vehicle approaching the leg of an intersection is labeled as *Entering*, leaving the intersection as *Exiting*, and located in other areas of the intersection as *Middle/other areas*.

As shown in the table, only a few PBCAT crash types contain the majority of e-scooter crashes. The most common types of e-scooter crashes at an intersection were S-CR and R-CR, which accounted for 31% and 29% of all e-scooter intersection crashes, respectively. As depicted in Fig. 6 (a), the S-CR crash type indicates a motor vehicle moving straight with an e-scooter arriving from the right of the motor vehicle, while the R-CR type indicates a motor vehicle turning right with an e-scooter arriving from the right. 12% of e-scooter crashes at intersections were S-CL, where a motor vehicle was moving straight and an e-scooter collided from the left of the motor vehicle.

In contrast to the e-scooter crashes, the bicycle crashes are somewhat evenly distributed among the PBCAT crash typology. L-PO is the most common type with 17% of bicycle crashes at intersections. As depicted in Fig. 6 (b), the L-PO crash type indicates a motor vehicle and bicycle traveling in opposite directions, and a collision occurs while the motor vehicle is turning left. The R-PS type accounts for 15% of bicycle crashes at intersections, where both the motor vehicle and bicycle are traveling in the same direction, and the motor vehicle turns right. Other bicycle crash typologies are R-CR, S-CR, and S-CL, each containing about 10% of bicycle crashes at the intersection.

3.2.2. Severity levels of crash typology

Approximately 1 in 10 e-scooter- and bicycle-motor vehicle crashes led to a reported injury. The distribution of severity by location is similar for both bicycle and e-scooter crashes; most crashes with injury and minor/no or unknown severity occur at the intersection, followed by driveway access and non-junction. The only fatal e-scooter crash reported in Nashville during the study period occurred at an intersection when the motor vehicle was traveling straight, and the e-scooter crossed from the right of the motor vehicle (S-CR).

Four e-scooter riders were injured among the 52 e-scooter crashes, with none of the motorists being injured. The predominant crash types for these e-scooter crashes are: (a) the motor vehicle entering roadway with the e-scooter rider crossing from the right (E-CR) in a driveway; (b) the motor vehicle moving straight with the e-scooter crossing from the right (S-CR) at an intersection; (c) the motor vehicle turning right with the e-scooter crossing from the left (R-CL) at an intersection; and (d) the motor vehicle moving straight with e-scooter also moving in the same direction (S-PS) along a non-junction roadway.

Six out of 79 bicyclists were injured in bicycle-motor vehicle crashes, while none of the motorists were injured. Two such crashes occurred at intersections while the motor vehicle was moving straight and the bicyclist was crossing from the right side of the motor vehicle (S-CR). Two other crashes occurred while the

Table 2
PBCAT crash typology at intersections.

Motorist maneuver	Location at intersection	CL: From the Motorist's Left		CR: From the Motorists' Right		PO: Opposite Direction as the Motorist		PS: Same Basic Direction as the Motorist		UO: Unknown/ Other Circumstances		Grand Total of motorist maneuver	
		B	S	B	S	B	S	B	S	B	S	B	S
D: Slowing or Stopped	Entering			2%					3%			**2%**	**3%**
	Middle/Other area			2%								**2%**	**0%**
E: Entering Roadway	Entering			2%								**2%**	**0%**
L: Turning Left	Entering				3%							**0%**	**3%**
	Exiting	2%		2%		12%	3%	6%	3%	2%		**23%**	**6%**
	Middle/Other area			2%		6%		2%				**10%**	**0%**
O: Other/Unknown											3%	**0%**	**3%**
R: Turning Right	Entering		3%	10%	23%			8%	3%	4%		**21%**	**29%**
	Exiting			2%	6%	2%	6%	8%				**12%**	**12%**
	Middle/Other area	2%		2%								**4%**	**0%**
S: Going Straight	Entering	2%	3%	2%	11%			2%			3%	**6%**	**17%**
	Exiting	2%			11%					4%		**6%**	**11%**
	Middle/Other area	6%	9%	8%	9%							**13%**	**18%**
Grand total of either bicycle or e-scooter crashes		**13%**	**15%**	**33%**	**63%**	**19%**	**9%**	**25%**	**9%**	**10%**	**6%**		

Note: the percentage indicated in the table is the percentage of either bicycle or e-scooter crashes.
Legend: B = Bicycle and S = E-scooter.

motor vehicle was turning left with the bicyclist traveling in the same direction in the exiting leg of the intersection (L-PS). We reviewed one bicycle crash each for motor vehicles turning right with a bicyclist moving in the same direction (R-PS) at the intersection (a typical "right hook" crash) and a motor vehicle moving straight with unknown maneuver for the bicyclist (S-UO) at a non-junction roadway.

4. Discussion

Based on the findings of bicycle- and e-scooter-motor vehicle crashes in Nashville, Sections 4.1–4.4 provide a discussion on the general crash characteristics of bicycles or e-scooters colliding with a motor vehicle. Sections 4.5 and 4.6 emphasize the location and maneuver of bicyclists/e-scooter riders and motorists before the crash, while section 4.7 ends with the limitations of the study and a discussion on future research.

4.1. Temporal and spatial distribution of crash

We observed higher crash rates during the summer. A higher number of bicycle and e-scooter trips could contribute to an increase in exposure, as e-scooter ridership is predominantly high during weekends and summer months (Shah, 2019) and bicycle volumes are also higher in summer (Miranda-Moreno, Nosal, Schneider, & Proulx, 2013). Additional hours of daylight during the summer could also contribute to increased exposure. Therefore, educational campaigns on bicycle and e-scooter safety could be most effective during weekends and summer months, as ridership and crash rates are highest during these times. Furthermore, COVID-19 may have affected the crash rates at the end of the study period by contributing to lower motor vehicle traffic, a change in e-scooter/bicycle ridership, or a combination of both.

The compact spatial distribution of e-scooter crashes around downtown Nashville and Vanderbilt University is consistent with the general e-scooter usage locations revealed by other studies (Bai & Jiao, 2020; Shah, 2019). E-scooters have high levels of exposure in this area, which is influenced by device availability, as most e-scooters are distributed in densely built environments. On the other hand, bicycle crash locations were also spread outside the core part of the city. E-scooter safety measures should be prioritized in downtown and university areas, while bicycle safety measures should also target areas further away from downtown areas.

4.2. Crash characteristics

Most of the e-scooter- and bicycle-motor vehicle crashes occur during daylight. However, the second-highest proportion of e-scooter crashes occurred during nighttime in lit conditions, whereas bicycle crashes occurred more frequently during nighttime in no-light conditions. E-scooters are mainly used in the densely built environments of downtown Nashville and Vanderbilt University (Shah, 2019), which are usually well-lit, while bicycle crash locations, which are usually away from the core area of the city, might not have adequate lighting. Therefore, additional confounding factors other than lighting could contribute to e-scooter crashes at night, whereas improving lighting at nighttime bicycle crash hotspots could reduce bicycle crash rates.

Other crash characteristics can reveal safety implications to reduce e-scooter and bicycle-related crashes and injuries. Despite common perceptions, only a few e-scooter or bicycle riders were reported as intoxicated at the time of the crash, even in nighttime entertainment districts. But 1 out of 5 crashes involved a hit-and-run, with most hit-and-run cases including motorists and a few cases of the bicyclist or e-scooter riders leaving the crash scene

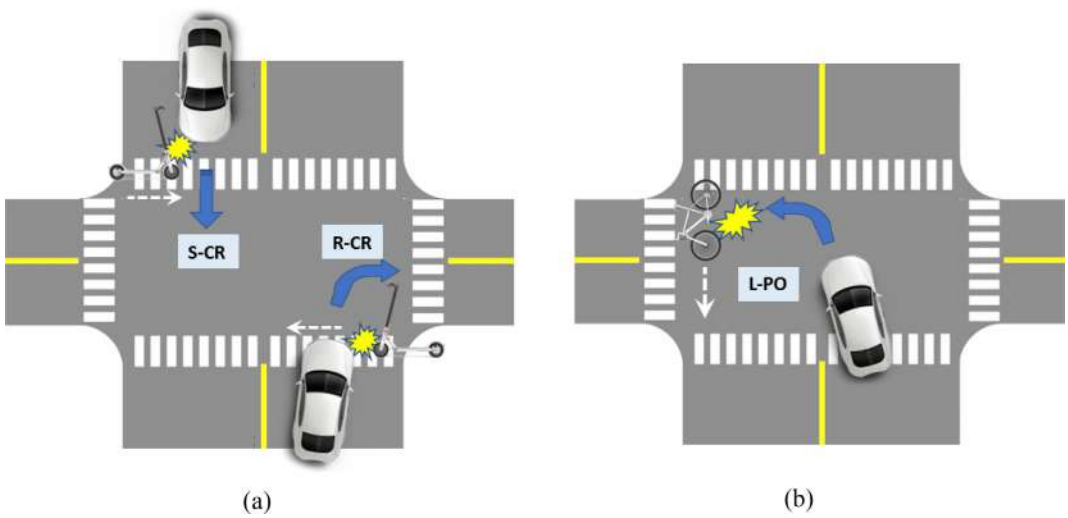


Fig. 6. Most common PBCAT crash typology at intersection: (a) e-scooter; (b) bicycle.

before the arrival of police. The reduction of such hit-and-run might require stronger education and enforcement, such as a surveillance camera at crash hotspots. Of those involved in crashes with motor vehicles, 1 in 10 bicycle/e-scooter riders were injured while none of the motorists were injured. This disproportionate injury rate reinforces that bicyclist and e-scooters riders are vulnerable road user group who requires additional safety measures compared motor vehicles.

4.3. Demographics of crash victims

Bicyclist and e-scooter riders who collided with a motor vehicle in Nashville were predominantly male. Amongst the crashes involving female riders, the proportion e-scooter crashes are higher than bicycle crashes (29% vs. 13%) in our police-reported data. Pilot evaluations of shared e-scooter programs also reported that approximately one-third of e-scooter riders are females (City of Chicago, 2020; Portland Bureau of Transportation, 2018). Women are generally more represented as e-scooter riders than as bicyclists. Therefore, the e-scooter safety campaign should also be geared toward female riders.

The e-scooter riders crashing with a motor vehicle are younger than bicyclists involved in crashes. This does not necessarily prove that younger age groups have risky riding behavior, as younger demographics have higher ridership and crash exposure on e-scooters (Bai & Jiao, 2020; Caspi, Smart, & Noland, 2020; City of Chicago, 2020). The survey result of e-scooter pilot programs also found that these emerging modes are popular among the age group of 18–40 years (Austin Public Health, 2019; City of Chicago, 2020). Adapting safety campaigns to the ridership age group could increase their effectiveness, such as e-scooter campaigns targeted towards younger adults and bicycle campaigns geared towards older age groups.

We found that 13% of all e-scooter riders were below the age of 18 in our police crash report, despite the legal age of 18 to ride an e-scooter in Nashville. Although the crash report does not necessarily represent the actual ridership for this age group, a significant number of minors could be riding e-scooters. Organizations such as the American Academy of Pediatrics (AAP) do not recommend children below the age of 16 to operate e-scooters (Morgan, 2019). More vigilant enforcement, as well as educational strategies, by law enforcement agencies and advocacy groups could help discourage the use of e-scooters amongst this vulnerable age group. As e-scooter service operators require users to upload a valid driver's license before the first trip (Fawcett, Barboza, Gasvoda, & Bernier, 2018), the e-scooter service operators could also take proactive steps to ensure that their active users are above the legal age to operate e-scooters.

4.4. Crash distance from home

The home location of e-scooter riders, bicyclists, and motorists can influence riding or driving behavior and road safety approaches. Over 70% of bicyclists lived within three miles of the crash location. Additionally, 38% of e-scooter crashes occurred more than 50 miles from home, compared to 7% for bicyclists. In the absence of extensively available bikeshare options, it is possible that a majority of bicyclists in Nashville own their bikes, and the limitation in the geographical coverage of bicycling could therefore explain the number of bicycle crashes near home. In contrast, shared e-scooters are more visible and accessible to visitors in Nashville, which could explain that a high number of e-scooters rider crashed more than 50 miles from home. Visitors using e-scooters might not be familiar with roadway and traffic conditions of Nashville, which could have led to crashes. Still, even in a tourist-oriented city, more than half of the crash-involved scooter riders are local to Nashville.

Similarly, motorists involved in a crash live further from home than e-scooter or bicycle riders. As e-scooters are popular in dense urban areas, motor-vehicle drivers living in suburban or rural areas could be unfamiliar with the interaction of e-scooters, leading to crashes. Other studies have also found the crash distance from home as a significant predictor of mode of travel (Haas et al., 2015; Steinbach, Edwards, & Grundy, 2013).

A combination of educational, wayfinding, and infrastructure improvements could reduce e-scooter- and bicycle-motor vehicle crashes that involve visitors to metro areas. Educational efforts could focus on educating drivers to expect e-scooters and bicyclists when entering the downtown area, while visitors could be cautioned about the specific risk of riding e-scooters in the city. Multimodal street design that accommodates e-scooters in combination with well-visible signs and markings could also guide e-scooter users to avoid crash risks and dangerous infrastructure.

4.5. Crash locations

We did not find any difference in the distribution of e-scooter- and bicycle-motor vehicle crash locations by road type in the police crash report database of Nashville, Tennessee. Both bicycle and e-scooter crashes followed the national average distribution of bicycle crashes by location (NHTSA, 2008). Traffic designs, enforcement, and education for bicycle and e-scooter safety should prioritize intersections, as more than 60% of e-scooter- and bicycle-motor vehicle collisions occur at these locations. Protected intersection designs that slow down vehicles and emphasize vulnerable road users, such as raised pavements, can reduce conflicts among road users.

Safety measures to increase visibility of e-scooters and bicyclists can also reduce intersection crashes. We recommend intersection design to increase the conspicuity of e-scooters and bicyclists, and at night, combined with improved head and taillights and retro-reflectivity on bicycles and e-scooters may help overcome this visibility challenge. The infrastructure design should be complemented with enforcement strategies and educational campaigns that deter traffic rule violations and risky behaviors. For example, the combination of corridor improvement approach and speed camera enforcement reduced the likelihood of incapacitating or fatal injury by 39% in Virginia (Hu & McCartt, 2016).

4.6. Maneuvers before the crash

Only a few PBCAT crash typologies could explain most e-scooter-motor vehicle crashes in Nashville, Tennessee. Of all e-scooter crashes, 54% occurred at an intersection with a motor vehicle traveling straight or turning right and an e-scooter rider entering the crosswalk from the right. Intersection safety designs, like curb extensions and raised pavement, can force drivers to reduce speed and check their far-side view for vulnerable road users. Removing right-turn-on-red allowance could reduce conflicts by allowing drivers to focus on traffic from all directions. Educating both motor drivers and e-scooter users on these common crash mechanisms could improve risk awareness and reduce such crashes.

In contrast, bicycle-motor vehicle crashes were distributed among several PBCAT crash typologies. We found significant bicycle-related crashes in some maneuvers, such as a motor vehicle turning left while a bicycle was traveling in the opposite direction of the motor vehicle, but there were few such e-scooter crashes. We cannot reasonably speculate why those crash mechanisms differ. Nevertheless, the difference in crash typology distribution points to different collision mechanisms between e-scooter- and bicycle-motor vehicle crashes. Therefore, safety measures targeted towards bicycles, for example, might not reduce e-scooter crashes.

4.7. Limitations of the study and future research

This study has several limitations. First, the relatively small sample size of the e-scooter and bicycle crashes did not allow rigorous multivariate statistical analysis. A breakdown of variables increases the degree of freedom to reduce the power of statistical analysis and mask any significant relationship. This limitation did not allow us to scrutinize the crash typology and injury severities further. Second, the results should not be generalized for every city. This study is based on evaluation e-scooter and bicycle crashes with motor vehicles in Nashville, Tennessee. Other cities have different rider and driver norms and behaviors and likely have different policies. Third, we only evaluated motor-vehicle collisions, whereas bicycle and e-scooter crashes can also occur due to additional causes, such as falling and colliding with stationary objects.

Furthermore, crashes are generally underreported as some of the non-injury and small property damage incidents are not reported to the police. Severity of crashes is reported by police and emergency department data are known to provide better diagnostic performance. Future work linking emergency department and crash data would illuminate this area. Finally, the crash database lacks exposure information, total ridership, which would allow for the evaluation of scalable risks relative to the number of road users and the use of infrastructure.

Future research can combine methods and multiple data sources to provide better nuances of e-scooter safety. For example, naturalistic data collection methods, like video cameras and sensors, can evaluate near-miss crashes involving e-scooters. The comparison of multiple crash databases, such as police crash reports and hospital data, can help to derive correction factors for estimating accurate crash statistics. Furthermore, a comparison of e-scooter safety among different cities could provide insights on the geographical heterogeneity of e-scooter crashes, as well as the impacts of certain safety-related policies, such as no riding on the sidewalk.

5. Conclusions

We evaluated two years of bicycle and e-scooter crashes in the urban part of Nashville, Tennessee, using the police crash report maintained by the Tennessee Department of Transportation. We noted differences in e-scooter- and bicycle-motor vehicle crashes in temporal and spatial distributions, crash characteristics, crash distance from home, and maneuver of motorists and bicyclists or e-scooter riders before the crash. However, we did not find an apparent difference concerning the locations by road type of the crashes. Additionally, we made design, enforcement, and education recommendations to prevent and reduce those crashes in the future. Moreover, this study reinforces the importance of standardization of crash records that would better enable the data-driven evaluation of emerging transportation modes like e-scooters.

Acknowledgments

This project included financial support by the Southeastern Transportation Center and the Collaborative Science Center for Road Safety, both University Transportation Centers funded by the US Department of Transportation. The authors would like to thank Libby Thomas for providing access to the recent prototype version of the PBCAT crash typology and Chantal Davis for editorial review of the manuscript. This research was conducted under the approval of UTKs institutional review board for human subjects (UTK IRB-19-05600-XP).

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Nitesh Shah is a doctoral student at the University of Tennessee at Knoxville (UTK). He is also a Graduate Advancement Training and Education (GATE) fellow at Oak Ridge National Laboratory (ORNL). Some of his research interests include micro-mobility, travel behavior, sustainability, and a big data approach in transportation. He also did an internship at the New Urban Mobility Alliance (NUMO) hosted by the World Resource Institute (WRI) in the 2019 summer, working on different issues of tech disruption in mobility. He completed his MS in Transportation Engineering from UTK and Bachelor's in Civil Engineering from the Institute of Engineering, Nepal.

Sameer Aryal is a Civil Engineering PhD student at University of Tennessee-Knoxville. His primary research interests are pedestrians and bicycle safety and facility design and machine learning for big data. He received his master's degree in Structural Engineering from University of Missouri Kansas City. He received his BS in Civil Engineering and later served as Assistant Lecturer for Civil Engineering at Himalaya College of Engineering, affiliated to Tribhuvan University in Nepal.

Yi Wen is a Ph.D. student majoring in transportation engineering at the University of Tennessee, Knoxville. His main research agenda is to investigate the various impacts of emerging transportation options. Prior to his pursuit of a doctoral degree, he received his BS in Environmental Science from Beijing Normal University – Hong Kong Baptist University United International College in China and his Master's Degree in Environmental Science and Management from the University of California, Santa Barbara.

Dr. Christopher R. Cherry is a Professor at the University of Tennessee. Some of his research interests include bicycle and pedestrian safety and system design, the role of e-bikes on the transportation system. He leads the Light Electric Vehicle Education and Research (LEVER) Initiative, a consortium of universities and industry to explore the role of emerging and potentially disruptive classes of lightweight and low speed electric vehicles on transportation, sustainability, and health. He also chairs the TRB joint subcommittee on emerging vehicles for low speed transportation. Dr. Cherry received his PhD in Civil and Environmental Engineering from the University of California, Berkeley in 2007.

Journal of Safety Research 77 (2021) 288–295

Contents lists available at ScienceDirect

Journal of Safety Research

journal homepage: www.elsevier.com/locate/jsr

Continued trends in older driver crash involvement rates in the United States: Data through 2017–2018

Aimee E. Cox *, Jessica B. Cicchino

Insurance Institute for Highway Safety, United States

ARTICLE INFO

Article history:
Received 6 November 2020
Received in revised form 19 January 2021
Accepted 16 March 2021
Available online 2 April 2021

Keywords:
Aging
Fatal crash trends
Crash survivability
Police-reported crash trends
Motor vehicle travel

ABSTRACT

Introduction: With the growing older adult population due to the aging baby-boom cohort, there was concern that increases in fatal motor-vehicle crashes would follow. Yet, previous analyses showed this to be untrue. The purpose of this study was to examine current trends to determine if previous declines have persisted or risen with the recent increase in fatalities nationwide. *Methods:* Trends among drivers ages 70 and older were compared with drivers 35–54 for U.S. passenger vehicle fatal crash involvements per 100,000 licensed drivers from 1997 to 2018, fatal and all police-reported crash involvements per vehicle miles traveled using the 1995, 2001, 2009, and 2017 National Household Travel Surveys, and driver deaths per 1,000 crashes. *Results:* Since the mid-1990s, fatal crashes per licensed driver trended downward, with greater declines for drivers ages 70 and older than for middle-aged drivers (43% vs. 21%). Fatal crash rates per 100,000 licensed drivers and police-reported crash rates per mile traveled for drivers ages 70–79 are now less than those for drivers ages 35–54, but their fatal crash rates per mile traveled and risk of dying in a crash remain higher as they drive fewer miles. As the economy improved over the past decade, fatal crash rates increased substantially for middle-aged drivers but decreased or remained stable among older driver age groups. *Conclusions:* Fatal crash involvements for adults ages 70 and older has recently increased, but they remain down from their 1997 peak, even as the number of licensed older drivers and the miles they drive have increased. Health improvements likely contributed to long-term reductions in fatal crash rates. As older drivers adopt vehicles with improved crashworthiness and safety features, crash survivability will improve. *Practical Application:* Older adults should feel confident that their independent mobility needs pose less risk than previously expected.

1. Introduction

Over the last several decades, the United States has seen an increase in life expectancy at birth, from 76.5 years in 1997 to 78.6 years in 2017 (National Center for Health Statistics [NCHS], 1999; NCHS, 2019). Life expectancy at age 65 was an additional 17.7 years for males and 20.3 years for females in 2010, an improvement of 4.7 and 3.5%, respectively, since 1970 (Crimmins et al., 2016). Americans are not only living longer but are enjoying more years of disability-free life. Using estimates derived from questions about performing various activities of daily living and instrumental activities of daily living from the National Health Interview Survey and National Long Term Care Survey, Americans at age 65 have seen increases in estimates of active life expectancy, or years free of severe disability, that have outpaced those in remaining life expectancy with a disability (Crimmins et al., 2016; Freedman & Spillman, 2016).

This increase in life expectancy and the delay in the onset of severe morbidities can be attributed to advances in medical treatments that have allowed for the reduction of many acute diseases, enhanced screening for and management of chronic conditions, and a general decline in adverse health behaviors (Cichy et al., 2017; Wolf et al., 2005). The gains in overall life expectancy and disease-free life expectancy, combined with the aging of the American baby-boom cohort (born between 1946 and 1964) will result in an estimated 53 million people over age 70 in the United States by 2030 (United States Census Bureau, 2017). This demographic shift, coined the "gray tsunami," will result in roughly 10,000 people reaching age 65 per day between the years 2010 and 2030 (United States Census Bureau, 2019). This equates to an increase in the percentage of the population that is 65 years old or older from 13% to 20% during that timeframe (Ortman et al., 2014).

Historical trends have shown that fatal and police-reported crash involvements per mile traveled begin to increase with age

* Corresponding author at: Insurance Institute for Highway Safety, 4121 Wilson Boulevard, 6th Floor, Arlington, VA 22203, Unite States.

E-mail address: acox@iihs.org (A.E. Cox).

https://doi.org/10.1016/j.jsr.2021.03.013
0022-4375/

beginning at age 70 (Cicchino & McCartt, 2014). This higher crash risk can be credited to age-related declines in cognitive, visual, and physical function (Anstey et al., 2005; Owsley et al., 1991). With increases in age-related declines come increases in frailty, which is an increased vulnerability to sudden, drastic health status changes that are brought on by relatively minor events (Clegg et al., 2013). Higher fatal crash involvement may be related to the prevalence of frailty that increases with age, and an estimated 3% increase in risk of death when involved in a crash for each year of aging (Clegg et al., 2013; Kahane, 2013).

Higher crash risk and the projected increase in the older population due to the aging baby-boom cohort led to concern in the past that an increase in fatal crashes among older adults would follow (Lyman et al., 2002), yet previous research showed a decline from the mid-1990s through 2012 (Cicchino & McCartt, 2014). With the continued increase in older adult population size and longevity, profound implications remain for the safe and independent mobility of older adults. Given the recent increase in motor-vehicle fatalities in the United States over the last decade, reassessing trends among older drivers is warranted.

The purpose of this study was to explore current trends in fatal and police-reported crash involvement for drivers ages 70 and older, specifically to evaluate if the crash rates for older drivers continued to decline despite the recent increase in fatal motor-vehicle crashes in the United States. This study serves as a third installment to Cicchino and McCartt (2014) and Cheung and McCartt (2011) to include the most recent data available. Continuing with prior studies of this series, trend analyses began in the mid-1990s, as 1997 was the year in which older driver fatal crash involvements peaked in the United States.

2. Materials and methods

This study compared trends of rates of involvement in fatal crashes per licensed driver for older drivers with rates for middle-aged drivers, ages 35–54 years, beginning in 1997. We also examined involvements in fatal and police-reported crashes of varying severity per vehicle mile traveled (VMT) and driver deaths per crash involvement for drivers ages 70 and older, relative to drivers ages 35–54, beginning in 1995.

2.1. Data sources

Data on fatal crash counts were derived from the National Highway Traffic Safety Administration's (NHTSA) Fatality Analysis Reporting System (FARS). FARS is a census of all vehicle occupant or other road user deaths due to and occurring within 30 days of a motor-vehicle crash on U.S. public roads. FARS data were used in conjunction with data on licensed drivers, vehicle miles traveled, and estimates of police-reported crashes to calculate fatal crash involvement rates and risk of driver death.

Additional data procured from NHTSA were U.S. police-reported crashes of all severities from the National Automotive Sampling System General Estimates System (NASS GES) and its successor, the Crash Report Sampling System (CRSS). NASS GES and CRSS are nationally representative probability samples that can be weighted to produce annual national estimates. Imputed data were utilized when available to account for missing data. NASS GES and CRSS data were used to calculate rates of police-reported crashes per VMT and the risk of a driver dying in a crash.

Yearly counts of U.S. licensed drivers by state and age in 1997–2018 were acquired from the Federal Highway Administration (FHWA). Data for drivers under age 70 are based on data submitted directly by the states, while data for older drivers (older than age 70) are estimates based on U.S. Census Bureau population figures for each state and age group (Federal Highway Administration, 2019).

Data on vehicle miles traveled were obtained from the National Household Travel Surveys (NHTSs) conducted by FHWA. The current study used data from the Nationwide Personal Transportation Survey (NPTS) conducted during 1995–1996 and the NHTSs administered during 2001–2002, 2008–2009, and 2016–2017. These surveys will be referred to as the 1995, 2001, 2009, and 2017 surveys from this point on.

Inclusion criteria of this study remained consistent with the Cicchino and McCartt (2014) study and consisted of passenger vehicle (car, van, SUV, and pickup) driver crash involvements. Miles driven calculations were also restricted to passenger vehicles. Police vehicles were excluded from analyses to align with participants of the NPTS and NHTSs used to derive VMT estimates. Older drivers remained defined as those age 70 years and older and were further stratified by the age groups 70–74, 75–79, and 80 years and older. Middle-aged drivers were defined as ages 35–54 years. Middle-aged drivers were selected as the comparison group due to the lower prevalence of cognitive or physical age-related impairments experienced by older adults, coupled with a lower likelihood of engaging in risky driving behaviors that are associated with increased crash involvement among drivers under age 30.

2.2. Analyses

Analysis of covariance (ANCOVA) was used to explore linear trends in annual passenger vehicle fatal crash involvement rates per 100,000 licensed drivers of ages 70–74, 75–79, and 80 years and older, relative to the comparison group of drivers aged 35–54 years. Parameter estimates from the ANCOVA models are reported as estimates of annual changes in crash rates for each age group and differences between groups (changes for each older driver group relative to middle-aged drivers). Trends in fatal crash involvement per licensed driver were examined from 1997 to 2018 and 2010 to 2018. The year 2010 was chosen as the start of the second analysis, as that was the year fatalities among people ages 70 and older first increased following the long period of decline.

In addition to trends of crash involvement per licensed driver, this study explored fatal crash involvements per 100 million vehicle miles traveled (VMT) using data from the 1995 NPTS and the 2001, 2009, and 2017 NHTSs. Crash data from April–March of 1995–1996, 2001–2002, 2008–2009, and 2016–2017 were used to approximately align with the data collection periods of the NHTSs. Fatally injured driver counts were derived for the same periods from FARS. For each of the four survey periods and age groups, fatal crash involvements per 100 million VMT were calculated. Rate ratio calculations were performed to examine trends within each age group over time, comparing fatal crash involvements per VMT rates from 2017 to 1995 and 2017 to 2009. Ratios of the rate ratios comparing each older driver group with the middle-aged group were then computed for the time periods of interest. This served to examine the magnitude of difference in change over time between groups.

Rates of all police-reported crash involvements per 1 million VMT were also examined, again using the same four NHTS periods as the source for estimates of VMT. Finally, counts of fatal and nationally weighted estimates of police-reported crash involvements were used to calculate the risk of a driver dying in a crash per 1,000 crash involvements. The same methods described to calculate rate ratios and ratios of rate ratios for fatal crash involvements per 100 million VMT were extended to all police-reported crash involvements per 1 million VMT and driver deaths per 1,000 crash involvements.

Confidence intervals of rate ratios and ratios of the rate ratios were derived to assess if the changes over time were statistically significant using the method described by Ulmer et al. (2000). Point estimates with confidence intervals less than one indicate significant declines over the specified period for drivers in that age group (rate ratios) or relative to middle-aged drivers (ratios of the rate ratios), whereas point estimates with confidence intervals greater than one indicate significant increases.

3. Results

3.1. Trends in licensure and fatal crash involvement for drivers ages 70 and older

Table 1 displays trends in licensed drivers and passenger vehicle fatal crash involvements among people ages 70 and older from 1997 to 2018. During the entire study period, the number of older licensed drivers consistently increased each year and were up by 65% in 2018 from 1997. Increases in older licensed drivers have been more rapid in recent years. The number of older licensed adults increased twice as much during the last 11 years of the study than during the first 11 years, with a 36% increase from 2008 to 2018 versus an 18% increase from 1997 to 2007. Passenger vehicle fatal crash involvement of drivers ages 70 and older declined from 1997 until about 2009. In the following years, fatal crash involvement trends reversed course and increased through 2018, with a total of 4,506 fatal crash involvements that year. The increase in fatal crash involvement in recent years resulted in a net decrease of 6.6% since 1997.

3.2. Trends in fatal crash involvement per licensed driver

Fig. 1 depicts trends in fatal crash involvement per number of driver licenses for each age group, 35–54, 70–74, 75–79, and 80 and older for 1997 through 2018. For drivers ages 35–54, fatal crash involvements per licensed driver decreased 21%, whereas drivers ages 70 and older experienced greater declines; a 39% decrease for drivers ages 70–74, a 44% decrease for drivers ages 75–79, and a 49% decrease for drivers 80 and older. Beginning in 2015, rates in the middle-aged group exceeded the rate for those aged 70–79. Fatal crash involvements per licensed driver for all drivers ages 70 and older declined 43% from 1997 to 2018.

Table 2 displays results of the ANCOVA model that examined linear trends in fatal crashes per 100,000 licensed drivers by age group. During the period of 1997–2018, there were significant average annual declines in the fatal crash involvement rates in every age group. These declines became larger with increasing age; −0.29 annually for drivers 35–54, −0.46 for those 70–74, −0.61 among 75- to 79-year-olds, and −0.88 for those aged 80 and older. The difference in average annual change in fatal crash involvement rate between drivers ages 70–74 and 35–54 was significant at $a = 0.10$ ($p = 0.0503$), with significant differences at $a = 0.05$ in average annual changes in fatal crash involvements for drivers 75–79 and 80 and older relative to the change for drivers 35–54.

From 2010 to 2018, changes in fatal crash involvement rates per licensed driver were stagnant and nonsignificant for each older driver group. There was a significant increase in the rate for middle-aged drivers, at 0.35 annually on average. The lack of change across the older driver groups compared with the increase in crash rates per licensed driver produced negative average annual differences in fatal crash involvement rates for all older drivers relative to those middle-aged, all of which were significant.

3.3. Trends in driving exposure

Table 3 displays estimates of annual passenger vehicle miles traveled per driver for each of the four travel survey periods: 1995, 2001, 2009, and 2017. Older drivers drove fewer miles in each survey period than the middle-age drivers, but experienced greater increases in miles driven since 1995. Drivers 75–79 years of age had the largest increase and nearly doubled the annual miles driven over the full period. Middle-aged drivers increased miles driven the least over the entire period, up a total of 37%. All age groups increased miles driven from 2009 to 2017.

3.4. Trends in crash involvement rates per mile driven and death risk

Fig. 2 depicts fatal crash involvements of U.S. passenger vehicle drivers per 100 million miles traveled, for all age groups for each period the NHTS was conducted. Fatal crash involvement rates were highest among the younger and older drivers, with teenagers and the oldest adults having similar rates since 2001. Drivers ages 80 and older have seen the most dramatic decreases since the 1995 NHTS. Rates of fatal crash involvements per VMT improved over the four study periods across the older driver age groups, but the historical pattern of fatal crash involvement rates per VMT that begin to rise at age 70 and continue to increase with age persisted through 2017; rates in 2017 were 25% higher among drivers ages 70–74, 57% higher among drivers ages 75–79, and about four times as high among drivers 80 and older compared with middle-aged drivers. The rates among the older driver groups followed a general downward trajectory over time, except for drivers 80 and older from 2009 to 2017 where there was no real change.

Changes in rates of fatal crash involvements per VMT between 2017 and 1995 and 2017 and 2009 for middle-aged and older driver groups are displayed in Table 4. Fatal crash involvement rates declined among each age group over the full study period, with the largest reductions experienced by drivers ages 75 and older (35–54, −15%; 70–74, −46%; 75–79, −60%; 80+, −55%). However, during 2009 to 2017, fatal crash involvements per VMT among middle-aged drivers significantly increased by 19%. Since 2009,

Table 1
National counts of licensed drivers and passenger vehicle driver fatal crash involvements for people ages 70 and older, 1997–2018.

Year	Older licensed drivers (in thousands)	Older driver passenger vehicle fatal crash involvements
1997	17,727	4,823
1998	17,911	4,808
1999	18,466	4,806
2000	18,940	4,574
2001	19,137	4,649
2002	19,877	4,543
2003	19,827	4,644
2004	19,966	4,355
2005	20,120	4,237
2006	20,589	4,064
2007	20,968	4,004
2008	21,567	3,739
2009	21,847	3,565
2010	22,264	3,630
2011	22,592	3,552
2012	23,117	3,651
2013	23,603	3,565
2014	24,435	3,720
2015	25,304	3,944
2016	26,358	4,302
2017	27,989	4,528
2018	29,307	4,506
Percent change, 2018 vs. 1997	65	−6.6

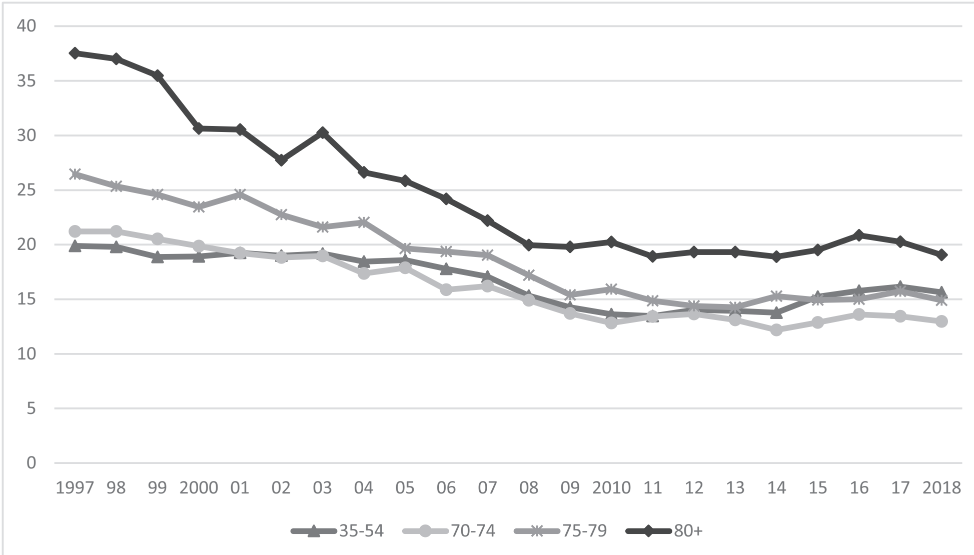

Fig. 1. Fatal crash involvements of U.S. passenger vehicle drivers per 100,000 licensed drivers by age group, 1997–2018.

Table 2
Average annual change in passenger vehicle driver fatal crash involvement rates per 100,000 licensed drivers by driver age group, 1997–2018 and 2010–2018: summary of ANCOVA models.

Driver age group and period	Annual change in fatal crash involvement rate	Difference in annual change in fatal crash involvement rate relative to change for drivers ages 35–54
1997–2018		
35–54	−0.29*	–
70–74	−0.46*	−0.17±
75–79	−0.61*	−0.32*
80+	−0.88*	−0.59*
70+	−0.62*	−0.33*
2010–2018		
35–54	0.35*	–
70–74	0.00	−0.34*
75–79	0.01	−0.34*
80+	0.05	−0.31*
70+	−0.02	−0.37*

±$p < 0.10$.
*$p < 0.05$.

rates declined approximately 20% among drivers ages 70–79 and did not change among drivers 80 and older.

All crash involvements per VMT follow a similar U-shaped curve to fatal crash involvement rates in which they are highest for the youngest and the oldest drivers (Fig. 3). However, police-reported crash involvements per 1 million miles is highest among the youngest drivers, unlike the nearly identical rates between the oldest and youngest driver age groups seen with fatal crash involvements. Where rates of fatal crashes per VMT were higher among all older drivers' groups than middle-aged drivers, police-reported crash involvements per VMT rates were lower for drivers ages 70–79 than ages 35–54 for the first time in 2017, with rates 16% lower for drivers ages 70–74 and 4% lower for ages drivers 75–79 than 35- to 54-year-old drivers. Police-reported crash rates for drivers 80 and older were 50% higher than for middle-aged drivers in 2017.

As with fatal crash involvement rates, police-reported crash involvements per 1 million VMT decreased among drivers in all age groups since 1995, but middle-aged drivers experienced a significant rise of 26% since 2009 (Table 4). There was a significant reduction of 6% among the 70- to 74-year-old and 80 and older driver age groups during the most recent period, and drivers ages 75–79 experienced a minor, nonsignificant increase of 1% since 2009. Over the entire study period of 2017 versus 1995, larger declines in all police-reported crash involvements per mile traveled occurred with increasing age.

Fig. 4 displays driver deaths per 1,000 crashes, or the risk of dying in a crash, for each NHTS period among all ages. A stable pattern is evident in which death risk increases with age. Compared with middle-aged drivers, death risk in 2017 was twice as high for drivers ages 70–74, 2.5 times as high for drivers ages 75–79, and climbed to nearly five times as high for the oldest drivers ages 80 and older.

Rate ratios of driver deaths per 1,000 police-reported crash involvements are similar between 2017 to 1995 and 2017 to 2009 for each age group (Table 4), indicating most of the declines seen since 1995 occurred in more recent years. Middle-aged drivers and drivers ages 70–79 experienced significant declines over

Table 3
Estimated average annual passenger vehicle miles traveled by driver age: 1995, 2001, 2009, and 2017.

Driver age group	Miles				Percent change
	1995	2001	2009	2017	2017 vs. 1995
35–54	12,673	16,983	15,379	17,364	37
70–74	6,848	10,375	9,512	10,667	56
75–79	5,571	8,786	8,936	10,755	93
80+	4,285	6,805	6,487	7,259	69
70+	5,948	9,000	8,446	9,830	65

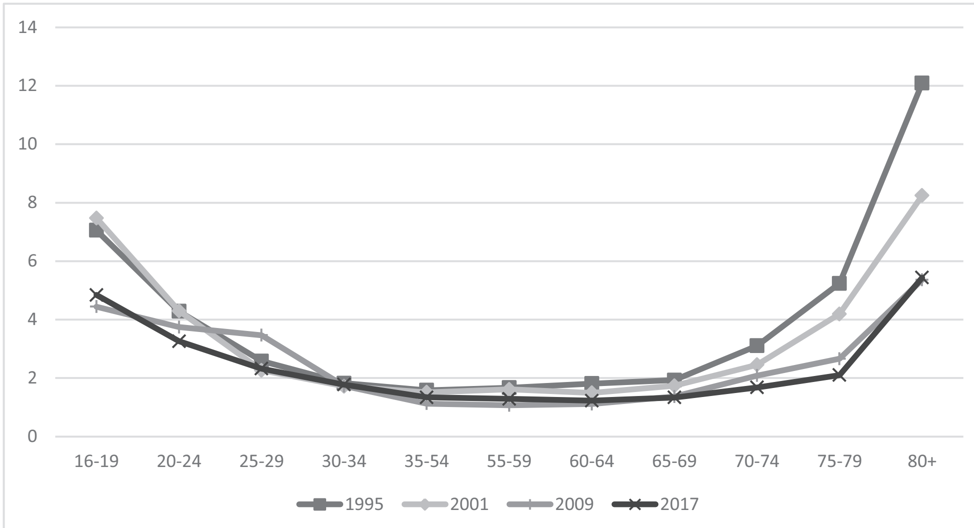

Fig. 2. Fatal crash involvements of U.S. passenger vehicle drivers per 100 million vehicle miles traveled by age group: 1995, 2001, 2009, and 2017.

Table 4
Rate ratios (RR) and 95% confidence intervals of fatal crash involvement rates per VMT, police-reported crashes per VMT, and driver deaths per police-reported crashes of 2017 relative to those of 1995, and rates from 2017 relative to those of 2009 by age.

Driver age group	Fatal crash involvements per 100 million VMT		Crash involvements per 1 million VMT		Driver deaths per 1,000 police-reported crashes	
	2017 vs. 1995	2017 vs. 2009	2017 vs. 1995	2017 vs. 2009	2017 vs. 1995	2017 vs. 2009
35–54	0.845 (0.824, 0.866) *	1.189 (1.159, 1.219) *	0.871 (0.865, 0.876) *	1.255 (1.248, 1.263) *	0.868 (0.836, 0.902) *	0.855 (0.822, 0.890) *
70–74	0.540 (0.503, 0.580) *	0.806 (0.746, 0.870) *	0.647 (0.633, 0.660) *	0.935 (0.912, 0.959) *	0.748 (0.680, 0.823) *	0.767 (0.692, 0.850) *
75–79	0.402 (0.371, 0.435) *	0.791 (0.727, 0.861) *	0.505 (0.494, 0.518) *	1.013 (0.986, 1.041)	0.744 (0.673, 0.824) *	0.737 (0.661, 0.821) *
80+	0.450 (0.420, 0.482) *	1.014 (0.946, 1.087)	0.451 (0.440, 0.461) *	0.942 (0.919, 0.965) *	0.964 (0.889, 1.045)	1.066 (0.982, 1.158)
70+	0.501 (0.481, 0.523) *	0.833 (0.798, 0.871) *	0.567 (0.560, 0.575) *	0.933 (0.919, 0.948) *	0.835 (0.793, 0.880) *	0.845 (0.799, 0.893) *

*denotes statistical significance, *a = 0.05*.

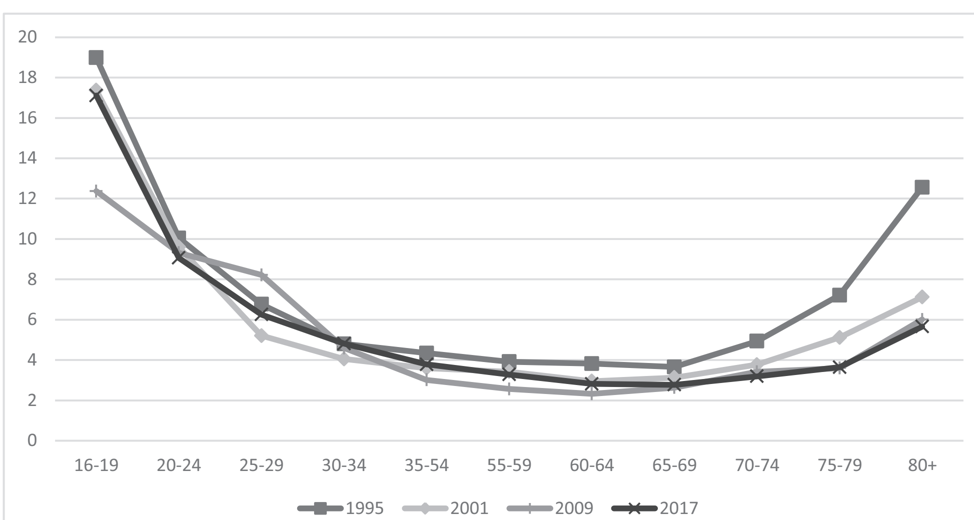

Fig. 3. Police-reported crash involvements of U.S. passenger vehicle drivers per 1 million vehicle miles traveled by age group: 1995, 2001, 2009, and 2017.

both periods, with the most substantial declines seen among drivers 75–79 (−26% both from 2009 to 2017 and over the entire study period). The risk of dying in a crash for drivers 80 and older was relatively unchanged with both comparisons.

Table 5 displays the rate ratios of fatal crash and police-reported crash involvements per VMT and driver deaths per 1,000 police-reported crashes for each older driver group relative to those of middle-aged drivers, for periods 2017 versus 1995 and 2017 versus 2009. Fatal crash involvements per VMT declined significantly for all older driver age groups relative to middle-aged drivers for both 2017 compared with 1995 and 2017 compared with 2009.

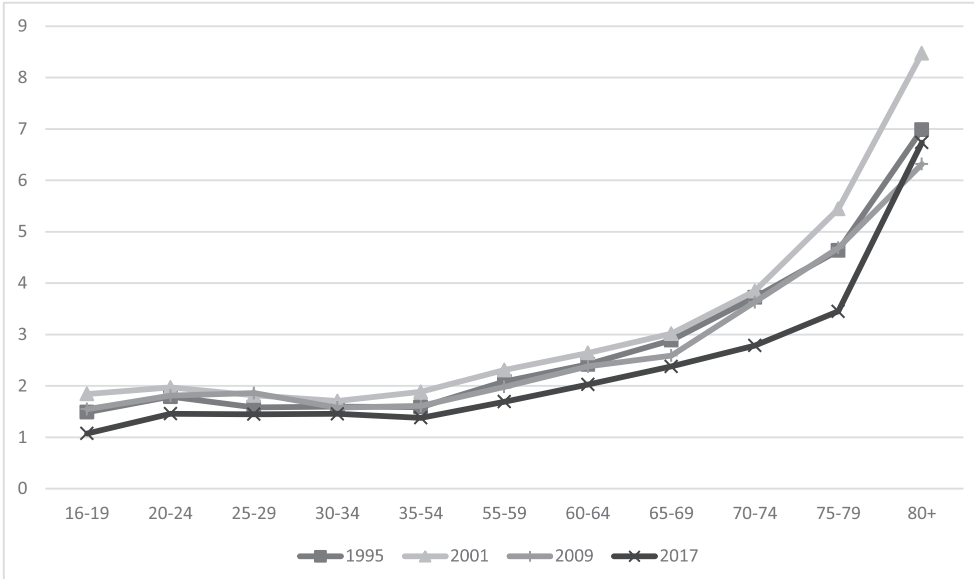

Fig. 4. Driver deaths per 1,000 crashes by age group: 1995, 2001, 2009, and 2017.

Table 5
Ratio of the rate ratio (RR) and 95% confidence intervals of driver fatal crash involvements per VMT, police-reported crashes per VMT, and driver deaths per police-reported crashes of older drivers compared with middle-aged drivers during 2017 relative to that during 1995, and 2017 relative to that during 2009.

Driver age group	Fatal crash involvements per 100 million VMT		Crash involvements per 1 million VMT		Driver deaths per 1,000 police-reported crashes	
	2017 vs. 1995	2017 vs. 2009	2017 vs. 1995	2017 vs. 2009	2017 vs. 1995	2017 vs. 2009
70–74	0.639 (0.593, 0.689) *	0.678 (0.625, 0.735) *	0.742 (0.727, 0.758) *	0.745 (0.726, 0.764) *	0.862 (0.778, 0.955) *	0.897 (0.803, 1.001)
75–79	0.476 (0.438, 0.517) *	0.666 (0.609, 0.727) *	0.580 (0.567, 0.594) *	0.807 (0.785, 0.829) *	0.858 (0.769, 0.956) *	0.861 (0.767, 0.966) *
80+	0.533 (0.495, 0.573) *	0.853 (0.793, 0.919) *	0.517 (0.505, 0.530) *	0.750 (0.732, 0.769) *	1.110 (1.016, 1.214) *	1.247 (1.137, 1.366) *
70+	0.594 (0.566, 0.623) *	0.701 (0.667, 0.738) *	0.651 (0.643, 0.660) *	0.743 (0.732, 0.755) *	0.962 (0.902, 1.027)	0.987 (0.923, 1.057)

*denotes statistical significance, $a = 0.05$.

The same holds for police-reported crash involvements per VMT. Driver deaths per 1,000 police-reported crashes declined significantly relative to middle-aged drivers for drivers ages 70–74 from 1995 to 2017 and drivers ages 75–79 in both comparisons. Risk of dying in a crash among drivers 80 and older increased relative to middle-aged drivers during both time periods, both significant.

4. Discussion

This study builds upon Cicchino and McCartt (2014) by including the most recent data available to further examine trends in older driver crash involvements. The number of older driver fatal crash involvements have remained below their peak since reaching it in 1997, even with vast increases in the number of older drivers and the miles they drive. However, a reversal began in 2010 where fatal crash involvements among older drivers increased. This parallels the rise in the number of motor-vehicle fatalities in the United States (Insurance Institute for Highway Safety [IIHS], 2019). Fatal crash involvement rates per mile traveled and per licensed driver have remained relatively stable in recent years among older drivers, but this is a marked contrast to what has been seen with middle-aged drivers, whose fatal and total crash involvement rates have spiked. Middle-aged driver fatal crash involvement rates per licensed driver and police-reported crash involvement rates per VMT now surpass those for drivers ages 70–79. Drivers 80 and older have the greatest declines in both fatal crash involvements per licensed driver and all police-reported crash involvements per VMT since the mid-1990s.

There has been a long-held agreement that traffic fatalities decline during recessions and increase with a strong economy (Evans & Graham, 1988; Ruhm, 1995). As the economy has largely rebounded from the economic recession that began in 2008, and miles driven and traffic-related fatalities are in direct relationship to the strength of the economy, it is expected that the number of fatalities and miles driven would increase given the lower unemployment level of 4% in December 2018 versus 10% in December 2010 (United States Bureau of Labor Statistics [BLS], 2011, 2019). Fatal crash involvements per miles traveled among middle-aged adults increased in the past decade, yet it is surprising that these rates declined among drivers ages 70–79 and remained stable among drivers 80 and older despite economic improvement.

It has been hypothesized that riskier forms of driving, such as alcohol-impaired driving and speeding, decrease most during a recession (Cotti & Tefft, 2011; He, 2016; Ruhm, 1995) and thus would be expected to rebound during economic recovery. Older people participate less in these types of risky driving (Rakotonirainy et al., 2012; Schroeder et al., 2013), which could explain the lack of a recent increase in their fatal crash involvement rates. Another contributing factor to differing fatal crash involvement rates over the past decade could be rising speed limits on limited-access roads, where older drivers more often restrict their travel (Naumann et al., 2011). Twenty states raised their maximum speed limits between 2011 and 2012, and such increases have been associated with an 8% rise in fatality rates on interstates and other freeways (Farmer, 2017).

A possible, partial explanation for the continued decline in older driver fatal crash involvement rates relative to middle-aged drivers since the mid-1990s is the evidence that shows Americans are living longer, healthier lives (Crimmins et al., 2016). Medical advancements associated with longer life expectancy and active life expectancy may be responsible for a delayed onset or improved management of severe age-related declines in cognitive, visual, and physical function that are associated with increased risk of crash involvement. These healthier older adults are more often staying in the workforce (BLS, 2008; Cichy et al., 2017), which is consistent with the increases seen in both the number of drivers ages 70 and older and the miles they drive.

Drivers 70 and older are overrepresented in intersection-related crashes and are more likely to be involved in multiple-vehicle crashes (Lombardi et al., 2017; Mayhew et al., 2006). Infrastructure adaptations that target the aging population by aiming to address the age-related declines that contribute to higher crash risk have been implemented since the FHWA first published the Older Driver Highway Design Handbook in 1998, with updates and expansions in 2001 and 2014 (Brewer et al., 2014). Its guidance includes recommendations to improve intersection design and traffic sign visibility, and calls for converting traditional intersections to roundabouts, which can eliminate the right-angle crashes in which older drivers are over-involved. As state and local engineering professionals have gradually implemented these treatments, it is likely that these and other infrastructure enhancements that have been proposed with the aging population in mind have contributed to the declines in crash risk among adults 70 and older since the mid-1990s.

Increases in crash survivability relative to middle-aged drivers also contributed to lower relative fatal crash involvement rates among drivers ages 70–79. This could be the result of better health and the adoption of vehicle safety improvements, such as side airbags, that have been more beneficial for older adults than younger adults (Kahane, 2013). The crashworthiness of the United States passenger vehicle fleet is continually improving, with the proportion of registered vehicles earning good ratings in Insurance Institute for Highway Safety crash tests increasing each year (Highway Loss Data Institute [HLDI], 2019a). This is likely why death risk decreased among all but the oldest drivers during the full study period and more recently. However, it can take three decades before 95% of vehicles on the road have a given safety feature once introduced (HLDI, 2019b). Older adults tend to hold onto their vehicles longer than younger drivers, therefore these advancements in crashworthiness and safety features are slower to reach and benefit them, as the proportion of newer model year vehicles driven or crashed by older drivers decreases with increasing age (Braitman & McCartt, 2008; Fausto & Tefft, 2018). Further improvements in crash survivability can be expected as more adults are driving today's new vehicles.

Some limitations of this study should be noted. Police-reported crash sampling methods changed when NHTSA converted from NASS GES to CRSS, which may have affected the comparability of the 2017 data on all crash involvements with earlier years. We chose to compare the 2017 CRSS data with the older data derived from NASS GES because there is not another source of national police-reported crash estimates, and there is no reason to believe that potential bias varied by driver age. Additionally, driver license information was obtained through counts from states for younger drivers but derived from population estimates for drivers ages 70 and older. Specific details on how these estimates were derived are not provided, therefore the directional effect and magnitude of this potential bias is uncertain. Estimates of VMT by age from household travel surveys for the older age groups are based on fewer respondents than the middle-aged group, and therefore may be less reliable. Despite the different shortcomings of license counts and miles traveled, it is promising that results were consistent when using both measures of exposure.

5. Conclusions

Results of this study demonstrate that fatal crash involvements among older adults remain lower than the peak levels seen in the mid-1990s. Although a slowing of declining trends can be seen, there is no evidence to suggest an increase in fatal crash rates among older adults, as had been hypothesized when considering the increasing proportion of older adults in the United States population and their elevated crash risk.

6. Practical applications

For adults ages 70 and older, fatal crash rates per 100,000 licensed drivers fatal and police-reported crashes of all severities per vehicle miles traveled have declined since the mid-1990s but have slowed or stagnated over the past decade. Given these results, the once feared spike in motor-vehicle crash rates due to the combination of a growing older adult population with their historically higher crash involvement was not realized. Thus, older adults can feel confident that their independent mobility needs pose less danger than previously hypothesized. As the growing body of evidence suggests older adults may greatly benefit from new vehicle safety features, older adults might consider the purchase of a new, more crashworthy vehicle equipped with modern safety equipment that may offer better protection in the event of a crash.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

This work was supported by the Insurance Institute for Highway Safety.

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Aimee Cox is a Research Associate at the Insurance Institute for Highway Safety. She holds an M.P.H. in Epidemiology from the University of South Florida and a B.S. from Eastern Michigan University.

Jessica Cicchino is Vice President, Research at the Insurance Institute for Highway Safety. Since joining the Institute in 2012, she has authored papers on topics such as the effectiveness and use of advanced driver assistance systems, automated traffic enforcement, and the safety of older drivers, pedestrians, bicyclists, motorcyclists, and child passengers. Dr. Cicchino holds a B.A. from Vassar College and a Ph.D. from Carnegie Mellon University.

Journal of Safety Research 77 (2021) 202–211

Contents lists available at ScienceDirect

Journal of Safety Research

journal homepage: www.elsevier.com/locate/jsr

Disaggregated traffic conditions and road crashes in urban signalized intersections

Lucas Tito Pereira Sobreira *, Flávio Cunto

Department of Transportation Engineering, Universidade Federal do Ceará, Fortaleza, CE, Brazil

ARTICLE INFO

Article history:
Received 28 July 2020
Received in revised form 30 October 2020
Accepted 3 March 2021
Available online 20 March 2021

Keywords:
Road safety
Condition based
Clustering
Signal cycle length
SCOOT

ABSTRACT

Introduction: Road safety studies in signalized intersections have been performed extensively using annually aggregated traffic variables and crash frequencies. However, this type of aggregation reduces the strength of the results if variables that oscillate over the course of the day are considered (speed, traffic flow, signal cycle length) because average indicators are not able to describe the traffic conditions preceding the crash occurrence. This study aims to explore the relationship between traffic conditions aggregated in 15-min intervals and road crashes in urban signalized intersections. *Method:* First, an investigation of the reported crash times in the database was conducted to obtain the association between crashes and their precursor conditions. Then, 4.1 M traffic condition intervals were consolidated and grouped using a hierarchical clustering technique. Finally, charts of the frequency of crashes per cluster were explored. *Results:* The main findings suggest that high vehicular demand conditions are related to an increase in property damage only (PDO) crashes, and an increase in the number of lanes is linked to more PDO and injury crashes. Injury crashes occurred in a wide range of traffic conditions, indicating that a portion of these crashes were due to speeding, while the other fraction was associated with the vulnerability of road users. Traffic conditions with: (a) low vehicular demand and a long cycle length and (b) high vehicular demand and a short cycle length were critical in terms of PDO and injury crashes. *Practical Applications:* The use of disaggregated data allowed for a stronger evaluation of the relationship between road crashes and variables that oscillate over the course of the day. This approach also permits the development of real-time risk management strategies to mitigate the frequency of critical traffic conditions and reduce the likelihood of crashes.

1. Introduction

In the 1990s and early 2000s, a significant amount of research was conducted on safety performance functions with the aim of assessing the relationship between the frequency of road crashes and features of the traffic environment, such as the traffic volume, operational and geometric road attributes, and land use (Cunto et al., 2011; Greibe, 2003; Hadayeghi et al., 2007; Hauer, 2004; Lyon & Persaud, 2002). In general, these functions were constructed by relating highly aggregated data for crashes (annual crash frequency) and exposure indicators (annual average daily traffic (AADT)), which provided a number of useful applications, such as estimations of the expected crash frequency of entities and the identification of crash hotspots. However, the use of highly aggregated and static data may reduce the model strength if variables that oscillate over the course of the day are investigated, such as the speed and traffic volume (Davis, 2004; Imprialou et al., 2016).

The advent of new intelligent transportation systems such as vehicle detection inductive loops, speed camera equipment, and GPS data provides tools for the development of dynamic traffic flow management (USDOT, 2014). In terms of road safety, the availability of disaggregated traffic information can enable a more confident understanding of the connection between traffic variables and crashes (Imprialou et al., 2016; Stempfel et al., 2016; Wang et al., 2018). It can also allow for the advancement of proactive real-time crash management strategies that target the prediction and control of crash-prone scenarios (Abdel-Aty et al., 2012; Abdel-Aty & Pande, 2005; Huang et al., 2017; Pirdavani et al., 2015).

The great majority of road safety studies that have utilized disaggregated traffic data were conducted on highways and freeways, which are characterized by an uninterrupted traffic flow environment. The presence of signalized intersections in the road network

* Corresponding author at: Campus do Pici, BL.703, Av. Mister Hull, s/n - Pici, Fortaleza, Brazil.

E-mail address: lucastito@det.ufc.br (L.T.P. Sobreira).

https://doi.org/10.1016/j.jsr.2021.03.003
0022-4375/

adds interruptions to the traffic flow, imposing stop-and-go movements that may increase the likelihood of the occurrence of traffic conflicts. Therefore, transferring assumptions obtained from uninterrupted traffic flow conditions to urban signalized environments may not be viable. Recently, Essa and Sayed (2019) and Yuan and Abdel-Aty (2018) conducted studies focusing on disaggregated analyses of signalized intersections; however, neither of these studies considered densely signalized urban networks, rather focusing on isolated signalized intersections, thus indicating a gap in the literature on this topic.

Imprialou et al. (2016) proposed a new method for the development of road safety analyses built on groups of homogenous traffic information. Instead of the traditional approach that relates road crashes to features of particular entities (entity-based), the authors suggested crashes should be aggregated according to the similarity of the pre-crash traffic conditions (condition-based).

The main goal of this study is to evaluate the relationship between disaggregated traffic data and road crashes in signalized intersections located in a densely signalized urban environment by applying the condition-based approach.

2. Literature review

The relationship between the crash frequency in signalized intersections and features that might impact the occurrence of crashes has been widely developed and investigated in research conducted using annually aggregated data. Increases in some variables were found to have a significant impact on an increase in crashes, such as the total entering AADT (Abdel-Aty & Wang, 2006; Castro et al., 2012; Chin & Quddus, 2003; Cunto et al., 2011), number of lanes (Abdel-Aty & Wang, 2006; Cunto et al., 2011), number of signal phases (Abdel-Aty & Wang, 2006; Chin & Quddus, 2003; Xie et al., 2013), and left-turn and right-turn AADT (Chin & Quddus, 2003). However, some authors found negative effects on crash frequency with increasing traffic flow (Oh et al., 2004; Wong et al., 2007). The authors hypothesized that during congested conditions, the risk of losing control of the vehicle is reduced, leading to a safer road environment. Another hypothesis is that in low-speed scenarios, crashes tend to be less severe and, therefore, less reported (Hauer, 2009).

Xie et al. (2013) performed an analysis of Chinese signalized corridors using taxi GPS data and identified that an increase in the average speed is associated with an increased crash risk. The authors also found that short signal spacing may result in more crashes at the intersections, which was corroborated by Abdel-Aty and Wang (2006).

In terms of traffic control, Guo et al. (2010) found that coordinated signalized intersections are an average of 53% riskier than conventional intersections, which was attributed to the development of higher speeds due to green waves and short signal spacing. Khattak et al. (2018) noted that the presence of adaptive signal control technology reduced total and injury crashes by 13% and 36%, respectively.

The studies mentioned above were based on annually aggregated traffic and crash frequency data; therefore, any hypotheses made regarding variables that oscillate over the course of a day lose their strength. As an illustration, we consider the example of a signalized intersection with an average speed of 80 km/h during the off-peak period and 20 km/h during the peak period. Assuming an equal duration for both periods, all of the crashes that occurred at that site would be associated with the average speed of 50 km/h, resulting in a loss of relevant information because the average indicator cannot accurately represent the crash precursor conditions.

For uninterrupted traffic flow environments, there have been a significant number of road safety studies based on disaggregated data, and the achieved results and hypotheses are diverse. However, a meta-analysis conducted by Roshandel et al. (2015) summarized the findings of several studies: (a) an increase in speed variation and speed difference among vehicles is associated with more crashes; (b) an increase in the average speed by one unit decreases the odds of crash occurrence by 4.8%; and (c) an increase in the average traffic volume by one unit increases the odds of crash occurrence by 0.1%.

Imprialou et al. (2016) evaluated the effect of speed, traffic volume, and geometric features on road safety in English highway segments by comparing entity-based and condition-based approaches. The entity-based methodology associated annual indicators of the total AADT, average speed, and crash frequency. The condition-based approach utilized speed and traffic volume data aggregated in 15-min intervals. To define each traffic scenario, the authors segregated the speeds into 50 intervals, traffic volume into 4 intervals, road gradient into 3 intervals, and road curvature and number of lanes into 2 intervals, resulting in a total of 2,400 scenarios to which 9,310 crashes were linked. The results obtained with the two approaches were completely different. While the entity-based methodology indicated a reduction in the crash frequency with an increase in the average speed, the condition-based methodology indicated an increase in the crash occurrence with an increase in speed from 0 km/h to 90–100 km/h, and then safer conditions when speeds were higher than 100 km/h. According to the author, the proposed method allowed much more reliable results to be obtained compared with the results of the traditional method.

Recently, some research has been conducted on the application of disaggregated data to road safety in signalized intersections. Essa and Sayed (2019) evaluated the safety of six isolated signalized intersections by applying traffic conflict models at the signal cycle level. The results indicated that the number of traffic conflicts is predicted to increase during signal cycles with lower platoon ratios and larger shock waves. The authors also found that the highest conflict frequency occurred at the beginning of the green time, whereas the highest conflict severity occurred at the beginning of the red time. Using data aggregated over 5-min intervals, Yuan and Abdel-Aty (2018) investigated two types of crashes in 23 signalized intersections: within intersection crashes and intersection entrance crashes. The results showed that for the first type of crash, the through-volume increased the likelihood of crash occurrence, while for the latter type of crash, the average speed decreased the odds of crash development.

Unfortunately, little research has been conducted on signalized intersections using disaggregated data. The research is even scarcer for densely signalized urban environments. These environments are characterized by constant stop-and-go movements that expose vehicles to regular traffic conflicts and by the significant presence of vulnerable users such as pedestrians and cyclists. Therefore, this study aims to contribute to this important gap in road safety research.

3. Method

The proposed method for evaluating the effect of disaggregated traffic data, geometric attributes, and operational features on the frequency of crashes in urban signalized intersections using a condition-based approach is presented in Fig. 1.

The condition-based approach relies on grouping the explanatory variables by similarity, regardless of the signalized intersection of origin. When dealing with attributes that vary over the course of a day, the condition-based approach allows for evaluation of the relationship between road crashes and traffic conditions that may fit each crash condition better than the traditional entity-

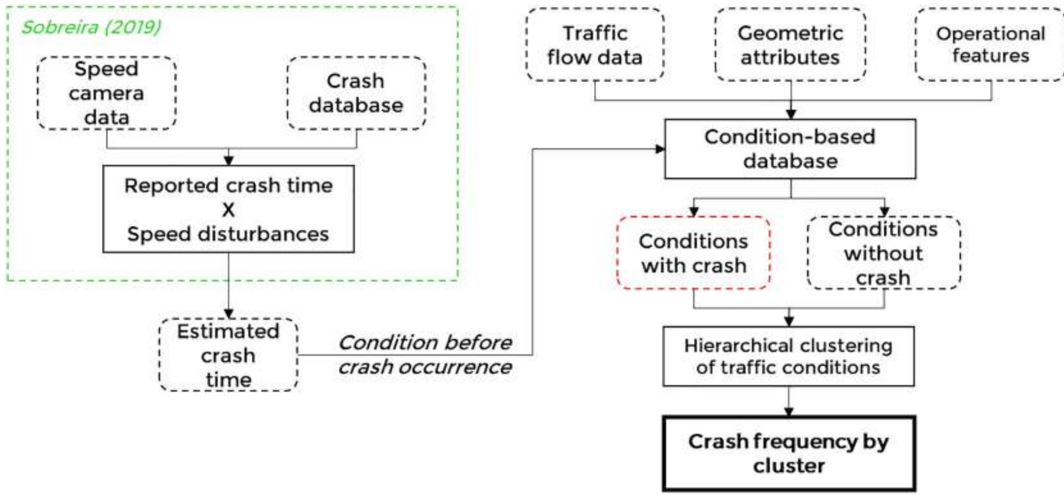

Fig. 1. Proposed method.

based approach. In contrast to the link between crashes and annually aggregated traffic variables in the entity-based approach, which can lead to the loss of relevant information, the condition-based approach aims to associate the crashes with their actual precursor conditions, representing the contribution of traffic conditions to the crash occurrence in greater detail. Conversely, condition-based studies are usually developed using big data for traffic, which requires a process of data mining that is more elaborate than that in the traditional entity-based approach.

The traffic data utilized in this study were obtained from the SCOOT (Split, Cycle, and Offset Optimization Technique) system of signal management and optimization, which provides traffic information at intervals of 15 min.

3.1. Differences between reported crash times and speed disturbances

The use of traffic data aggregated in 15-min intervals demands a better understanding of the differences between reported crash times and the moment at which the crashes actually occurred to allow for the association of crashes with their precursor traffic conditions (Zheng, 2012). Therefore, the first step in the proposed method is to investigate these differences for crashes in the city of Fortaleza, Brazil. This analysis was performed using automated speed cameras located at signalized intersections. The speed profile around the reported time and date of the crash was compared to the speed under typical conditions (without crashes), allowing the detection of significant speed disturbances linked to the most probable time of the crash occurrence. In this analysis, the difference between the reported time of the crash and the time of the detected disturbance was measured (Fig. 2). This approach is further discussed in Sobreira (2019) and in Sobreira et al. (in press).

Sobreira (2019) explored 273 crashes that occurred in the region of the SCOOT signals in the city of Fortaleza, Brazil. An average difference of 19 min was found between the reported crash times and the moment of the detected disturbance. Additionally, there was a statistically significant variation (p-value = 0.01) between the differences for property damage only (PDO) and injury crashes.

Following the methodology applied by Christoforou et al. (2011), Golob et al. (2008), and Quddus et al. (2010), who considered fixed correction times to adjust the reported crash times, it was decided to correct the crash times by employing the 95th percentile of the differences based on the crash severity: (a) PDO crashes: 66 min and (b) injury crashes: 44 min. The intersections that have camera enforcement devices are not necessarily the same as those that have the SCOOT technology; however, both are located in the same region of the city, allowing the fixed correction times to be used for the intersections without enforcement. The 95th percentile was selected with the intention of associating most of the crashes with the conditions prior to their occurrence. It has been shown that this approach may develop links between some crashes and conditions slightly different from those immediately before the crash occurrence; however, it allows some confidence that mostly precursor intervals are considered. Moreover, with the use of 15-min data aggregation, which is not extremely disaggregated, rapid changes in the traffic flow conditions are not

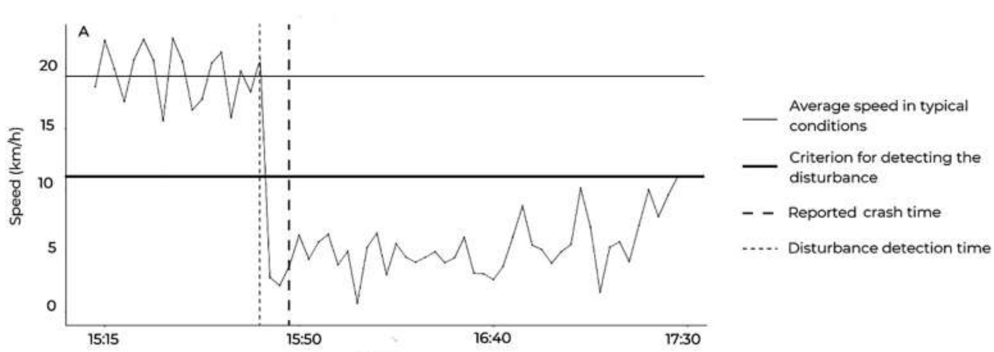

Fig. 2. Method for comparing reported crash times and speed disturbances.

expected. The accuracy of this approach is investigated in Section 6, which demonstrates satisfactory performance of the 15-min aggregation.

3.2. Condition-based database

Traffic information was extracted from the SCOOT system, which operates with inductive loops placed upstream of the stop line. The system estimates two types of indicators based on loop occupancy: (a) basic, which are obtained directly from the vehicular loop occupancy (e.g., the traffic volume, degree of saturation, and vehicular delay); and (b) derived, which are estimated from the basic variables (e.g., the speed and travel time). It is important to highlight that the speed is not directly measured by the loop, but is estimated from the relationship between the travel time during free flow conditions and the vehicular delay, meaning that the speed indicator includes the time the vehicles are stopped. The variables are available in 15-min intervals for each signal approach. The indicators were then aggregated at the intersection level by considering the traffic flow as the sum of the indicator at all of the approaches, while the other variables were considered as a weighted average of the approach flow.

The condition-based database included traffic information (total entering traffic flow, speed, degree of saturation, signal cycle length, and flow split between the approach directions), geometric attributes (number of lanes and approaches), and operational features (presence of camera enforcement and number of allowed left or right turns). The variables were gathered such that each line represented a traffic condition. Thus, in the condition-based database, the crashes within a 50 m radius of each signalized intersection were associated with the location and the adjusted crash time.

3.3. Clustering traffic conditions

The traffic conditions were grouped by similarity using the hierarchical clustering (HC) technique. Initially, some considerations were made: (a) aiming to facilitate data visualization, a principal cluster structure was obtained based on two variables; then, the other variables were incorporated into this structure in categories. For example, if the main structure was formed from 10 clusters of the speed and traffic flow variables, adding the number of lanes, which is segmented into X categories, would result in 10 clusters for each category. (b) As the HC technique relies on a distance matrix, a stratified sample of the traffic conditions is required when using large datasets. The stratification was based on the percentiles of the two main variables considered.

The number of clusters was selected based on the total within sum of squares (TWSS) indicator, which measures the sum of the distances between the center of each cluster and each element belonging to that cluster. An approach similar to that used by Chen et al. (2014) was applied: the authors identified the greatest number of clusters (K_i) that represented a 5% reduction in the TWSS when compared to the TWSS of the previous configuration (K_{i-1}). In other words, as increasing the number of clusters reduces the TWSS, the authors selected the greatest number of clusters that showed a "marginal benefit" of 5%. In this study, aiming to present some possibilities for the cluster configuration, the greatest numbers of clusters that produced marginal benefits of 15%, 10%, and 5% were evaluated. The selected cluster arrangement was that which exhibited the best balance between the data disaggregation and the available crash sample. Then, by reverting the sampling process, each element of the complete sample was associated with its nearest cluster. The road safety analyses were performed by examining charts containing the frequency of crashes within each cluster.

4. Study location

This study was conducted in the city of Fortaleza, which is located in the northeast region of Brazil. Fortaleza has an area of 313 km^2 and a population of 2.6 million. Fig. 3 shows a map of the city, including the traffic signals with and without SCOOT technology. Both types of signals are concentrated in the north-central region of the city, and 209 signals are located in the highlighted region of approximately 9.6 km^2. As a result, this is a highly signalized environment (22 traffic signals per km^2) that subjects drivers to frequent stop-and-go movements.

In terms of land use, the north-central zone of Fortaleza is characterized by a large number of commercial establishments, representing 23% of the land use in the region, which promotes an intense flow of vehicles, pedestrians, and cyclists. Almost all of the rest of the land use in the region is residential buildings. Fortaleza has approximately 1.1 million vehicles, of which 54% are automobiles and 27% are motorcycles. In 2018, there were 10,931 injury crashes in the city, mostly injuring vulnerable road users.

5. Results and discussion

This section is divided into three parts. The first section provides a descriptive analysis of the condition-based database, the second section describes the data clustering process, and the third section presents the results and discussion of the association between the clustered traffic conditions and road crashes.

5.1. Condition-based database

Data from 95 signalized intersections controlled by the SCOOT system were extracted from 2015 to 2017 to create a database with 4,102,567 intervals of 15 min. Table 1 presents a summary of this database.

There is a strong linear correlation between the traffic flow per lane and the degree of saturation ($R = 0.78$) and between the number of lanes or approaches and the allowed left or right turns ($R > 0.75$). Thus, it was decided to consider only the traffic flow per lane and the number of lanes in the analyses. Only four intersections had automated speed camera enforcement.

Within a 50 m radius of each intersection, 668 crashes were collected and associated with corresponding traffic conditions. There were 432 PDO crashes and 236 injury crashes. It is important to highlight that 172 of the injury crashes involved vulnerable users — mostly motorcyclists — evidencing the urban environment of the study location, where the typical absence of high speeds rarely results in injury to four-wheeled vehicle users.

Fig. 4 shows an evaluation of the crash, speed, and traffic flow distribution during the hours of the day. There is a significant difference in the occurrence of crashes depending on the time of day: from 6 a.m. to 8 p.m., most of the reported crashes were PDO, whereas injury crashes were dominant in the other time interval. This contrast may be linked to multiple factors, such as the notable difference in traffic flow between periods; the sporadic development of high speeds during scenarios with low traffic demand; drinking and driving, which is more frequent in the evening; and the difference in crash reporting rates between periods. Therefore, PDO and injury crashes were evaluated separately.

5.2. Traffic condition clustering

To group all 4.1 M traffic condition intervals by similarity, the data were clustered using the HC technique by applying Ward's distance. The speed and traffic flow variables were selected to con-

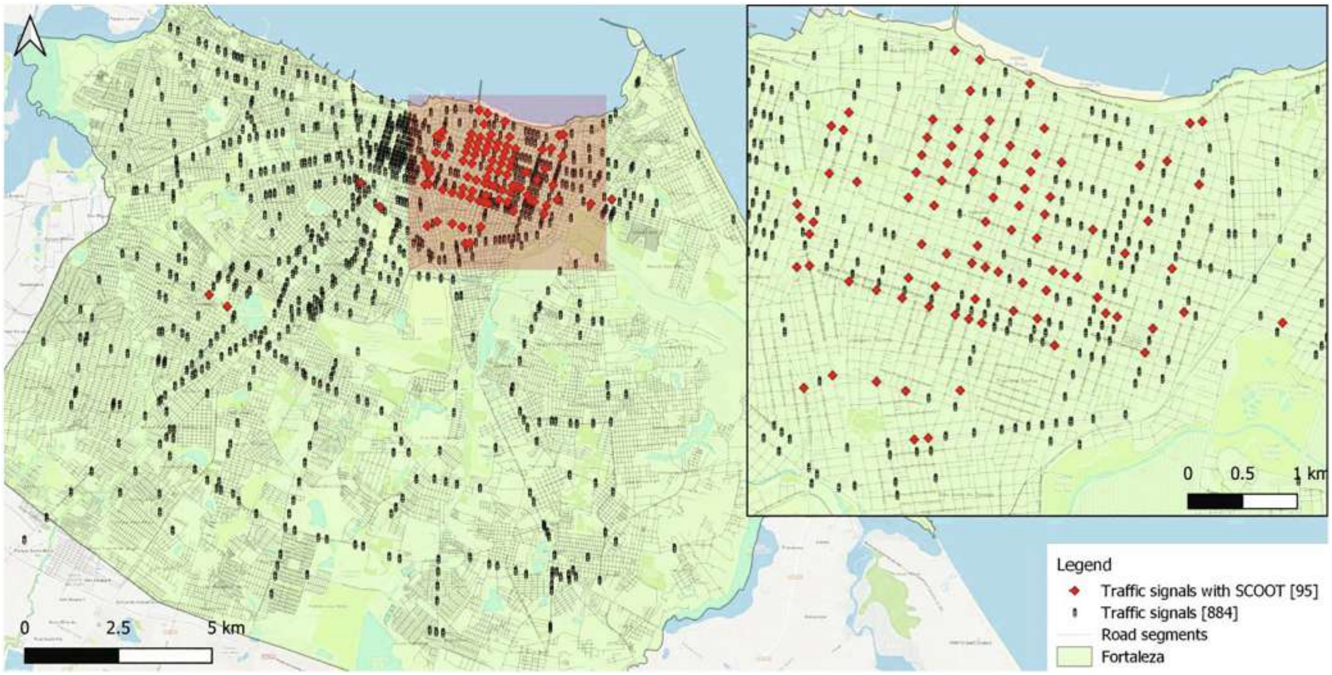

Fig. 3. Study location.

Table 1
Descriptive analysis of the condition-based database.

Variable	Mean	Std. Dev	Min	Max
Total entering traffic flow rate per lane (veh/h/lane)	297	144	10	768
Speed (km/h)	19	6	1	55
Degree of saturation (%)	47	26	1	250
Signal cycles per hour	37	13	22	90
Traffic flow split between approach directions (major/minor)	2.1	1.6	1.0	20.0
Number of lanes	5.3	1.4	4	10
Number of approaches	2.5	0.6	2	5
Number of allowed left or right turns	2.5	0.7	1	6

struct the principal cluster structure, mainly because they represent the basis of traffic fundamentals and have a moderate linear correlation ($R = -0.48$).

Limited by computational capacity, a viable number for the sample size was 9,000 traffic conditions, which resulted in a 9,000 × 9,000 distance matrix. The stratified sampling considered 4,500 percentiles for each variable in an attempt to maintain the amplitude and the distribution for both variables.

The number of clusters was selected based on the TWSS indicator (Fig. 5). The configurations with the greatest number of clusters that provided marginal benefits of 15%, 10%, and 5% were selected. For example, the TWSS for three clusters was 6,647, while that for four clusters was 5,238, representing a marginal gain of 19% with inclusion of a fourth group. Continuing, the TWSS for five clusters was 4,459, and thus the addition of the fifth cluster provided a gain of 14.8%. Therefore, the cluster configuration for a marginal benefit of 15% was four clusters. Continuing with the same approach, the combinations of 8 and 17 clusters were the greatest numbers of clusters that marginally improved the indicators by 10% and 5%, respectively. Balancing the data aggregation and the relatively small crash sample (668), the number of clusters in the principal structure was set at eight. Reverting the sampling procedure, each observation of the complete sample of speed and traffic flow conditions was associated with its nearest cluster.

5.3. Traffic conditions and road crashes

The crash evaluation was performed by calculating the frequency of each cluster divided by the number of elements in that cluster. In summary, the clusters with the greatest and the least number of elements contained 751 K and 190 K elements, respectively. As each element represents an interval of 15 min, the indicator considered was the frequency of crashes per 15 min. To avoid extremely small values of the indicator, the time exposure was converted to 10,000 h. Fig. 6 shows the association between crashes and clusters of speed and traffic flow.

The PDO crashes exhibit a pattern in which clusters with a combination of higher traffic demand and lower speeds were generally more susceptible to PDO crashes than clusters that combined lower traffic flows and higher speeds. In numerical terms, the cluster with an average speed of 10 km/h and traffic flow of 442 vehicles per hour per lane (vphpl) exhibited around six PDO crashes per 10,000 h. This is considerably higher than the conditions of 24 km/h and 90 vphpl, which showed approximately two PDO crashes per 10,000 h.

The graph of injury crashes suggests that the conditions with the highest crash frequencies are distributed through the amplitude of the variables. In comparison to the PDO crashes, there is a notable displacement of crashes to the clusters with low vehicu-

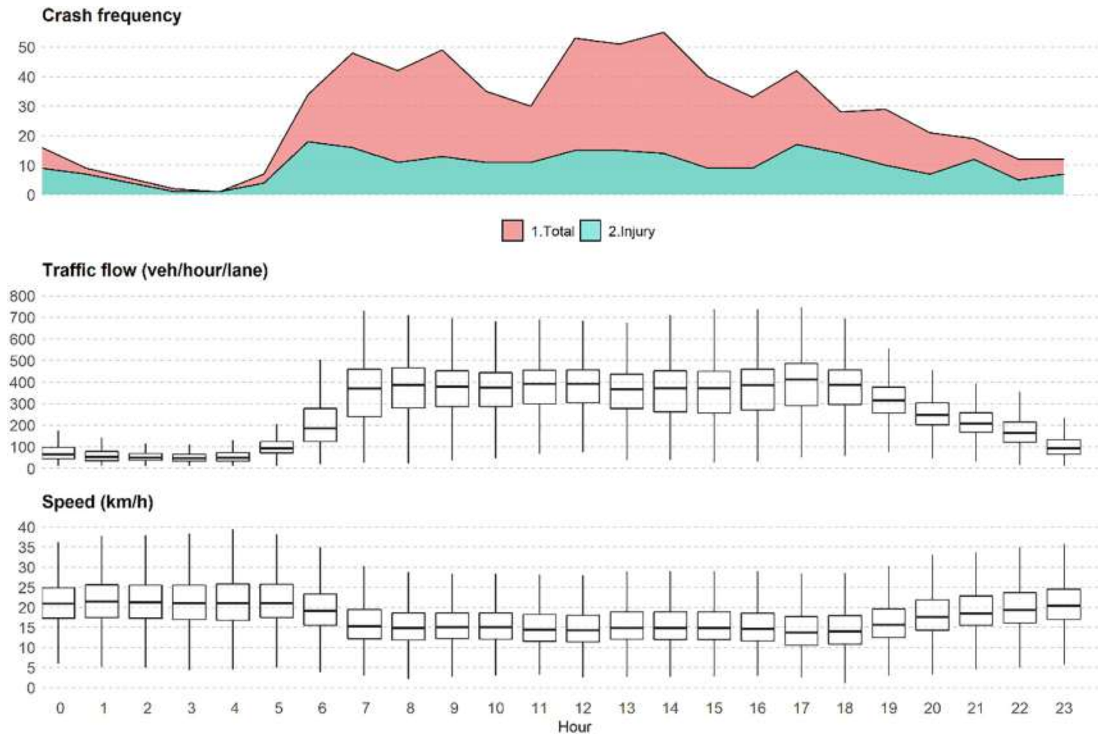

Fig. 4. Crashes, traffic flow, and speed distributions throughout the day.

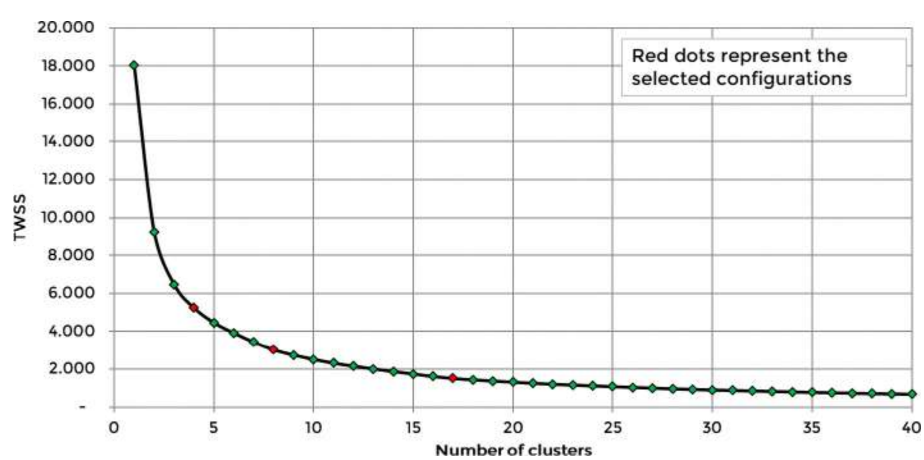

Fig. 5. Total within sum of squares indicator.

lar demand, while the occurrence in congested situations remains. However, one might expect that injury crashes would occur only in circumstances in which medium–high speeds are developed. Thus, some hypotheses are suggested to explain these somewhat unanticipated findings: (a) the majority of the injury crashes involved vulnerable users (73%), so it is likely that crashes occurred at low speeds would harm a pedestrian or a motorcyclist; (b) only a portion of the injury crashes were related to speeding: in conditions with low vehicular demand, the development of high speed was preponderant to the crash occurrence; (c) the method of speed estimation by the SCOOT was not able to capture vehicles that can develop medium or high speeds even in congested situations, such as motorcycles. In summary, in the urban environment of Fortaleza, injury crashes occurred independently of the traffic conditions.

As expected, injury crashes involving only four-wheeled vehicle users were even more displaced to less congested conditions, illustrating the role of speeding when protected users suffer crash injuries.

In the bivariate evaluation, other variables were added to the principal cluster structure by dividing it according to the quartiles of the inserted variables. Figs. 7 and 8 present the inclusion of the number of lanes and number of signal cycles per hour, respectively. The variable related to camera enforcement was removed from the analysis owing to the small sample of traffic conditions with this feature (5%). For the traffic flow split between traffic directions, no relevant standard or trend was detected in the graphs.

Fig. 7 shows that an increase in the number of lanes is associated with higher PDO and injury crash frequencies. Particularly with 8 or 10 lanes, it is observed that critical situations for PDO crashes occur under high vehicular demand conditions. One might expect some bias in these findings owing to the use of the traffic flow indicator divided by the number of lanes, meaning that an increase in the number of lanes also represents an increase in the

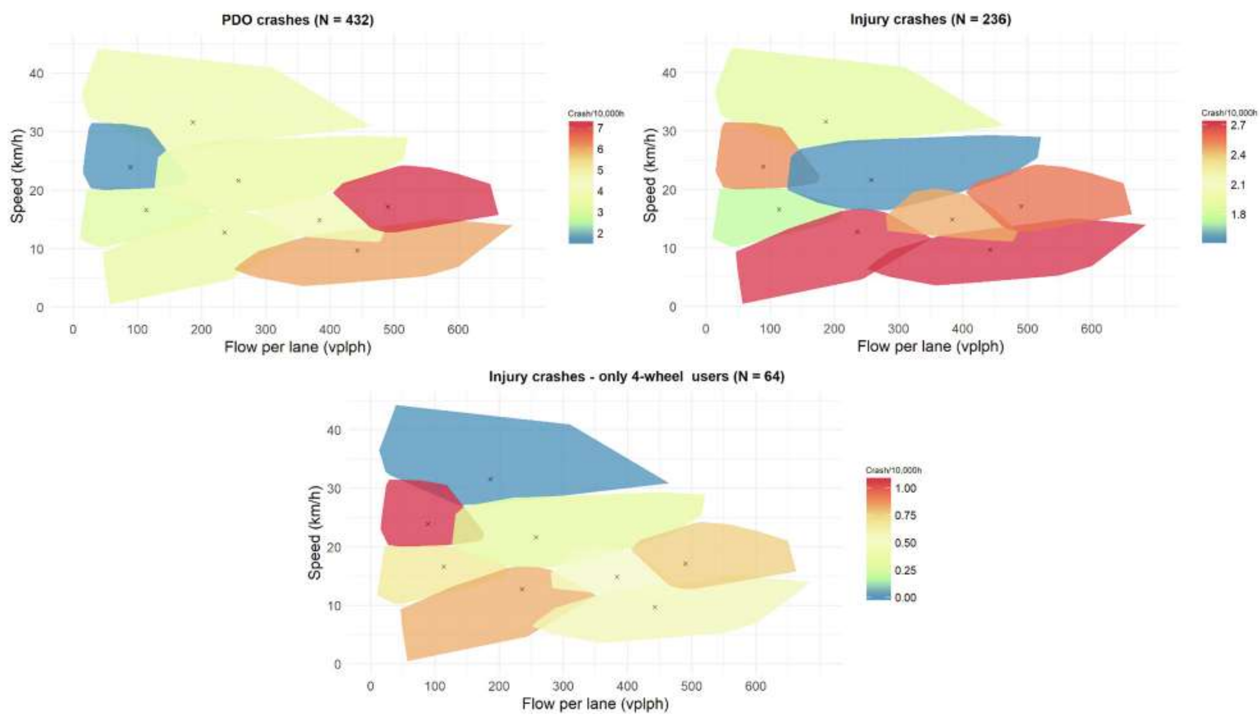

Fig. 6. Frequency of crashes in 10,000 h per cluster: speed and traffic flow.

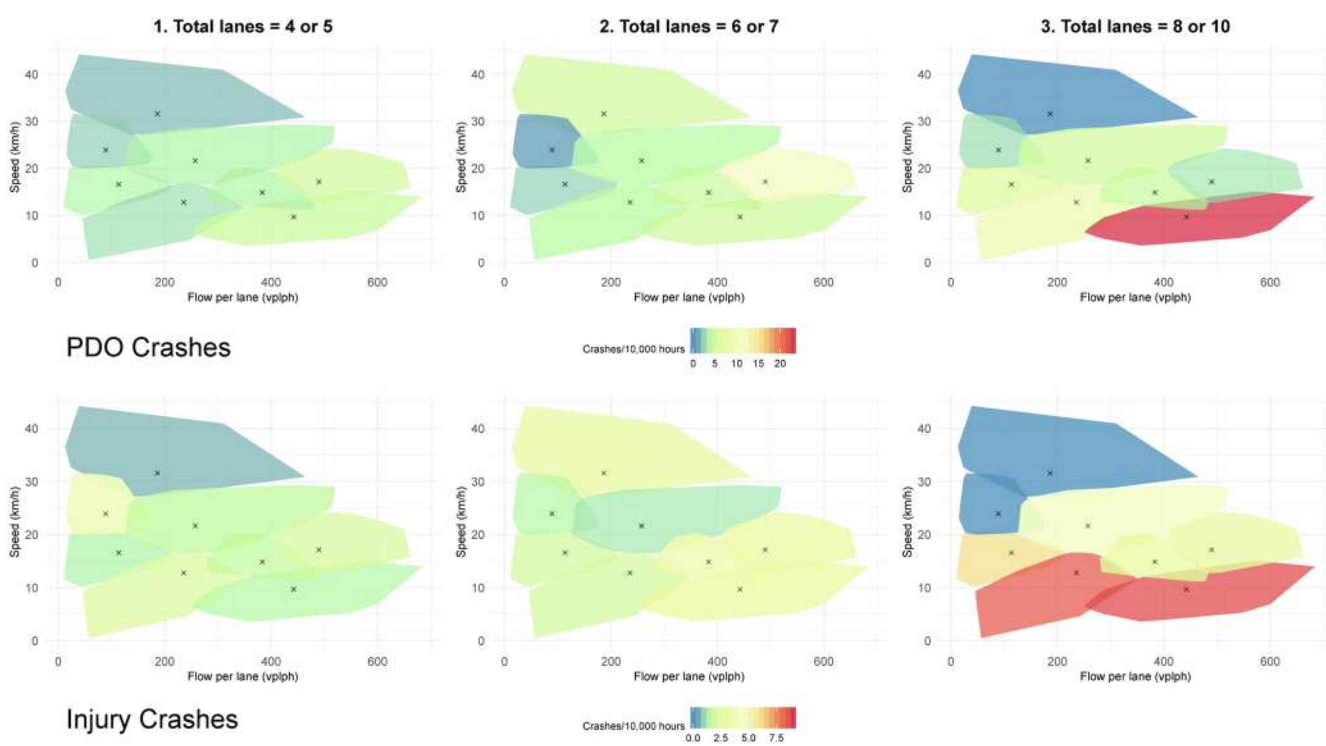

Fig. 7. Frequency of crashes in 10,000 h per cluster: speed, traffic flow, and number of lanes.

traffic exposure. However, the number of lanes is also related to the possibility of vehicular lateral movement, and thus the addition of lanes is related to an increase in lateral conflicts and, consequently, crashes. Unfortunately, both effects are somewhat mixed in the results.

Regarding the number of signal cycles per hour, the cycle duration is expected to be strongly correlated with stop-and-go movements and transversal interactions: assuming an equal traffic flow, short cycle lengths increase the odds of longitudinal conflicts in the intersection approach and of transversal conflicts within the intersection. Fig. 8 corroborates this hypothesis for both PDO and injury crashes. Conditions with short cycle lengths (40–60 s) and high vehicular demand were critical for both types of crashes.

Moreover, there are also critical conditions for injury crashes in situations that combine long cycle lengths (128–164 s) and low vehicular demand. This finding can be explained by the

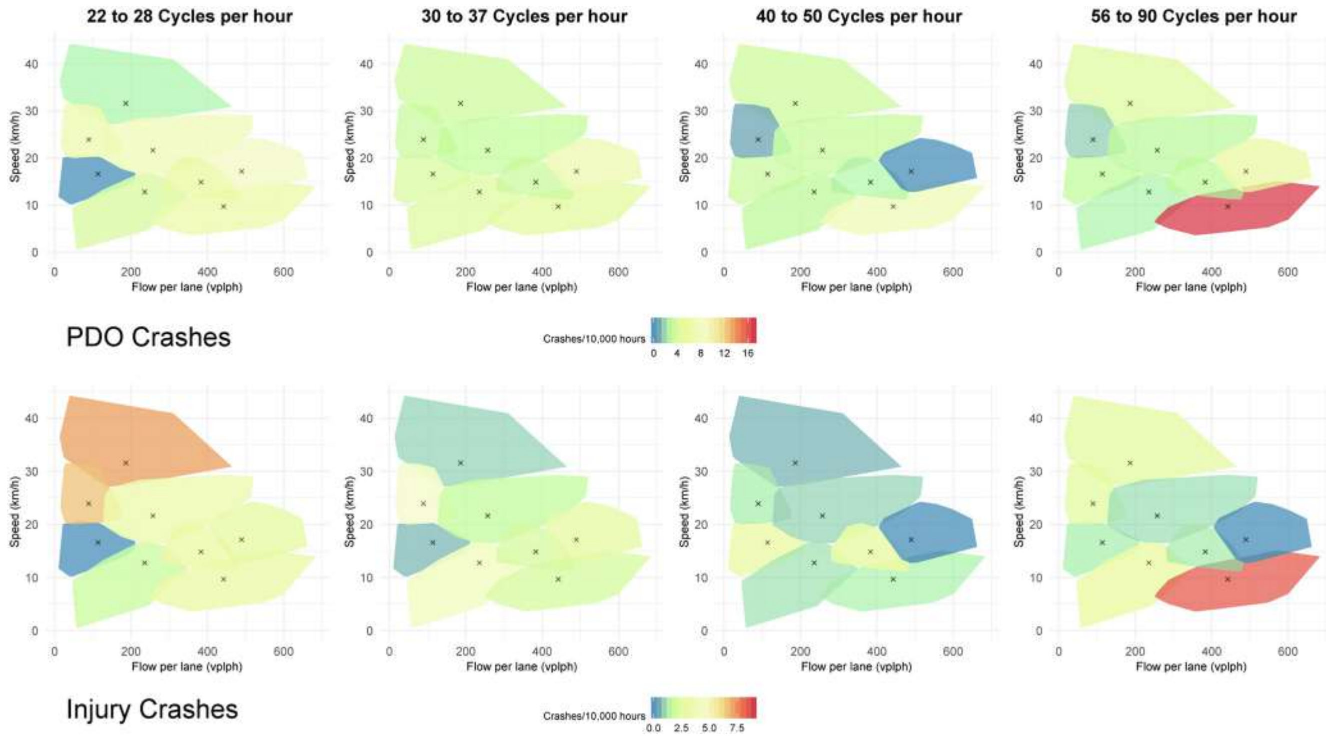

Fig. 8. Frequency of crashes in 10,000 h per cluster: speed, traffic flow, and number of signal cycles per hour.

hypothesis that long cycles, mainly when there is good signal coordination, allow drivers to develop high speeds, consequently increasing the severity of an eventual crash, as was also found by Guo et al. (2010).

Usually, in scenarios of high vehicular demand, the cycle length tends to be longer than in situations of low traffic flow. The two traffic conditions mentioned previously are examples in which the relationships between vehicular demand and cycle length are somewhat unexpected. This may be an indication that poor traffic signal timing is a relevant factor leading to an increase in crash frequency. To quantify this effect, the cluster with the lowest traffic demand in Fig. 6 showed an injury crash indicator of two crashes per 10,000 h, and the same cluster considering only the category of 22–28 cycles per hour had a crash indicator value of approximately six. A similar phenomenon is seen in the cluster with the highest vehicular demand. In the general case, the indicator is around three injury crashes, whereas the category of 56–90 cycles per hour has nearly eight crashes per 10,000 h. An application for this approach is the identification of critical traffic conditions in real-time, followed by the modification of certain controlled features to produce safer traffic conditions. For instance, the injury crash likelihood can be reduced by simply adjusting the cycle length when a critical condition is detected.

6. Complementary analysis: effect of the fixed time correction applied to the reported crash times on the traffic conditions

The goal of this complementary analysis is to evaluate the impact on the traffic conditions caused by the fixed time correction applied to the reported crash times. In other words, this section aims to address the following: assuming that an injury crash occurred (and was correctly reported) at 10 h 25 m, the fixed correction of 44 min would adjust this time to 09 h 41 m. Thus, the "real" 15-min precursor interval is 10 h 00 m–10 h 15 m, while the interval considered in the analysis is 09 h 15 m–09 h 30 m. Therefore, we aim to determine whether the traffic conditions of the second interval differ considerably from those of the first interval.

To develop this evaluation, 50,000 traffic conditions were randomly selected and defined as base intervals. Considering the same intersection, four successive previous intervals were extracted for each base interval. The traffic condition comparison was performed by determining whether the cluster of the previous interval is identical to or neighboring the cluster of the base interval. In cases where the cluster is the same, it is indicative that the temporal setback does not impact the traffic conditions at the level of aggregation applied. In cases where the clusters are neighbors, it implies that the setback moderately affects the traffic conditions associated with the crashes. Fig. 9 presents a summary of this evaluation.

As expected, the farther from the base interval, the smaller the percentage of identical and neighboring clusters; however, in all of the setback categories, there is a combined percentage of greater than 90%. The average difference between the reported crash time and the speed disturbances found by Sobreira (2019) for injury crashes was 15 min, whereas the fixed correction used was 44 min (95th percentile). Thus, on average, there was a setback of two intervals (29 min), resulting in perfect cluster association in 68.8% of the cases and a neighboring relationship in 25.2%. In general, it is considered that the method for obtaining precursor conditions while avoiding interference of the crash on the traffic variables was satisfactory, given that the main requirements were met: (a) the use of traffic conditions without the influence of the crash and (b) a low impact on the traffic conditions due to the temporal setback.

7. Conclusion

This study presented an evaluation of the relationship between traffic conditions aggregated in 15-min intervals and road crashes in signalized intersections in Fortaleza, Brazil. The considered intersections are located in the north-central region of the city, which is characterized by a relevant parcel of commercial land

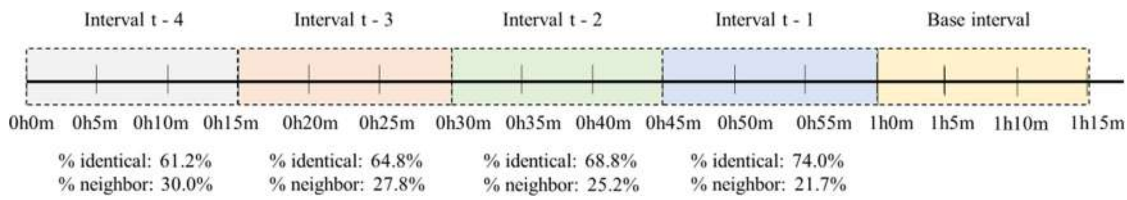

Fig. 9. Impact of the temporal setback on the traffic conditions.

use (23%) and a large number of traffic signals (22 signals per km^2). The reported crash times were adjusted to obtain more representative crash precursor conditions, and a total of 4.1 M traffic conditions were aggregated into eight clusters.

The main findings suggest that the likelihood of occurrence of PDO crashes was three times greater in high vehicular demand conditions (400–600 vphpl) than in scenarios with low traffic flow (100–300 vphpl). The results also showed that an increase in the number of lanes is related to increases in PDO and injury crashes. Moreover, it was found that injury crashes in the urban environment occurred in a wide range of traffic conditions, indicating that a portion of these crashes were due to speeding, while the other fraction was associated with the vulnerability of road users. Additionally, the signal cycle length played an important role in this phenomenon. It was observed that conditions with: (a) low vehicular demand and a long cycle length (128–164 s) and (b) high vehicular demand and a short cycle length (40–60 s) were critical in terms of PDO and injury crashes.

The use of disaggregated data allowed for a more confident understanding of the relationship between road crashes and variables that oscillated over the course of the day. This approach also permits the development of real-time procedures to mitigate the frequency of critical conditions with the aim of reducing the likelihood of crashes.

However, there are some limitations to this study that must be highlighted. The use of indicators aggregated in 15-min intervals leads to the loss of some important microscopic variables, such as vehicular headways and speed variation among vehicles and lanes. The estimated speed based on travel time and vehicular delay provides a "big picture" of the speeds developed, but it does not take into account vehicles that are traveling at high speeds or exceeding the speed limit. Regarding the crash sample evaluated, the ideal scenario would be to use crashes for which the most probable time of occurrence is identified, which would increase the reliability of the precursor conditions associated with the crashes by avoiding the application of the fixed time correction to the reported crash time. Additionally, other factors that might influence crash likelihood were not considered, such as the percentage of motorcycles in the traffic flow, pedestrian flow, drinking and driving, use of safety devices, land use, and other aspects. In addition, if a larger crash sample was available, a more complex stratification of transport modes and injury severity levels could provide relevant findings.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

The present work was realized with the support of the Coordination for the Improvement of Higher Education Personnel – Brazil (CAPES) – Funding Code 001 and the National Council for Scientific and Technological Development – CNPq.

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Lucas Tito Pereira Sobreira, M. Sc. is a Civil Engineering with Master's degree in Transportation Engineering from the Federal University of Ceará, Brazil. Since 2018 has been working in the speed camera enforcement coordination of the city of Fortaleza-Brazil. His main interests as a researcher focus on: statistical safety modeling applied to the prediction of crash frequency and severity, big data on traffic engineering, risk factors associated to road crashes and road safety spatial modeling.

Flávio Cunto, Ph.D. is Associate Professor and Coordinator of the Transportation Engineering Graduate Studies Program at the Federal University of Ceará State, Brazil. Since 2015 has been the Director of the Brazilian National Association for Transportation Research and Education (ANPET) and Level 1D Researcher of the Brazilian National Council for Scientific and Technological Development (CNPq). His main interests as a researcher focus on: statistical safety modeling applied to the prediction of crash frequency and severity, traffic conflict studies using computer vision and microscopic simulation and application of causal models to assess road safety of vulnerable road users.

Journal of Safety Research 77 (2021) 46–55

Contents lists available at ScienceDirect

Journal of Safety Research

journal homepage: www.elsevier.com/locate/jsr

Does formal mentoring impact safety performance? A study on Chinese high-speed rail operators

Yunshuo Liu *, Long Ye, Ming Guo

School of Economics and Management, Beijing Jiaotong University, Beijing 100044, China

ARTICLE INFO

Article history:
Received 13 March 2020
Received in revised form 10 November 2020
Accepted 1 February 2021
Available online 11 March 2021

Keywords:
Formal mentoring
Self-expansion
Self-efficacy
Safety performance
Power distance orientation

ABSTRACT

The importance of mentoring as a developmental resource in organizational settings is well documented. However, the mechanism underlying the association between formal mentoring and safety performance is not well defined. Based on the self-expansion theory, this study examines the relationship between formal mentoring and individual safety performance in the high-speed railway operation. We postulate that formal mentoring enhances individual safety performance through the sequential mediation of self-expansion and self-efficacy. We also argue that the relationship between formal mentoring and individuals' self-expansion is weaker when individuals possess high power distance orientation. Using paired data from 421 protégés and 102 mentors operating high-speed railways of China, we tested the proposed model. This study contributes to the understanding of formal mentoring by; i. establishing that formal mentoring positively relates to protégés' safety performance, ii. empirically validating the sequential mechanisms by which formal mentoring promotes positive outcomes for the organization and the employees, and iii. revealing the moderating effect of power distance orientation on the relationship between formal mentoring and self-expansion. The findings of this research provide practical implications for managers to understand the positive effects of formal mentoring and make rational use of it in safety-critical organizations.

1. Introduction

High-speed railway (HSR) has rapidly developed globally. It is associated with comfort and speed, large passenger traffic, safety and reliability, all-weather, low energy consumption, low pollution, and high efficiency (Doomernik, 2015). Safety is the primary focus for HSR operations (Liu, Ye, & Guo, 2019). However, accidents/incidents are still rampant in HSR operations. Majority of these accidents/incidents within the HSR system are attributed to human errors (Christian, Bradley, Wallace, & Burke, 2009; Guo, Wei, Liao, & Zhang, 2016; Guo, Liu, Chu, Ye, & Zhang, 2019). The survey performed by Tabai, Bagheri, Sadeghi-Firoozabadi, and Sze (2018) revealed that more than 80% of all accidents in railway transport operations per year are due to human errors. People, especially HSR operators, play a crucial role in the railway system,. HSR operators play the most important role in the guarantee of transport safety (Chu, Fu, & Liu, 2019; Stackhouse & Turner, 2019). Therefore, it is imperative to evaluate the factors that affect the safety performance of HSR operators (Chu et al., 2019). Due to the different degrees of adaptation of different employees at work, many safety operation enterprises have realized the need to implement "formal mentoring" to help employees adapt better to the complex work environment and improve safety performance. However, few studies have theoretically explored the influence and mechanisms of formal mentoring on protégés' safety performance (Hoffmeister, Cigularov, Sampson, Rosecrance, & Chen, 2011).

Different from the leader-subordinate relationship, mentoringing focuses on learning and development to the career progression of the protégés (Haggard, Dougherty, Turban, & Wilbanks, 2011). Several studies have shown the positive effects of mentoring at work in career development and functioning during the past 30 years (Ghosh, Hutchins, Rose, & Manongsong, 2020). HSR is no exception. Formal mentoring, being the most traditional talent-training mode, was once the primary way for young employees to master skills in the railway industry. Each new employee is supervised by a designated mentor. After the expiration of the guidance period, the organization assesses and evaluates whether the new employees meet the post competency requirements. Compared to other industries, formal mentoring is especially important in the HSR industry for it improves the HSR safety management

* Corresponding author at: No. 3 Shangyuancun, Haidian District, Beijing 100044, China.

E-mail addresses: 18113085@bjtu.edu.cn (Y. Liu), yelong@bjtu.edu.cn (L. Ye), gming@bjtu.edu.cn (M. Guo).

https://doi.org/10.1016/j.jsr.2021.02.001
0022-4375/

level. Safety is the lifeline of HSR operations. The mentor provides guidance to the protégé on safety (Hoffmeister et al., 2011). Mentoringing is a traditional and effective measure for improving employees' safety skills, standardize work behavior, and fundamentally prevent accidents/incidents. It has unique educational advantages and strong pertinence (Rowe-Johnson, 2018). Formal mentoring is also an important way of training and developing talents in railway operating companies. Railway operating enterprises have a high number of employees. To some extent, it is difficult for companies to accurately train every new employee (Chu et al., 2019). The mentoring system can easily solve this problem. With mentoring as the core of internal talent development, new employees can better integrate into the company under the guidance and help of their mentors. This helps in promoting the realization of individual socialization (Allen, Eby, Poteet, Lentz, & Lima, 2004; Eby et al., 2008, 2013; Ghosh et al., 2020). Furthermore, mentoring provides psychological support to protégés and reduces work associated pressure (Carter & Youssef-Morgan, 2019). HSR employees are subjected to various work associated pressures, such as heavy workload, boring work content, monotonous repetition, and work-family conflict (Chu et al., 2019; Wei, Guo, Ye, Liao, & Yang, 2016). The mentor provides support and encouragement to the protégé, thereby, enhancing the protégé's self-efficacy and alleviating the protégé's work pressure (Hu, Wang, Wang, Chen, & Jiang, 2016).

However, studies have argued that research on workplace mentoring is limited in at least three ways (Chen, Liao, & Wen, 2014; Eby & Robertson, 2020). First, previous studies focused on the characteristics of mentoring and how informal mentoring is influential (Wanberg, Welsh, & Hezlett, 2003). There are differences between formal and informal mentoring, and most studies have overlooked the benefits of formal mentoring in safety management (Chen, Wen, & Hu, 2017). Questions such as whether the formal mentoring affects protégés' safety performance have not been answered. Studies have documented that mentoring can offer a unique function on incident involvement, as mentors are more likely to play a key role in enhancing workplace health and safety in the construction industry (Hoffmeister et al., 2011). However, the prior empirical study is limited and cannot assess whether the safety performance of protégés is correlated with formal mentoring. Second, previous studies have majorly focused on the social exchange or social learning perspective and failed to outline the essential characteristics of mentoring (Michael, Napier, Moeller, & Williams, 2010; Raina et al., 2013). The process by which formal mentors exert influence on employees' performance is not clearly defined (Chen et al., 2017). Third, according to Chen et al. (2014), cultural value orientations play a significant role on how protégés respond to mentors. Therefore, to practice effective protégé management, more knowledge on how cultural values that protégés hold influence their understanding of formal mentoring, as well as on how formal mentoring interacts with protégés cultural values to affect protégés' self-concept and behavioral outcomes is needed. While studies have extensively focused on the relationship between mentoring and the significant protégé outcomes, less is known on how individual cultural values contribute to formal mentoring (Chen et al., 2014). Studies have documented the need for examining potential moderators in the formal mentoring process (Qian, Han, Wang, Li, & Wang, 2014).

We, therefore, comprehensively analyze how formal mentoring is associated with protégés' safety performance by developing a sequential model. Furthermore, we confirmed the boundary effect of protégés' power distance orientation in the relationship between formal mentoring and protégés' self-expansion. Generally, this study makes the following contributions to literature on formal mentoring, self-expansion and safety performance. First, its extends research beyond the benefits of informal mentoring focus by examining the relationship between formal mentoring and safety performance, especially in the HSR context. Second, this study enriches literature by examining self-expansion and self-efficacy as mediating mechanism for explaining how formal mentoring affects safety performance. This study elucidates on how formal mentoring correlates with safety performance from the self-expansion perspective, which contributes to the available literature on the psychological mechanisms by which formal mentoring affects protégés' work outcome. Third, this study advances existing studies by examining individual difference variables, namely power distance orientation, as a boundary condition that moderates the strength of the effect of formal mentoring on the perceived self-expansion of protégés. Finally, we provide practical insights on how formal mentoring can help strengthen safety peformance in the HSR context, which is essential for creating a guarantee of safe railway operations.

2. Theoretical background and hypothesis

2.1. Formal mentoring and self-expansion

As an effective way for organizations to nurture talent, mentoring plays a significant role in improving employees' skills, disseminating knowledge and information, and building talent teams (Orpen & Christopher, 2013). The conceptual mentorship framework was formulated by Levinson, Darrow, Klein, Levinson, and McKeen (1978) research of Americas successful man. According to the framework, successful people got guidance at the beginning of their work from their mentors, and that extensively promoted their later career success. However, the research failed to conceptualize mentoring.

Various attempts have been made to expand mentoring' conceptualization. According to Kram (1983), mentoring is a developmental relationship in which more experienced and knowledgeable employees (i.e., mentors) provide support or advice to junior employees (i.e., the protégés) with less experience or skills (Kram, 1983, 1985); this is the most accepted definition. Although the traditional understanding of mentoring has dramatically changed in the past few decades as a result of changes such as work and occupation, there is a broad consensus in both theoretical and practical fields on the role of mentoring in organizational development. Different from informal mentoring that focuses on natural mutual attraction, formal mentoring is usually matched and developed by organizations (Chen et al., 2017). This study focuses on formal mentoring that encompases general functions and management guidance methods that are aimed at elevating the protégé's professional skill and psychological state (Joo, Yu, & Atwater, 2018). Generally, studies argue that mentors offer three functions; career coaching, psychosocial support, and role modeling (Scandura & Ragins, 1993). Career coaching helps in promoting career advancement of the protégés. Specifically, the mentor provides the protégés with sponsorship, protection, exposure and visibility, coaching, and challenging assignments. In psychosocial support, mentors enact the roles of a friend, role model, a counselor, or even a parent to enhance protégés' confidence, identity, and effectiveness (Kram, 1985). Role modeling is described as; "mentoring can be role modeling-based, with the mentors' attitudes, values, and behaviors serving as a template for the protégés" (Kao, Rogers, Spitzmueller, Lin, & Lin, 2014, p. 192). Empirical studies have provided evidence for a three-factor, parsimonious structure of mentoring (Kram, 1985). This study combines career coaching, psychosocial support, and role modeling as an aggregate measure of mentoring. Mentoring has always existed in the inheritance of Chinese culture and technology. Bozionelos and Wang (2006) documented that mentoring is highly prevalent and related to career success among protégés in China. Liu, Liu, Kwan, and Mao (2009) also pointed out that mentoring is positively correlated with the social status promotion.

Close relationships are a fundamental need for individuals with an affinity to obtain various resources such as knowledge, property, power, social status, and physical health. Self-expansion is a process by which one person includes another into his or her concept of the self (Aron & Aron, 1986, 1996). Self-expansion can happen in a workplace context, especially between leader and subordinate or mentor and protégé (Aron, Lewandowski, Mashek, & Aron, 2013; Eby & Robertson, 2020). By forming close relationships with others, individuals gradually expand their self-identity to incorporate other people and become better and then view the other people as a part of their self-overlap (Mao, Chiu, Owens, Brown, & Liao, 2019). Additionally, humans experience positive emotions during the self-expansion process (Aron, Aron, & Norman, 2001). Mentoring is a long term, typical close relationship that is relatively unchangeable (Zhou, Lapointe, & Zhou, 2019). Self-expansion is a human process that allows mentoring and acts as a precursor for relationship development. It is a valuable aspect for understanding the underlying mechanisms of mentoring.

According to the self-expansion theory (Aron et al., 2001), desirability and inclusion possibilities are the two factors that individuals need to consider when including others. The self-expansion desirability focuses on whether the object meets the individual's needs and whether the object has the necessary resources for the individual's growth. The inclusion possibility of self-expansion refers to the probability of a close relationship between the individual and the object. This study predicts that mentoring leaders stimulates the self-expansion of protégés by facilitating desirability and possibility. In mentoring, protégés expand the self to include mentors. mentoring promotes desirability because; i. Mentors offer different types of physical and psychological support to proteges. Given that mentoring enhances emotional well being, protégés consider it to be desirable. ii. Formal mentoring involves a series of coaching activities and motivates protégés to accomplish challenging tasks. Confidence and professional capacity for coping with new and challenging task issues are enhanced. iii. Serving as a model, it strengthens the protégés' willingness to adopt the mentor's traits. A good mentoring should enhance the possibilities of self-expansion. Aron et al. (2001) documented that close relationships are a crucial factor in the inclusion possibility and that individuals tend to include close associates and people they can access. By individually imparting experience and regular friendships, mentors can establish a better relationship with the protégés. This coaching style reflects the themes of self-transcendence and expands the above mentioned protégé roles (Mitchell, Eby, & Ragins, 2015). For the above reasons, formal mentoring should make protégés feel comfortable while simultaneously activating their self-expansion.

Hypothesis 1:. *Formal mentoring is positively correlated with protégés' self-expansion*

2.2. Self-expansion and self-efficacy

Self-efficacy is a crucial aspect of an individuals' self-concept. It has attracted considerable attention in organizational management studies. Self-efficacy refers to people's judgment of their capabilities to organize and execute courses of action required to attain designated types of performance (Wood & Bandura, 1989). Self-efficacy is an estimate of individuals' ability to execute a specific task or to successfully impact their environment. High self-efficacy individuals have sufficient resources to achieve their goals (Breevaart, Bakker, Demerouti, & Hetland, 2012). Studies have shown that effective mentoring may increase an individual's self-efficacy (Allen et al., 2004; Kram, 1985). Day and Allen (2004) reported that people with high self-efficacy are more likely to actively engage in learning and improvement activities, and they tend to achieve attractive and desirable mentoring goals.

According to the self-expansion theory, after expanding the self to incorporate others, individuals are more confident about themselves as a result of being resourceful and having a positive emotional experience. After self-expansion occurs, protégés realize that they can easily get performance feedback, development opportunities, and other social resources from their mentors (Mao et al., 2019). Protégés become confident of their competencies when they acquire these critical resources. The take complicated achievement tasks as more challenging or beneficial rather than threatening. Self-efficacy may influence them to exert effort to overcome difficulties. Dys-Steenbergen, Wright, & Aron (2015) reported that individuals after self-expansion approach challenges in a more positive dimension. Dansereau, Seitz, Chiu, Shaughnessy, and Yammarino (2013) documented that individuals' self-expansion stimulates individual motivation, enhances personal cognitive aspects and necessitates competency to perform complex tasks. Therefore, we proposed the following hypothesis:

Hypothesis 2:. *Self-expansion is positively correlated with self-efficacy*

2.3. Self-efficacy and safety performance

Studies indicate that self-efficacy is associated with individual task performance (Frayne & Geringer, 2000; Judge, Erez, & Bono, 2001). Breevaart, Bakker, Demerouti, & Hetland (2012) founded that high self-efficacy enhances an individuals' persistence when handling challenging tasks. Judge, Jackson, Shaw, Scott, and Rich (2007) documented that self-efficacy is positively correlated with job performance. Additionally, two meta-analyses exploring the impact of self-efficacy on work-related performance revealed that self-efficacy promotes performance by motivating individuals to competently and successfully perform their duties (Judge et al., 2007). In the safety-related context, self-efficacy is more successful in making sense of the safety behavior of individuals in organizations. Several empirical shreds of evidence show that individuals who experience self-efficacy exhibit exemplary safety performance (Wang, Wang, & Xia, 2018). For instance, Stratman and Youssef-Morgan (2019) established that self-efficacy intervention was effective in curtailing irresponsible behavior. According to He, Jia, McCabe, Chen, and Sun (2019), self-efficacy is the antecedent of the safety performance of construction workers.

Individuals with self-efficacy regarding safety can work on unsafe situations in the workplace. Alternatively, self- efficacy can buffer the effect of negative factors on safety-related outcomes. Therefore,

Hypothesis 3:. *Self-efficacy is positively correlated with protégés' safety compliance (Hypothesis 3a) and safety participation (Hypothesis 3b).*

2.4. Mediating roles of self-expansion and self-efficacy

In Hypothesis 1, formal mentoring is positively associated with protégés' self-expansion. Hypothesis 2 states that self-expansion could elevate individuals' self-efficacy and, in turn, improve their safety performance. From the two hypotheses, this study proposes that a formal mentoring improves safety performance through a sequential mediation effect. After attaining self-expansion through formal mentoring, individuals are more likely to view their mentors as part of themselves and gain new attributes, such as resources, perspectives, and identities (Davies, Wright, & Aron, 2011). They change positive expectancy into actual engagement and increase confidence in their work, thereby, regulating their safety performance. This study aimed at evaluating the mediator roles of self-expansion and self-efficacy between formal mentoring and safety performance. This was done to elucidate our understanding on how formal mentoring is associated with safety performance and to provide valuable insights for safety management. Therefore, we proposed the following hypotheses:

Hypothesis 4. *a*: *Formal mentoring is positively correlated with protégés' safety compliance through a sequential indirect effect by enhancing individual (a) self-expansion and subsequent (b) self-efficacy.*

Hypothesis 4. *b*: *Formal mentoring is positively correlated with protégés' safety participation through a sequential indirect effect by enhancing individual (a) self-expansion and subsequent (b) self-efficacy.*

2.5. Moderating effect of power distance orientation

Although high quality mentoring is likely to promote individual self-expansion, this study proposes that individual differences play a vital role in the relationship. Therefore, not everyone can successfully achieve self-expansion through formal mentoring. This study focused on personal power distance orientation, which has a more direct relationship with mentoring (Kirkman, Chen, Farh, Chen, & Lowe, 2009). Power distance orientation is defined as "the extent by which an individual accepts unequal power distribution in institutions and organizations" (Lian, Ferris, & Brown, 2012, p. 108). Individuals with high levels of power distance orientation in the workplace identify the power difference and organizational hierarchy. As subordinates, they trust, respect, and obey their supervisors' directives (Lee & Antonakis, 2014). Alternatively, power distance orientation creates a gap that allows individuals to fulfill their supervisor's expectations rather than seek empowerment.

Power distance orientation has an adversarial relationship with individual reactions to mentoring (Chen et al., 2014). Strong power distance orientation weakens the relationship between mentoring and self-expansion. Specifically, individuals with high power distance orientations typically legitimize power differences and maintain greater distance with their superiors. People of high-level power distance orientation have less contact with mentors (Qian et al., 2014). Consequently, even though these relationships are right for their development, they are not included in the scope of self-expansion. Alternatively, the relationship between formal mentoring and self-expansion weakens when individuals have high levels of power distance orientation. However, individuals with low power distance orientation have almost the same status, and they are likely to form close relationships with their mentors (Feldman and Bolino, 1999; Rutti, Helms, & Rose, 2013). To them, mentors are approachable. Therefore, low-power-distance individuals experience the benefits of career mentoring and gain much value for their safety performance. From the above theoretical arguments, power distance orientation serves as a vital individual difference and influences a positive relationship between mentoring and self-expansion. The following hypothesis was, therefore, proposed:

Hypothesis 5:. *Power distance orientation moderates the relationship between formal mentoring and individuals' self-expansion, such that the effect is strong among low power distance individuals and weak among high power distance individuals.*

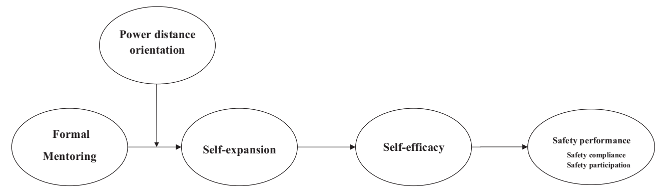

Fig. 1. Research model.

Based on the above hypotheses, the research model is shown in Fig. 1.

3. Methods

3.1. Samples and procedures

This study was performed in 18 railway bureau group companies located in mainland China. Participants were HSR operators (for example, HSR machinics, HSR drivers, and HSR communication facility maintenance workers) who were involved in a unified training programme for a period of nine months to three years. Questionnaires were distributed from June 2018 to August 2019.

The data collection method of protégé-mentor pairing was used. Before determining the target of the survey, we asked whether the HSR operator has a "formal mentor" or "protégé" in the railway enterprise, and they were listed as survey targets after they gave a clear affirmative reply. The sample included 116 mentors with certain workplace status and work experience in railway enterprise, as well as 459 protégés. On average, each mentor evaluated 4 protégés. The questionnaire was divided into parts A and B. Questionnaire A encompassed formal mentoring, self-expansion and self-efficacy questions that were completed by the protégés. Questionnaire B measured the protégé's safety performance as evaluated by the mentor. Before distributing the questionnaire, the protégé employee list was numbered, the numbers were written on each questionnaire A, and protégé employee names were marked corresponding to the number on questionnaire B.

All the questionnaires were administrated on site by the authors. Participation was entirely voluntary and participants were promised information confidentiality. They were also assured that the information would only be used for academic purposes. The overall response rate was 98% and 95% for mentors and protégés, respectively. After eliminating questionnaires with missing data and unmatched responses, the final analysis sample included data from 421 protégés and 102 mentors. In the protégé sample, the average age was 27.5 years (*SD* = 4.282), and the average organizational tenure was five years (*SD* = 0.634). In the mentor sample, the average age was 45.3 years (*SD* = 5.950), while the average organizational tenure was 10 years (*SD* = 4.340).

3.2. Measures

All items were rated on a five-point Likert scale of 1 (strongly disagree) to 7 (strongly agree). The scales were translated into Chinese based on the translation and back-translation procedures. Two proficient bilingual researchers translated the scale.

3.2.1. Formal mentoring

Formal mentoring was assessed using a 15-item scale developed by Scandura and Ragins (1993). The scale has three dimensions: career support, psychosocial support, and role modeling. Examples of the scale items were as follows: "My mentor and I trust each other," "My mentor gave me some advice about promotion opportunities," "I consider my mentor to be a model for learning and an object of imitation" among others. Cronbach's alpha was 0.75.

3.2.2. Self-expansion

Fourteen items were used according to Aron, Aron, & Smollan, 1992, to measure self-expansion. Sample items were "My mentor made me have a better understanding of many things," "My mentor often provides many experiences," "My mentor offers a broad perspective on things." Cronbach's alpha was 0.90.

3.2.3. Self-efficacy

Self-efficacy was determined using a 10-item measure developed by Schwarzer, Born, Iwawaki, and Lee (1997), which assesses the performance competency of an individual on a particular task or objective. Sample items include: "I am confident in solving unexpected events," "I can calmly handle challenging tasks because I believe in my capacity to solve problems," "It is quite easy for me to stick to my dream and accomplish my goals." The Cronbach's alpha coefficient for the measure of self-efficacy was 0.86.

3.2.4. Power distance orientation

Power distance orientations were estimated using the Dorfman and Howell (1988)' scale, which consists of 6 items. Sample items were "The superiors make decisions without consulting the subordinates," "The supervisor rarely consults their subordinates," "The supervisors should avoid contact with subordinates outside the scope of work." Cronbach's alpha score was 0.77.

3.2.5. Safety performance

According to Neal, Griffin, and Hart (2000), six items were used to assess safety performance. Safety performance was divided into safety compliance and safety participation, with each dimension having three items. Items included, "My protégé follows the prescribed safety procedures to perform his/her duties," "My protégé voluntarily performs tasks or activities that are beneficial to enhance workplace safety, "My protégé ensures the highest level of safety when performing his/her duties." The Cronbach's alpha for this scale was 0.86.

3.2.6. Control variables

Studies suggest that safety performance is associated with employees' demographic characteristics (Eby, Allen, Evans, Ng, & DuBois, 2008; Haggard et al., 2011; Richard, Ismail, Bhuian, & Taylor, 2009). Therefore, a number of the demographic variables (gender, age, work experience, education level, and technical level) were controlled.

3.3. Analysis strategy

The empirical analysis for the present study aimed at testing the effects of formal mentoring on HSR operators' safety performance through self-expansion and self-efficacy. Following the suggestion of Anderson and Gerbing (1988), we utilized a two-step approach that consists of the measurement and the structural model. First, we performed confirmatory factor analysis (CFA) to check the validity of the measurement model. Then, sequential mediation analysis with SEM was performed to test the structural model using the Mplus 7.0 statistical software. We adopted the robust maximum-likelihood estimator (MLR) to perform SEM (Muthén & Muthén, 2014). MLR was adjusted for skewness in the data and provided parameter estimates with robust standard errors. Last, bootstrapping analysis was used to test whether our mediation hypothesis was supported.

To evaluate the appropriation of the model fit, This study considered some goodness-of-fit indices. Specifically, they included comparative fit index (CFI), the Tucker-Lewis index (TLI), and the root mean square error of approximation (RMSEA). As documented by Browne and Cudeck (1993), an adequate fit is indicated by CFI and TLI values greater than 0.90 and an RMSEA less than or equal to 0.06.

4. Results

4.1. Descriptive statistics and correlations

Table 1 shows the descriptive and correlation data. It is shown that all correlations were consistent with our expectations. Interestingly, the correlation between self-expansion and power distance orientation was negative and significant ($r = -0.414$, $p < 0.01$). This result is basically consistent with our speculation. In general, people with higher power distances exhibit more concerns about leaders or mentors, which inhibits the generation of self-expansion (Lammers, Galinsky, Gordijn, & Otten, 2012). Therefore, power distance orientation and self-expansion show a negative correlation.

4.2. Measurement model

Before testing the hypotheses, CFA was done to determine discriminant validity of the constructs included in this study. As shown in Table 2, the CFA results revealed that the baseline six factor model fits the data better ($\chi^2 = 2482.473$, df = 1133, $p < 0.001$, CFI = 0.910, TLI = 0.902, RSMEA = 0.051) than the other alternative models. For example, the five-factor model where formal mentoring and self-expansion were combined ($\chi^2 = 2594.029$, $df = 1139$, $p < 0.001$, CFI = 0.902, TLI = 0.896, RSMEA = 0.054), the four-factor model where formal mentoring, self-expansion and self-efficacy

Table 1
Means, standard deviation and correlations of variables.

Variable	*Mean*	*SD*	1	2	3	4	5	6	7	8	9	10	11
1. Gender	1.230	0.435	1										
2. Age	2.190	4.282	−0.205**	1									
3. Organizational tenure (Year)	3.180	0.634	−0.035	0.618**	1								
4. Education	3.010	0.539	−0.009	−0.390**	−0.263**	1							
5. Technical	3.030	0.393	−0.035	0.197**	0.182**	−0.024	1						
6. Formal mentoring	5.702	1.118	−0.002	−0.029	−0.077	0.149**	0.038	1					
7. Self-expansion	5.751	1.104	0.020	−0.042	−0.060	0.154**	0.059	0.629**	1				
8. Self-efficacy	5.179	1.015	−0.033	0.007	−0.004	0.108*	0.027	0.436**	0.456**	1			
9. Safety compliance	6.243	1.099	−0.004	−0.023	−0.087	0.049	0.015	0.433**	0.427**	0.510**	1		
10. Safety participation	5.947	1.099	0.062	−0.037	−0.100	0.085	−0.001	0.437**	0.462**	0.477**	0.651	1	
11. Power distance orientation	4.771	1.028	−0.046	−0.014	0.001	0.152**	−0.018	0.442**	−0.414**	0.492**	0.229**	0.375**	1

Note: $^{*}p < 0.1$, $^{**}p < 0.01$

Table 2
Confirmatory factor analysis results.

Model	χ^2	df	χ^2/df	CFI	TLI	RSMEA
Six factor model	2482.473	1133	2.191	0.910	0.902	0.051
Five factor model	2594.029	1139	2.277	0.902	0.896	0.054
Four factor model	3572.185	1169	3.056	0.840	0.821	0.072
Three factor model	4936.301	1172	4.212	0.760	0.761	0.085
Two factor model	5603.076	1174	4.773	0.707	0.694	0.095
One factor model	6747.120	1175	5.742	0.631	0.616	0.110

Table 3
Comparison of fit of alternative models.

Model	χ^2	df	CFI	TLI	RMSEA	$\Delta\chi^2(\Delta df)$
hypothesized model (full mediation model)	3091.017	1063	0.890	0.820	0.055	–
Alternative Model 1 (M1)	2829.460	1048	0.910	0.900	0.054	261.557(15)**
Alternative Model 2 (M2)	2617.420	1047	0.920	0.927	0.051	212.04(1)**
Alternative Model 3 (M3)	2196.600	1046	0.940	0.931	0.050	420.82(1)**

were combined ($\chi^2 = 3572.185$, $df = 1169$, $p < 0.001$, CFI = 0.840, TLI = 0.821, RSMEA = 0.072), three-factor model where formal mentoring, self-expansion, self-efficacy and safety compliance were set to load on one factor ($\chi^2 = 4936.301$, $df = 1172$, $p < 0.001$, CFI = 0.760, TLI = 0.761, RSMEA = 0.085), two-factor model where formal mentoring, self-expansion, self-efficacy, safety compliance, and safety participation were combined ($\chi^2 = 5603.076$, $df = 1174$, $p < 0.001$, CFI = 0.707, TLI = 0.694, RSMEA = 0.095), and the one-factor model ($\chi^2 = 6747.120$, $df = 1175$, $p < 0.001$, CFI = 0.631, TLI = 0.616, RSMEA = 0.110). Therefore, this study confirms that the six variables were distinct.

4.3. Structural model

Structural equation modeling was used to assess hypothesized associations among study variables. In the current study, the proposed relations among constructs are tested through a structural model using Mplus software (Muthén & Muthén, 2014). To find the best mediation model, we compared fit indices among our hypothesized model (full mediation model) and possibly several alternative models by fit indices. As showed in Table 3, overall fit indices of hypothesized model showed moderate fit ($\chi^2 = 3091.017$, df = 1063, CFI = 0.890, TLI = 0.820, RSMEA = 0.055). The first alternative model (M1) in which safety compliance and safety participation were predicted by formal mentoring, self-expansion and self-efficacy, and self-expansion and self-efficacy were predicted by formal mentoring was estimated. The result showed that ($\chi^2 = 2829.460$, df = 1048, CFI = 0.910, TLI = 0.900, RSMEA = 0.054) was clearly better than the fit of the full mediation model. However, the direct effects of formal mentoring on safety participation was not significant. Therefore, we removed the direct effects of formal mentoring on safety participation from M1. Based on M1, the second alternative model (M2) was estimated ($\chi^2 = 2617.420$, df = 1047, CFI = 0.920, TLI = 0.927, RSMEA = 0.051). However, the direct effects of self-expansion on safety compliance was not significant. So, we removed the path and established the third alternative model (M3). All in all, the M3 had a better than the fit indices of any other alternative models ($\chi^2 = 2196.600$, df = 1046, CFI = 0.940, TLI = 0.931, RSMEA = 0.050). Hence, M3 was selected as the optimal model to test the hypotheses.

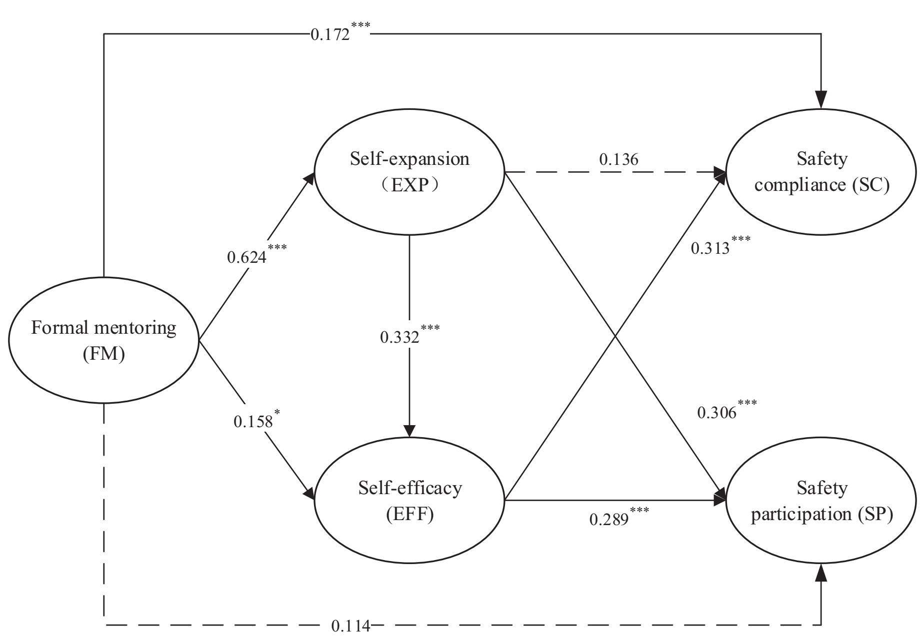

Fig. 2. Path coefficients of the study model Notes: Dotted lines represent non-significant paths; $^{**}p < 0.01$; $^{***}p < 0.001$.

Table 4
Indirect effects for mediation models.

	Indirect effects		
	Estimate	LL95%CI	UL95%CI
Total indirect effect			
FM → SC	0.199**	0.046	0.341
FM → SP	0.296**	0.176	0.572
Indirect effect			
FM → EXP → SC	0.085	−0.026	0.169
FM → EFF → SC	0.049**	0.002	0.128
FM → EXP → EFF → SC	0.065**	0.029	0.250
FM → EXP → SP	0.191**	0.028	0.393
FM → EFF → SP	0.046**	0.017	0.224
FM → EXP → EFF → SP	0.059**	0.018	0.212
Direct effect			
FM → SC	0.172**	0.062	0.359
FM → SP	0.114	−0.075	0.135
Total effect			
FM → SP	0.410**	0.259	0.641
FM → SC	0.371**	0.178	0.527

Notes: FM = formal mentoring; EXP = self-expansion; EFF = self-efficacy; SC = safety compliance; SP = safety participation; $^{**}p < 0.01$; CI = 95% confidence level (Bootstrapping).

4.4. Hypothesis testing

4.4.1. Hypothesis testing of direct effects

Fig. 2 and Table 4 presents the results from the SEM used to test the hypotheses in this study. They also present the path coefficients. Formal mentoring was positively correlated with self-expansion ($\beta = 0.624$, $p < 0.001$), supporting hypothesis 1. Additionally, results showed that self-expansion had a positive, direct effect on self-efficacy ($\beta = 0.332$, $p < 0.001$), demonstrating support for hypotheses 2. Finally, the direct effect of self-efficacy was positively correlated with safety compliance ($\beta = 0.313$, $p < 0.001$) and safety participation ($\beta = 0.289$, $p < 0.001$). Therefore, hypotheses 3a and 3b were supported.

4.4.2. Hypothesis testing of mediation effects

Williams and MacKinnon (2008) study revealed that bootstrapping is more useful than the Sobel test and the causal steps approach when testing mediation effect. The bootstrap analysis approach was used to test the indirect effects in multiple mediator and the 95 percent bias-corrected confidence intervals, with 5000 samples (Hayes, 2015; Hayes Hayes, 2013). If the 95 percent confidence interval (CI) do not contain zero, the inference is statistically significant (Preacher & Hayes, 2008).

Hypothesis 4a states that self-expansion and self-efficacy can sequentially mediate the relationship between formal mentoring and safety compliance. Table 4 shows that the indirect effect of formal mentoring on safety compliance through self-expansion and then self-efficacy was significant (indirect effect = 0.065, 95% CI [0.029, 0.268]), thereby, supporting hypothesis 4a. Hypothesis 4b states the same sequential mediation pattern when predicting safety participation. Table 3 also shows that the indirect effect of formal mentoring on safety participation through self-expansion and then self-efficacy was significant (indirect effect = 0.059, 95% CI [0.018, 0.212]), thereby, supporting hypothesis 4b. In summary, these findings indicated that the indirect relationship between formal mentoring and safety performance (for both safety compliance and safety participation) is sequentially mediated by self-expansion and self-efficacy.

4.4.3. Moderating effect analysis

Hypothesis 5 posits that power distance orientation moderated the mechanism of formal mentoring on self-expansion. Following the procedure suggested by Aiken and West (1991), interactions shown in Fig. 1 were plotted. First, the self-expansion was set as the dependent variable, and the control variable, independent variable, moderating variable, and interaction terms then put into the regression equation in turn. As shown in Fig. 3, the interaction between formal mentoring and power distance orientation was found to be negatively correlated to follower self-expansion ($\beta = -0.164$, $p < 0.05$), indicating the moderation relationship. Additionally, simple slopes were compared as recommended by Stone and Hollenbeck (1989). The results showed that the relationship between formal mentoring and self-expansion was weakened as the power distance orientation increased (+1*SD*) rather than low (−1*SD*). Thus, Hypothesis 5 was supported.

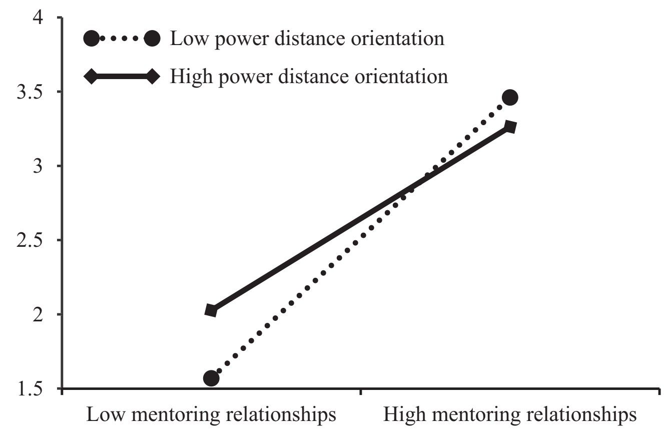

Fig. 3. The interactive effect of formal mentoring and power distance orientation on self-expansion.

5. Discussion

From the self-expansion theory, we investigated the underlying mechanisms and boundary conditions that explain why and when formal mentoring relates to safety performance in the context of HSR industry. Specifically, the results of current study indicate that formal mentoring has a positive influence on protégés' safety performance. In addition, self-expansion and self-efficacy were found to serve as the sequential mediating mechanisms in the relationship between formal mentoring and safety performance. Furthermore, power distance orientation weaken the effects of formal mentoring on protégés' self-expansion.

5.1. Theoretical applications

This study has several theoretical implications as follows. First, we identified formal mentoring as a predictor of protégés' safety performance, thereby, elucidating our understanding of the impact of formal mentoring on the safety management field. Compared to informal mentoring which has been extensively studied (e.g. Allen & O'Brien, 2006; Mayer, Maier, & Waloszek, 2009), limited attention has been directed to understanding the influence of formal mentoring on protégés' safety outcomes. Our study advanced this body of knowledge by establishing positive associations of formal mentoring with safety compliance and safety participation. This study underscores the importance of formal mentoring on motivating HSR operators and improving their safety performance. Moreover, we examined the impact of mentoring on the self-concept level of an individual. This is important because self-concept is the core of individual psychology—the source of ideas, desires, attitudes, and ultimate behavior. Although previous studies have explored the potential benefits of mentoring, explanatory mechanisms from such studies focus on social exchange theory and social learning theory and lack the theoretical mechanism of individual cognition and motivation psychology (i.e. self-concept). Therefore, whereas previous studies elucidate the relationships between informal mentoring and protégés' attitude (Chun, Sosik, & Yun, 2012; Richard et al., 2009), our study theorizes and explores a more foundational influence of formal mentoring on the safety performance of protégés.

Second, few studies have investigated the potential sequential mediation effects of the mechanisms underlying the link between formal mentoring and employee safety performance. Our results confirm that self-expansion and self-efficacy mediate the effects of formal mentoring on safety performance. We employed the self-expansion theory directly to the formal mentoring field and revealed the underlying mechanisms between formal mentoring and safety performance, which responds to the call for more person-centric perspective to understanding formal mentoring (Allen & Poteet, 2011). The results reveal that formal mentoring promotes self-expansion and nurtures self-efficacy leading to higher safety performance. We examined the sequential mediating model by employing the self-expansion theory. We found that that formal mentoring indirectly regulates safety performance through self-expansion and self-efficacy in the HSR industry. This presents a new perspective for understanding the function of mentoring, and shows that self-expansion and self-efficacy enhance safety performance. Although the self-expansion theory effectively uncovers the underlying mechanisms of the relationship between mentors and protégés (Dansereau et al., 2013; Mao et al., 2019), few empirical studies have employed the self-expansion perspective to explore formal mentoring. This study is consistent with the findings of Mao et al. (2019) in which leader humility through self-expansion and self-efficacy were found to reinforce the task performance of the follower. Our results further reveal that self-efficacy enhances safety performance, which consistent is with a previous report (Kim & Jung, 2019).

Third, we demonstrate the role of power distance orientation as a boundary condition that weakens the effect of mentoring on self-expansion. This finding reveals the boundary conditions of formal mentoring relationships (Eby, Butts, Hoffman, & Sauer, 2015; Pan, Sun, & Chow, 2011). We show that protégés with lower power distance orientation perceive higher trust levels and tend to trigger self-expansion. This positive relationship may be devitalized or eliminated if the individual has high power distance orientation. People with high power distance orientation are more likely to detach from their mentor, which reduces the possibility of self-expansion. This finding concurs with a study by Chen et al. (2014) who reported that power distance orientation reflects individual cultural values, and contributes to the effect of formal mentoring on perceived psychological safety. In summary, high levels of power distance orientation may suppress self-expansion among protégés, thereby, subtracting its benefits on safety performance.

Finally, the research model in this study was tested on a sample from HSR of China. Although several large studies have explored the mentoring concept, such studies have been based on student or general enterprise employees in Western countries (Carter & Youssef-Morgan, 2019; Hu et al., 2016). Previous studies has revealed that mentoring varies with context (e.g. Allen, Eby, Chao, & Bauer, 2017; Wanberg et al., 2003). Formal mentoring is practically ubiquitous in eastern societies when compared to the western societies (Bozionelos & Bozionelos, 2010; Zhou et al., 2019). Therefore, our study adds to our understanding on formal mentoring in the Chinese HSR context.

5.2. Practical implications

This study offers important practical implications. First, organizations should establish a talent training mechanism based on mentorings. Our results reveal that mentoring improves safety performance at the workplace. Therefore, organizations should implement mentoring programs for their workers to optimize their safety performance. Formal mentoring programs at workplaces may help new employees adapt to the organization and easily acquire the desired skill. Organizations should ensure that the mentoship design programs are reasonable and that the mentor has the appropriate training and resources to manage high-quality guidance (Carter & Youssef-Morgan, 2019). It should also ensure that the guidance plan is properly designed. For example, timely and accurately identify people in the organization with the potential for being mentors. If the mentor does not have the corresponding conditions (knowledge level, emotional cognition, formal or informal authority in the organization, etc.), he or she cannot provide effective work guidance and emotional support to the protégé (Ghosh et al., 2020). Organizations may also develop corresponding training courses for employees with the potential for being mentors so that they can learn how to provide professional career guidance, how to better encourage protégés, and how to discover and develop protégés' strengths. In addition, Organizations should incorporate the mentoring system into the traditional performance evaluation system, that is, to evaluate the effectiveness of the mentors's instructing apprentices, and encourage the mentors and protégés to contribute to the organization with higher salaries and benefits.

Furthermore, organizations should pay attention to the role of self-expansion and self-efficacy among HSR operators. In this study, self-expansion and self-efficacy were found to act as distinct sequential mediators between formal mentoring and safety performance. Therefore, organizations direct resources towards building strong relationships among workers to enhance self-expansion (Mitchell et al., 2015). As an example, organizations may perform personality tests before the start of the formal mentoring program to foster good relationships between mentors and HSR operators. Collective activities that increase the chances of communication between mentors and the HSR operators should also be implemented.

Finally, the interactive findings associated with the moderating effect of power distance orientation also have some practical implications. In formal mentoring programs, mentors should pay attention to individual differences, i.e., each HSR operator should be given a personalized treatment. Mentors should adopt flexible strategies that are customized to the power distance orientation level of each HSR operator (Vidyarthi, Anand, & Liden, 2014). For low-power-distance HSR operators, mentors should invite them for open communication and provide positive feedbacks to their responses. For HSRss operators with high levels of power distance orientation, mentors should show concern about their daily work and provide more specific directions to boost their safety performance.

5.3. Limitations and future research

Despite the aforementioned contributions and implications, this study has some limitations. First, although data was collected from different sources, the cross-sectional design of this study made it impossible to study the causal conclusions of our results. Thus, a longitudinal design is needed to explore how formal mentoring affects the safety performance of HSR operators over time. Second, we only tested the moderating effect of power distance orientation of HSR operators. However, it is still not clear whether individual characteristics (e.g., gender, personality, cognitive style) of the mentors have similar effects. Further tests using cross-cultural study are needed to establish this possibility. Third, this study used Chinese samples, therefore, the results may not be generalized to other cultural contexts, especially for people with lower power distance orientation. In future, cross-cultural comparative studies should be performed to explore the influence of the mentoring system on the safety performance of HSR operators (Bozionelos & Wang, 2006). For example, scholars can explore the differences in the attitudes of protégés towards mentoring and the impact of the differences on safety outcomes under different cultural backgrounds (Zhou et al., 2019). Finally, although the safety performance of this study is evaluated by others, there is a great deal of personal subjectivity. Further research could utilize objective safety performance data to more accurately reveal the causal relationship between formal mentoring and protégés' safety performance.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

This work was supported by the Fundamental Research Funds for the Central Universities [grant numbers: 2020YJS051].

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Yunshuo Liu is a Ph.D candidate in the School of Economics and Management of Beijing Jiaotong University, His research interest is organizational behavior and human resource management.

Long Ye doctor in management science, is a professor in the School of Economics and Management of Beijing Jiaotong University. He has long been engaged in the research of human resource management and safety management. He established the theoretical system and research framework of "safety human resource development and management based on human cognitive and behavioral characteristics" and be applied to Chinese railway filed. He created a new branch of human resource management – security human resource development and management. In recent years, he has published 27 academic papers in authoritative journals at home and abroad, including eight SSCI/SCI and EI papers.

Ming Guo doctor in business management, is an associate professor in the School of Economics and Management of Beijing Jiaotong University, Organizational behavior and human resource management is his research interests. He has published more than 20 academic papers in core journals such as Accident Analysis and Prevention (SSCI), Safety Science (SCI), Social Behavior and Personality (SSCI), and Pakistan Journal of Statistics (SCI), etc.

JOURNAL OF SAFETY RESEARCH

Journal of Safety Research 77 (2021) 311–323

Contents lists available at ScienceDirect

Journal of Safety Research

journal homepage: www.elsevier.com/locate/jsr

Evaluating safety-influencing factors at stop-controlled intersections using automated video analysis

Joshua Stipancic [a,*], Paul G. St-Aubin [a], Bismarck Ledezma-Navarro [b], Aurélie Labbe [a], Nicolas Saunier [c], Luis Miranda-Moreno [d]

[a] Department of Decision Sciences, HEC Montréal, 3000 Chemin de la Côte-Sainte-Catherine, Montréal, Québec H3T 2A7, Canada
[b] Department of Civil Engineering and Applied Mechanics, McGill University, Room 391, Macdonald Engineering Building, 817 Sherbrooke Street West, Montréal, Québec H3A 0C3, Canada
[c] Department of Civil, Geological and Mining Engineering, Polytechnique Montréal, C.P. 6079, succ. Centre-Ville, Montréal, Québec H3C 3A7, Canada
[d] Department of Civil Engineering and Applied Mechanics, McGill University, Room 268, Macdonald Engineering Building, 817 Sherbrooke Street West, Montréal, Québec H3A 0C3, Canada

A R T I C L E I N F O

Article history:
Received 4 September 2020
Received in revised form 3 December 2020
Accepted 8 March 2021
Available online 24 March 2021

Keywords:
Traffic control
Stop signs
Computer vision
Pedestrians
Surrogate safety
Regression models

A B S T R A C T

Introduction: Although stop signs are popular in North America, they have become controversial in cities like Montreal, Canada where they are often installed to reduce vehicular speeds and improve pedestrian safety despite limited evidence demonstrating their effectiveness. The purpose of this study is to evaluate the impact of stop-control configuration (and other features) on safety using statistical models and surrogate measures of safety (SMoS), namely vehicle speed, time-to-collision (TTC), and post-encroachment time (PET), while controlling for features of traffic, geometry, and built environment. *Methods:* This project leverages high-resolution user trajectories extracted from video data collected for 100 intersections, 336 approaches, and 130,000 road users in Montreal to develop linear mixed-effects regression models to account for within-site and within-approach correlations. This research proposes the Intersection Exposure Group (IEG) indicator, an original method for classifying microscopic exposure of pedestrians and vehicles. *Results:* Stop signs were associated with an average decrease in approach speed of 17.2 km/h and 20.1 km/h, at partially and fully stop-controlled respectively. Cyclist or pedestrian presence also significantly lower vehicle speeds. The proposed IEG measure was shown to successfully distinguish various types of pedestrian-vehicle interactions, allowing for the effect of each interaction type to vary in the model. *Conclusions:* The presence of stop signs significantly reduced approach speeds compared to uncontrolled approaches. Though several covariates were significantly related to TTC and PET for vehicle pairs, the models were unable to demonstrate a significant relationship between stop signs and vehicle–pedestrian interactions. Therefore, drawing conclusions regarding pedestrian safety is difficult. *Practical Applications:* As pedestrian safety is frequently used to justify new stop sign installations, this result has important policy implications. Policies implementing stop signs to reduce pedestrian crashes may be less effective than other interventions. Enforcement and education efforts, along with geometric design considerations, should accompany any changes in traffic control.

1. Introduction

Policy on stop sign implementation at urban intersections in North America is unique in the Western world. Unlike their European counterparts, where the priority-to-the-right rule is implemented in the absence of other traffic control, the rule is rarely employed in Canada or the United States despite its existence in highway safety codes. Instead, most urban intersections without full signalization (traffic lights) are stop-controlled. In North America, stop-controlled intersections are either fully stop-controlled, with stop signs controlling all approaches, or partially stop-controlled, with at least one approach without control by way of a stop sign. In the United States, the Manual on Uniform Traffic Control Devices (MUTCD) (MUTCD, 2012) describes warrants for implementing partial or full stop-control, and in Canada, provincial stop-control warrants are frequently based on the MUTCD guideli-

* Corresponding author.
E-mail addresses: joshua.stipancic@hec.ca (J. Stipancic), paul.st-aubin@hec.ca (P.G. St-Aubin), bismarck.ledezmanavarro@mail.mcgill.ca (B. Ledezma-Navarro), aurelie.labbe@hec.ca (A. Labbe), nicolas.saunier@polymtl.ca (N. Saunier), luis.miranda-moreno@mcgill.ca (L. Miranda-Moreno).

https://doi.org/10.1016/j.jsr.2021.03.006
0022-4375/

nes (MUTCDC, 2014). In the province of Québec, full stop-controlled intersections are warranted by the Québec Ministry of Transportation guidelines (VolumeV, 2016) in cases where (a) the minor street faces high traffic volumes or delays, (b) visibility (sight distance) is inadequate, or (c) historical crash statistics are a major concern. Warrants may also prohibit full stop-control in several scenarios, including when an intersection is too close to other stop signs and/or signalized intersections.

The widespread use of full-stop control in North America has become controversial in recent years, particularly in cities like Montreal, Québec, Canada. Often at the demand of local residents and politicians, full stop-control has been implemented in residential areas as a traffic calming measure to reduce vehicular speeds and improve pedestrian safety and security, whether supported by local policy or not. Stop signs have been added at pedestrian crossings where there was previously no explicit instruction for motorists to yield to pedestrians. Despite the positive perception of the general public, there is little evidence, especially using direct road user observations, about the impact or effectiveness of stop-control both in terms of traffic operations (delays, noise, emissions) and safety (crash occurrence, vehicle speeds). Therefore, studies determining which factors are quantifiably related to safety are valuable for influencing policy decisions for the protection of vulnerable users. Existing studies also rely heavily on historical crash data for safety diagnosis, which has many shortcomings including long collection periods to accumulate necessary data (Lee, Hellinga, & Ozbay, 2006), errors, omissions, and underreporting in crash databases (Kockelman & Kweon, 2002), and reactivity. In response, there has been a growing interest in surrogate measures of safety (SMoS), from the development of traffic conflict techniques in the 1970s (Laureshyn et al., 2016) to the advent of automated data collection and processing in the mid 2000s (Jackson, Miranda-Moreno, St-Aubin, & Saunier, 2013).

The purpose of this research is to evaluate the safety of different stop-control configurations using SMoS (vehicle approach speed and user interaction safety measures) while controlling for traffic conditions, intersection geometry, and built environment. A large video data collection campaign was completed at nearly 100 intersections in the City of Montreal for this purpose. High-resolution road user trajectory data were collected using video sensors and processed using computer vision techniques, capturing continuous trajectories for more than 130,000 road users at 336 partially and fully stop-controlled approaches. First, minimum speed and minimum speed location were determined for each motorist trajectory. Second, each pair of road users simultaneously passing through an intersection (interaction) was considered and safety automatically quantified using time-to-collision (TTC) and post-encroachment time (PET). Finally, each SMoS is modelled using a linear mixed-effects model to capture within-site and within-approach correlations. These models reveal which elements of intersection geometry, built environment, and vulnerable road user microscopic exposure are significantly related to safety at stop-controlled intersections.

2. Literature review

2.1. Stop-control terminology

Terminology describing the level of stop-control at intersections varies considerably in the scientific and technical literature. Intersections which implement partial stop-control have been referred to as "minor-road-only stop" (McGee et al., 2017), "priority unsignalized intersections" (Kaysi & Abbany, 2007), and "two-way stops," while intersections with full stop-control are sometimes termed "multi-way stops" (McGee et al., 2017), "all-way stops," or "four-way stops." This terminology is often confusing for several reasons. Minor road designation is frequently ambiguous, and many intersections have fewer than four branches (T-intersections). Furthermore, many intersections have fewer approaches than branches. To maintain clarity and consistency with the range of possible intersection configurations, this work uses the terms "partial stop-control" and "full stop-control" exclusively. At a fully stop-controlled intersection, all wheeled road users are required to come to a complete stop, proceeding in a first-in-first-out order while maintaining other traffic laws including priority-to-the-right and yielding right-of-way to pedestrians and (sometimes) cyclists. At partially stop-controlled intersections, only those wheeled road users whose approach is stop-controlled must stop and yield to other road users. Generally, only one (for T-intersections) or two approaches may be uncontrolled at a time, with those two approaches being in opposing directions. Uncontrolled approaches are typically provided along the higher-volume axis of travel, thereby benefiting the greatest number of road users (Eck & Biega, 1988). Although uncontrolled and yield-controlled configurations are also possible (McGee et al., 2017), they are rare in the North American context.

2.2. Safety studies of stop-controlled intersections

Existing safety studies of stop-controlled intersections are broadly categorized as either safety studies or behavioral studies, with safety studies traditionally based on historical crash data. El-Basyouny and Sayed (2010) used full Bayes analysis to demonstrate that when uncontrolled intersections are converted to partially stop-controlled intersections in an alternating pattern, collisions were reduced by around 50 % in residential neighborhoods. Eck and Biega (1988) showed that, in low-volume residential neighborhoods, while mid-block motorist speed was not affected by stop-control, full stop-control was effective in reducing the 85th percentile speed at the intersection, though stop violations increased. Stokes (2004) demonstrated that full stop-control may be effective at reducing vehicle collisions at low-speed rural intersections, but not at high-speed ones. In these cases, multiple control, geometric, and traffic calming treatments may be necessary to achieve the desired safety outcomes (Fitzpatrick, Turner, & Brewer, 2007). Other studies have found that geometric elements only have a minimal effect on intersection safety (Arndt & Troutbeck, 2001). While several studies suggest that full stop-control is more effective at reducing crashes than partial stop-control or no stop-control, some conflicting findings exist. In a study of 28 intersections, Polus (1985) found that introducing a stop sign at an uncontrolled intersection increased the average number of crashes threefold, although daytime pedestrian crashes were reduced by 60%. Others have compared the safety performance of stop signs with that of traffic lights. Retting, Ferguson, and McCartt, 2003) found that pedestrian collisions decreased by 25% when signalized or partially stop-controlled intersections were converted to full stop-control at low volume urban intersections. Persaud, Hauer, Retting, Vallurupalli, and Mucsi (1997) found a 24% decrease in crashes when traffic lights were replaced with full stop-control on one-way streets. Others found no significant reduction in pedestrian-vehicle crashes when signals were introduced (Short, Woelfl, & Chang, 1982).

2.3. Behavioral studies of stop-controlled intersections

Behavioral studies at stop-controlled intersections deal mostly with stopping behavior (i.e., full stop, rolling stop, or no stop), which is affected by several variables. Woldeamanuel and Hankes (2011) found that motorist age, law enforcement presence, headlight use, and time of day significantly influenced stopping behavior at urban intersections. Kaysi and Abbany (2007) considered characteristics of driver, vehicle, and traffic to model aggressive driving behaviors at a partially stop-controlled intersection. In the 1980s, a study in eight Québec towns found that when approaching a stop sign, 42% of drivers came to a complete stop, 43% slowed down, and 15% did not slow down at all (Mc Kelvie, 1987). Ten years later, Trinkaus (1997) confirmed these findings in a residential neighborhood of metropolitan New York; over a 17-year period, rolling stops declined from 34% to 2% and full stops dropped from 37% to 1%. Smith and Lovegrove (1983) found that irregular commuters drove faster through residential intersections after a stop sign was installed, but regular commuters approached intersections more slowly after the installation. Gorrini, Crociani, Vizzari, and Bandini (2018) worked towards simulating pedestrian-vehicle interactions by describing the crossing behaviors of various classes of pedestrians. Fu, Miranda-Moreno, and Saunier (2018) proposed a new framework for assessing pedestrian safety, by classifying situations where the driver could or could not stop safely or at all, to define driver behaviors as "non-infraction non-yielding" maneuvers, "uncertain non-yielding" maneuvers and "non-yielding" violations. Stop-controlled crossings had improved yielding rates compared to uncontrolled crossings (Fu et al., 2018).

2.4. Shortcomings

Several shortcomings are apparent in the existing literature. First, despite the advancement of automated techniques for surrogate safety, few safety studies have implemented SMoS for safety analysis of stop-controlled intersections, with studies primarily quantifying safety using crash data. Studies of driver behavior have rarely considered influencing factors other than stop sign presence. Although Brow (2010) validated the Canadian traffic conflict technique for various intersection treatments, there was no conclusive result for partially stop-controlled intersections. Similar methods to those presented herein have been applied to roundabouts (St-Aubin, Saunier, & Miranda-Moreno, 2015), but not stop-controlled intersections. Additionally, existing studies have used relatively small sample sizes. This study aims to contribute to the existing literature by investigating intersection safety and driver stopping behavior using SMoS. This study leverages a large sample of stop-controlled intersections with geometric and built environment data. The use of video data allows for the use of SMoS and provides microscopic exposure data difficult to capture using other methods. Additionally, the proposed modelling approach quantifies the impact of various factors on the considered SMoS.

3. Methodology

3.1. Intersection typology and definitions

Intersection geometry varies greatly depending on number, layout, and direction of travel of the intersecting streets. Depending on street configuration, intersections can be categorized in many different ways, and it is therefore necessary to define several terms when discussing stop control.

- A *branch* (or leg) is a clearly defined, contiguous section of road that connects to one side of an intersection. Branches can be unidirectional streets serving as an entrance or exit to the intersection or bidirectional streets serving as an entrance and exit.
- An *approach* constitutes the portion of a branch dedicated to road users entering the intersection. Every intersection must have at least one approach, but no more than its number of branches.
- An *unbalanced intersection* has fewer approaches than branches while a *balanced intersection* has as many approaches as branches

These concepts are further illustrated in Fig. 1 using the example of a typical partially stop-controlled T-intersection between a one-way and a two way-street.

Approaches may vary in terms of design features, including the number and width of traffic lanes, presence of a crosswalk or sidewalks, and cycling infrastructure. In this study, crosswalk presence is of great interest as crosswalks often exist on uncontrolled approaches. Motorists approaching these crosswalks are expected to yield to pedestrians (often encouraged using appropriate signs or signals) though the requirement to come to a complete stop is neither explicit nor unconditional. The most important design feature is the presence of a stop sign. In Fig. 1, the approach on the unidirectional branch is uncontrolled, making the intersection partially stop-controlled. This is the chief distinction between partial stop-control and full stop-control. Consider a second example of a T-intersection between two unidirectional streets, having exactly three branches and two approaches. If both approaches are stop-controlled, then the intersection is fully stop-controlled despite having only two stop signs.

3.2. Traffic data collection

Traffic data are collected and processed using a high-resolution, video-based traffic data collection system. Large quantities of video data are recorded using ordinary video cameras installed at each studied site for a period of one working day. The camera resolution is generally not sufficient to distinguish features of faces or license plates and, as such, contains no personally identifiable information. The collected data are preprocessed to correct for lens distortion and high-resolution road user trajectories (positional data captured every frame, 15 times per second or more) are extracted using the open source computer vision project Traffic Intelligence (Jackson et al., 2013). Each trajectory represents one road user, with each user being classified as a pedestrian, cyclist, or motorized vehicle. This process is improved, automated, and validated using the tvaLib software (St-Aubin, 2016). Fig. 2 provides an example of typical site instrumentation, including the distortion-corrected video footage fully covering at least one uncontrolled approach and the extracted road user trajectories. Note that for this site, local norms dictate that the visible crosswalk be painted yellow given that it crosses the intersection perpendicularly to one or more uncontrolled approaches.

This method of automated video data collection and processing has many advantages over more traditional sources of behavioral or safety data, including:

- The instrumentation is installed in a public space external to the road user, making it mostly unobtrusive and limiting the effect on driver behavior
- Captured road-user trajectories are continuous with significantly greater resolution and precision than other forms of trajectory data (GPS, radar, etc.)
- All road users crossing the field of view are captured, minimizing the possibility for participation bias while collecting no personally identifiable data
- Data collection and processing are cost-effective (cameras are relatively cheap and easy to install)
- Manual review of the data is possible for optimization or validation purposes and the dataset may be conserved for comparison with future analysis or trajectory extraction algorithms

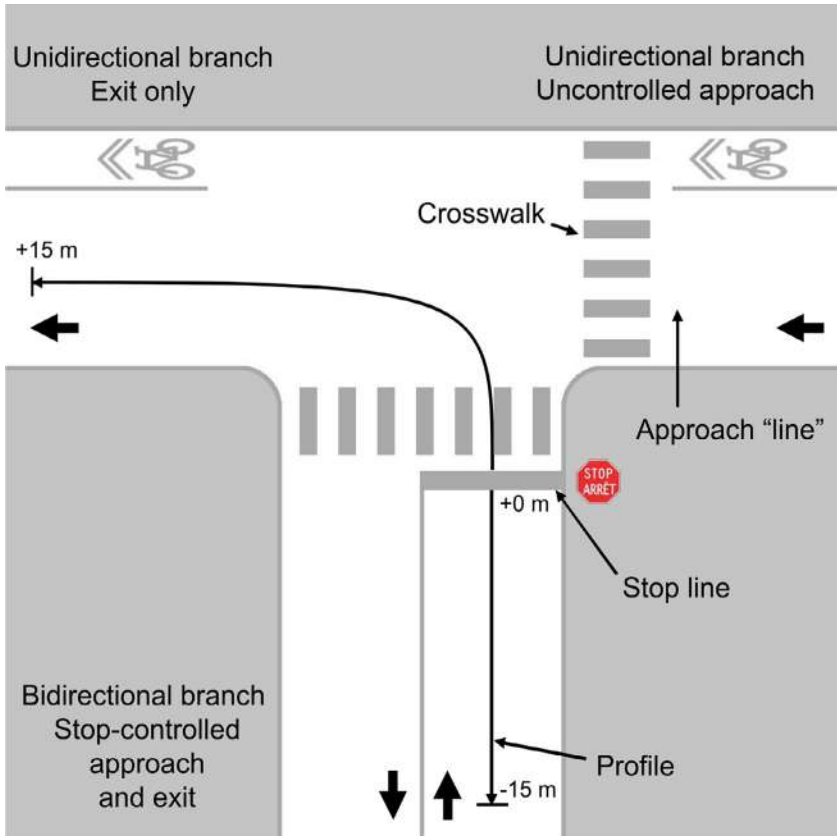


Fig. 1. Typical partially stop-controlled T-intersection featuring three branches and two approaches.

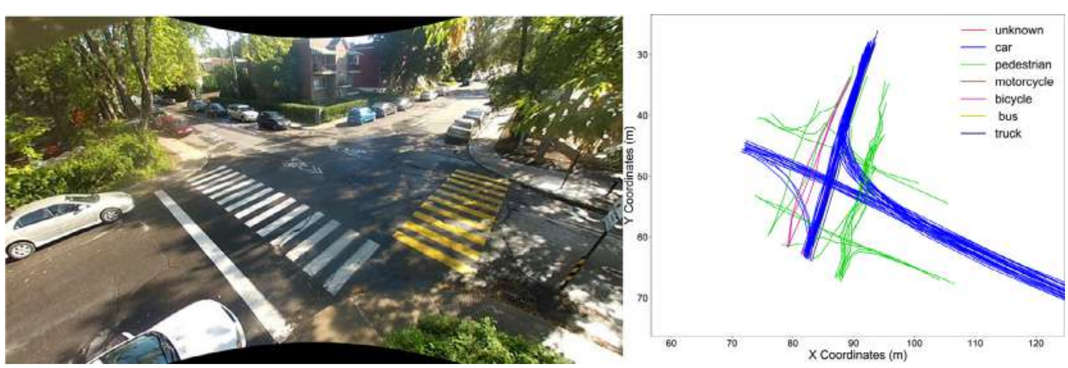


Fig. 2. Video frame corrected for lens distortion (left) and extracted trajectories for different road user categories (right).

One important limitation of the detection and tracking algorithm is that it struggles to track slow moving road users and cannot detect fully stationary road users, making it difficult to differentiate portions of trajectories where road users travel at less than 5 km/h and those where the road user is stopped. For this research, it is assumed that road users travelling at speeds less than 5 km/h come to a complete stop. This error exists specifically between non-moving and moving objects and observed speeds above 5 km/h are considerably more accurate than those below 5 km/h.

3.3. Definition and extraction of surrogate measures

3.3.1. Approach speed

For each approach, all motorists passing through the intersection are tracked and their speeds (km/h) are recorded for 15 m upstream and downstream of the stop bar (or the theoretical location of the stop bar if the approach is uncontrolled), yielding a speed profile covering a distance of 30 curvilinear meters. Considering this speed profile, the minimum speed for each motorist traversing a stop-controlled or uncontrolled approach is recorded if that user is not impeded by the presence of another stopped vehicle. Thus, the effects of even mild congestion along the approach are controlled. Specifically, the 5th percentile speed $(v_{5^{th}})$ within a 10 m curvilinear distance upstream or downstream from the stop line is recorded, along with the curvilinear distance from the stop line $(v_{5^{th}_{location}})$. The 5th percentile speed is used specifically because it is more robust against possible observational errors introduced by using video-based trajectory data.

3.3.2. User pairs

Fundamentally, an interaction between two road users that can lead to a conflict and a collision requires their simultaneous presence in both time and space. Every observed road user is paired with every other road user existing within a scene (the area where interactions of interest take place) during the same time interval. For this study, the scene includes the intersection conflict zone (the area where the intersecting roads overlap), all crosswalks, all approaches to and exits from the intersection (roughly 15 m of each branch) and all sidewalks along the branches. Most user pairs do not involve any actual interaction between the road users. For a user pair to result in a conflict or a crash, users must be on a collision course (a situation in which the road users would collide if their movements remain unchanged) (Laureshyn et al., 2016). Determining whether a given user pair is on a collision course at a specific time requires the prediction of the users' future positions.

The most basic and common motion prediction model is "constant velocity" (Laureshyn et al., 2016; Mohamed & Saunier, 2013), which assumes constant speed and heading under the assumption that no evasive action takes place to alter the collision course. Given that trajectories can be curvilinear, and that acceleration can arise from a variety of sources other than evasive action (frictional force, curves, non-evasive user input), more sophisticated motion prediction models have been developed. This study uses the "discretized motion pattern" model to predict naturalistic road user motion (St-Aubin et al., 2015; St-Aubin, 2016). This model is extremely flexible and adaptable automatically to any context or application. At any instant t_0, positions $[x_i, y_i]$ at future time t_i are predicted with probability $P(Event_{x_i,y_i,t_i})$based on initial conditions of road user type, speed, origin lane, and curvilinear distance along the lane, as illustrated in Fig. 3. The model learns by aggregating the behavior of all other road users matching those initial conditions in the same scene. A potential collision at point $[x_i, y_i]$ and time t_i is the predicted simultaneous arrival of any two road users at $[x_i, y_i]$ at time t_i, having the joint probability

$$P(AB_{x_i,y_i,t_i}) = P(A_{x_i,y_i,t_i}) \times P(B_{x_i,y_i,t_i}) \tag{1}$$

If two road users are determined to be on a collision course at time t_0, using the notation above and in Fig. 3, the TTC is computed as $\Delta t_i = t_i - t_0$. Motion prediction is typically done up to a given time horizon, chosen to minimize expensive computations of meaningless TTC values (usually 5 or 10 s). Each potential collision point is characterized by a probability and a TTC, with the overall TTC at t_0 for a given user pair computed as the expected TTC over all potential collision points (weighted by the probability of each collision point). TTC is computed for every frame of video data and, in the general case, results in a sequence or time series. TTC is then aggregated for every user pair, with the 15th centile used based on past research (St-Aubin, 2016). User pairs can also be quantified using PET, which measures the time between successive arrivals at a common crossing zone (Laureshyn et al., 2016). Therefore, there is, at best, only one PET value, and it does not rely on motion prediction, but is observed from any two trajectories, if they intersect each other.

3.4. Extracting covariates

Various covariates were extracted from the video footage, site visits, or complementary information in order to capture elements of stop control, geometry, built environment, and exposure at the studied intersections. A detailed description of the selected covariates is provided in the following sections.

Stop-control configuration. Two binary variables are used to indicate whether the intersection is fully stop-controlled or partially stop-controlled. In the user pair safety models, partial stop-control is further split based on the number of conflicting road users on an approach with a stop sign ("Partially stop-controlled, one stop" and "Partially stop-controlled, both stop"). In all cases, the reference category is when the considered road users have no stop sign on their approach.

Geometric variables. Two binary variables are used to indicate whether the intersection is balanced and whether a demarcated crosswalk is present on the approach.

Built environment characteristics. The built environment is described using the land use mix, calculated using the entropy index (Frank, Schmid, Sallis, Chapman, & Saelens, 2005). Considered land use types were those defined by Desktop Mapping Technologies Inc. including residential, commercial, institutional and governmental, resource and industrial, and park and recreation, as observed in the year 2007. To generate the land use mix near each intersection, the nine-cell grid approach proposed by Zahabi, Chang, Miranda-Moreno, and Patterson (2016) was used. A 500 m × 500 m grid was overlaid on the Montreal metropolitan area. The land use mix of each cell was calculated using the attributes of the eight neighboring cells. Each intersection is assigned the land use mix of the cell in which it is situated. Although other built environment indicators such as population or employment density and transit accessibility could be considered, these measures are often highly correlated.

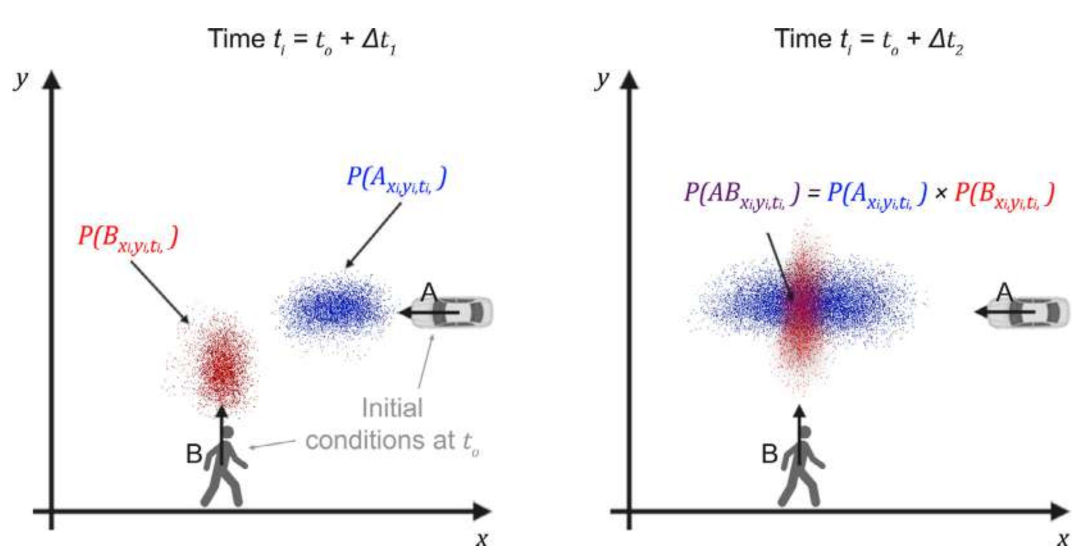


Fig. 3. Visualization of the discretized motion pattern motion prediction model for two road users, along with the probability of joint arrival at potential collision points.

Time of day. A binary variable is used to indicate if the observation was made during the afternoon rush hour, defined as between 4 p.m. and 6 p.m.

Collision course type. For the user pair safety models, two binary variables are used to indicate whether the interaction was of the type "side collision course" or "rear-end collision course" based on the relative angles of the trajectories for the road users.

Road user exposure. In the user pair safety models, the microscopic exposure of vulnerable road users is captured using two binary variables to indicate the presence of either a cyclist or pedestrian within 7.5 s before and after the observed event ("15 s cyclist presence" and "15 s pedestrian presence," respectively).

For the approach speed models, it was observed that a simple binary variable for pedestrian presence was not sufficient to capture the effect of pedestrians on vehicle approach speed. With up to four or more approaches at each intersection, and with the possibility of pedestrians crossing any branch, a variety of pedestrian-vehicle interactions are possible. The Intersection Exposure Group (IEG) measure was devised to classify the various possible safety-relevant pedestrian-vehicle interactions. IEG classifications are described below and illustrated in Fig. 4.

- $IEG = 0$: no pedestrian is present
- $IEG = 1$: pedestrian crosses the branch immediately in front of the approaching motorist
- $IEG = 2$: pedestrian crosses the branch opposite the approaching motorist, motorist travels straight through the intersection
- $IEG = 3$: pedestrian crosses the branch opposite the approaching motorist, motorist turns
- $IEG = 4$: pedestrian crosses a perpendicular branch, motorist travels through the intersection
- $IEG = 5$: pedestrian crosses a perpendicular branch, motorist turns onto that branch
- $IEG = 6$: pedestrian crosses a perpendicular branch, motorist turns onto another branch

If an intersection has fewer than four branches, the branch opposite the approaching motorist exists only if the approach has a branch opposite it or if it is obvious that the approach extends through another branch not immediately opposite from it. If an intersection has more than four branches, the branch that is the obvious extension of the approach is used (determined by street name or traffic volume) is the opposing branch. All other branches are considered to be perpendicular. IEG is ordered in descending order of interaction governance on behavior of the approaching motorist. For example, if pedestrians cross the branch in front of and opposite the motorist simultaneously, set $IEG = 1$ as it is the pedestrian in front of the motorist that governs its behavior (by blocking the motorist's path to other pedestrians). Similarly, by geometric constraint, $IEG = 5$ is considered only after considering $IEG = 0,\ 1,\ 2,\ 3,\ or\ 4$. $IEG = 1, 2, 4, and\ 5$ all involve encroachment (crossing trajectories) while others do not.

3.5. Statistical modelling

This study uses statistical models in order to perform inference; that is to determine which of the considered covariates is statistically and significantly related to the variable of interest (vehicle speed, TTC or PET). Given that the data are hierarchical, with covariates recorded at the level of the intersection, approach, road user pair, and or road user, a linear mixed-effects regression model was chosen to account for within-site and within approach correlations. These correlations arise due to unobserved factors at the

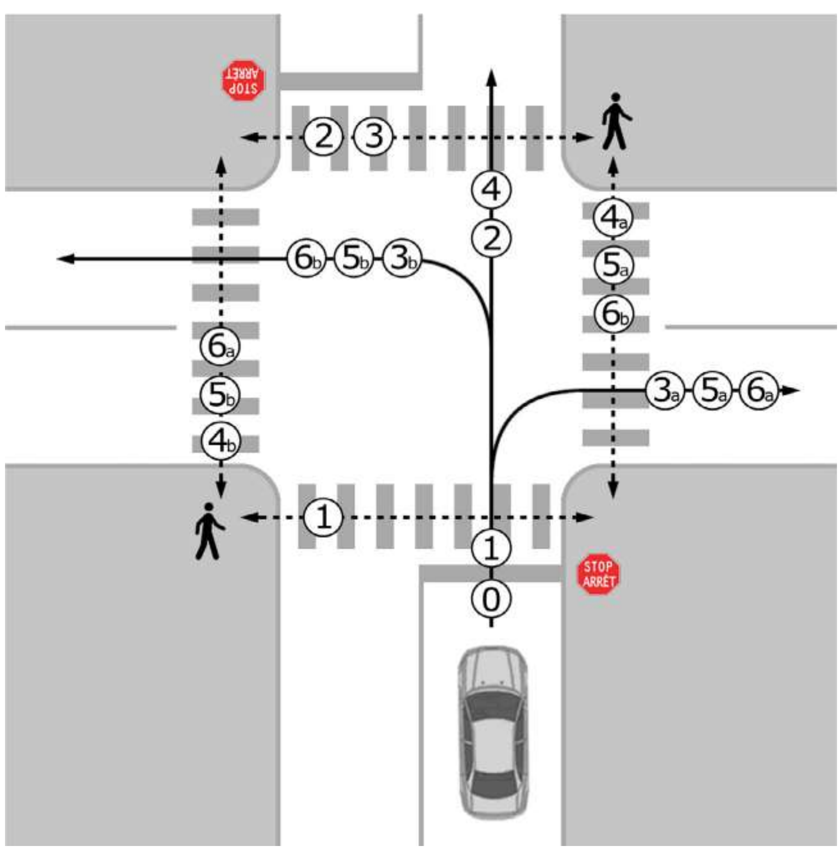


Fig. 4. Intersection Exposure Group (IEG).

intersection and approach level, potentially related to geometry, visibility, or otherwise, that could affect observations within the same site or approach. For approach speed, the model is of the form

$$y_{ijk} = \beta_0 + \sum_l \beta_l X_{ijkl} + u_{i0} + u_{ij0} + \varepsilon_{ijk} \tag{2}$$

where y_{ijk} is the minimum speed $(v_{5^{th}})$ or minimum speed location $(v_{5^{th}location})$ for site i, approach j, and road user k, β_0 is the intercept, β_l are the coefficients for p covariates X described earlier, u_{i0} and u_{ij0} are the site-specific and approach specific normally distributed random intercepts for site i and approach j, respectively, and ε_{ijk} is the normally distributed error term. Due to the nature of the data (each approach is contained in exactly one intersection) the random intercepts u_{i0} and u_{ij0} can be modelled as nested, with u_{ij0} nested in u_{i0} for each site i. For user pair safety, the model is of the form

$$y_{im} = \beta_0 + \sum_n \beta_n X_{imn} + u_{i0} + \varepsilon_{im} \tag{3}$$

where y_{im} is the TTC or PET for site i and user pair m, β_0 is the intercept, β_n are the coefficients for q covariates X described earlier, u_{i0} is the site-specific normally distributed random intercept for site i, and ε_{im} is the normally distributed error term. Preliminary analysis showed that the, although TTC is roughly normally distributed, PET is not. Therefore, the regression model for PET is transformed from (3) to

$$ln(PET + 1) = \beta_0 + \sum_n \beta_n X_{imn} + u_{i0} + \varepsilon_{im} \tag{4}$$

It should be noted that the utility in predicting collisions using TTC or PET values larger than 10 s (or arguably even above 5 s) is dubious given that conditions at the time of prediction are likely to change within this time span and that this amount of time is considerably larger than typical road user reaction times found in the literature. Although TTCs exceeding 10 s in duration are technically possible and quite common, rarely is enough of a road user's approaching trajectory captured in the video footage to measure these TTCs, which would also be biased toward lower speeds required for high TTCs. As the same is not true of PETs (it is relatively easy to observe PETs exceeding 5 s or 10 s using video data), the PET data are explicitly limited to only include measured PETs less than 5 s. All models were calibrated in R using the *lme* function, which uses a restricted maximum log-likelihood technique (REML). As the primary goal of the models is inference, rather than predicting levels of safety at stop-controlled intersections, the results focus on the significance of the covariates. However, goodness-of-fit (measured using R-squared), the intraclass correlation coefficient, and the significance of random effects are also reported for completeness.

4. Results

4.1. Site selection

A list of stop-controlled intersections within Montreal was generated using an existing database of intersections and GIS street data. This resulted in an initial list of 14,000 intersections across Montreal's 19 boroughs. This list was filtered according to several characteristics, with street classification being the most important. The City of Montreal uses nine street classifications including private street, local street, principal street, and highway. For this study, selected intersections were mainly on local streets, which have a city-wide speed limit of 40 km/h unless near a playground or school, where the speed limit is reduced to 30 km/h. From this list, 340 intersections throughout all boroughs were randomly selected as candidates for instrumentation and were further classified using aerial imagery. From this sample, 97 intersections were selected for instrumentation (a budgetary limitation), illustrated in Fig. 5. At each intersection, a camera was installed, and video data were collected for 6 to 8 hours on weekdays. Every approach was identified as either stop-controlled or uncontrolled, and the location of the painted stop line was recorded as a reference for the curvilinear speed profile data. On uncontrolled approaches, the theoretical location of the stop bar, had the approach been stop controlled, was used instead. Approaches with insufficient upstream video coverage or with less than 50 observed approaching road users were eliminated from the analysis.

4.2. Data description

4.2.1. Approach speed

Table 1 summarizes the number of intersections, approaches, and motorists included in the approach speed models. Stop-controlled and uncontrolled approaches are represented relatively equally, along with the number of motorists observed at each approach type. The smaller number of fully stop-controlled intersections compared to partially stop-controlled intersections is the result of the simultaneous requirement that intersections have stop signs on all approaches for full stop-control categorization.

Speed profiles and minimum speed location were observed to vary considerably between sites, and between individual road users at the same site or approach, suggesting that both are influenced by environmental factors and individual interactions. Yet, general trends are still observed, such as the distributions of minimum speed for controlled and uncontrolled approaches in Fig. 6. As noted earlier, all observations at or below 5 km/h are assumed to be complete stops. Considering the distribution for controlled approaches in Fig. 6a, most motorists were observed to be at or near this speed, although many road users are clearly above this speed, crossing the stop line at speeds above 10 km/h (rolling stops). Minimum approach speeds at uncontrolled approaches more closely follow an expected normal distribution centered around 33 km/h, with a secondary peak between 5 and 10 km/h for turning drivers.

Fig. 7 illustrates the average speed profiles across all stop-controlled and all uncontrolled approaches. Unsurprisingly, speeds were observed to decrease approaching a stop sign, while speeds remain relatively constant for the uncontrolled approaches. It should also be noted that the speed variability for uncontrolled approaches is much larger than for stop-controlled approaches, particularly closer to the stop-bar. High variability in the location of minimum approach speed results in mixed observations at different locations. For example, at the same approach, some drivers reach their minimum speed 3 m upstream of the stop line, while other drivers reach their minimum speed 1 m after the stop line.

4.2.2. User pairs

Of the 97 stop-controlled intersections in the inventory, 66 were selected for safety analysis, as summarized in Table 2. As with before, care was taken to balance stop-controlled and uncontrolled approaches, despite the comparatively larger number of partially stop-controlled intersections in the data set. The models consider over 135,000 road users in nearly 57,000 road user pairs (with approximately 90 % being vehicle-vehicle pairs, and the additional 10 % being vehicle–pedestrian pairs). Despite the considerable number of user pairs captured on video, no crashes were observed over the course of video collection, highlighting the advantage of such a surrogate safety approach. User pairs were sampled uniformly in time, in order to virtually eliminate instances of a single road user appearing in more than on user pair. Fig. 8 illustrates and compares the distributions of TTC and PET observations for vehicle-vehicle and vehicle–pedestrian user pairs. While TTC appears to be roughly normally distributed, PET values are not.

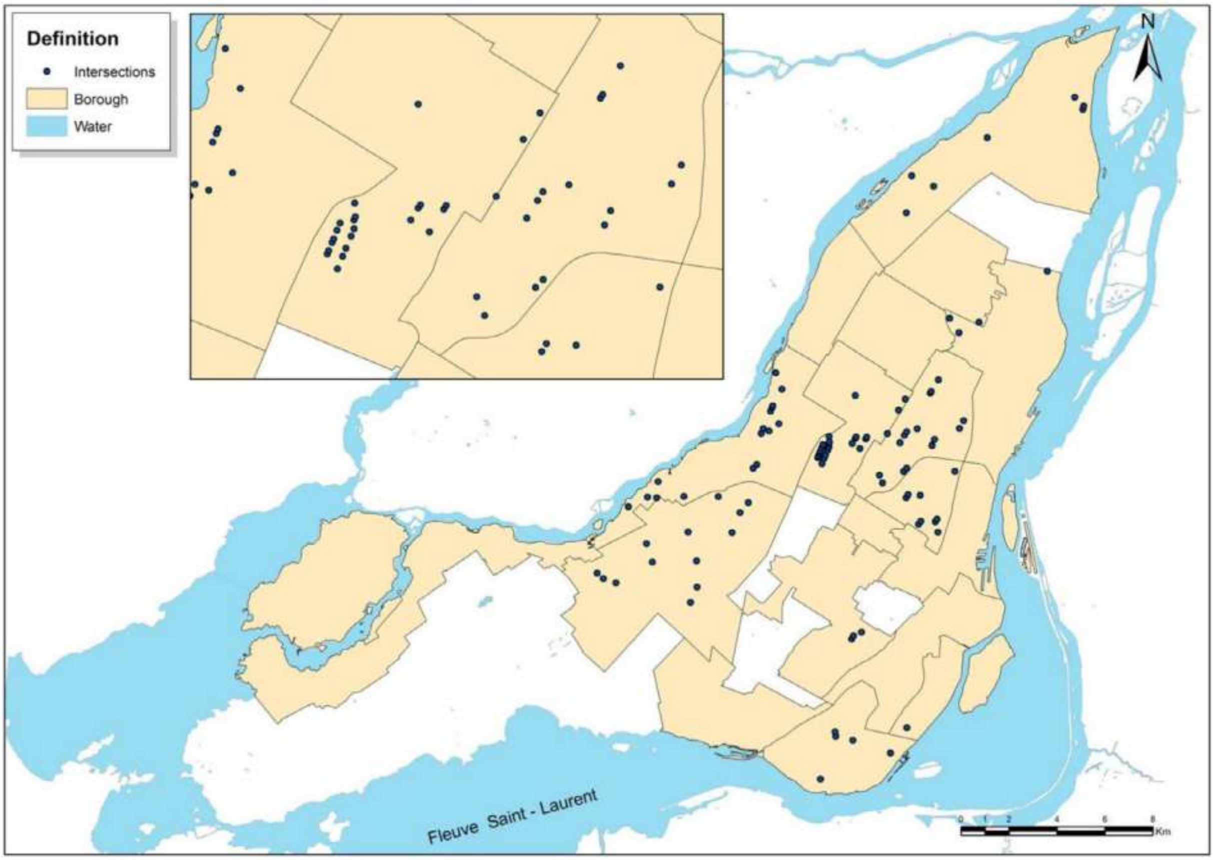


Fig. 5. Map of 97 investigated stop-controlled sites in Montreal, Quebec.

Table 1
Data inventory for approach speed analysis.

Total intersections	97
Partial stop-control intersections	80
Full stop-control intersections	17
Stop-controlled approaches	117
Uncontrolled approaches	159
Motorized vehicles	70,842
Motorists at stop-controlled approaches	31,339
Motorists at uncontrolled approaches	39,503

As PET is computed for user pairs even when there is no collision course, PET reflects safety as well as the distribution of arrivals.

4.3. Regression analysis

4.3.1. Approach speed

The primary goal of the regression analyses presented below is determining which considered factors are significantly related to the considered SMoS. Although model fit is not the primary concern, R-squared values (along with intraclass correlation and random effects) are reported for information only. As with other

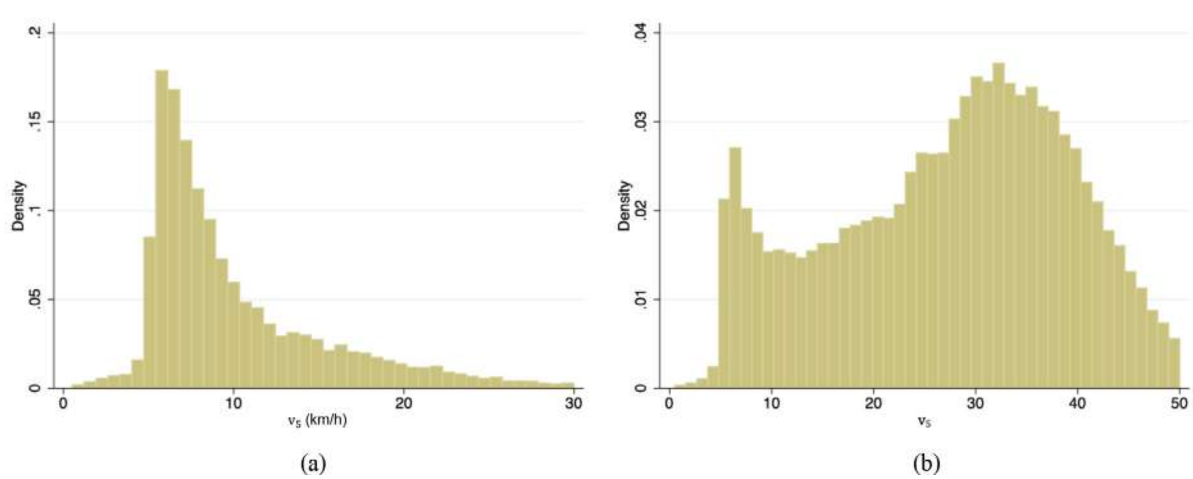
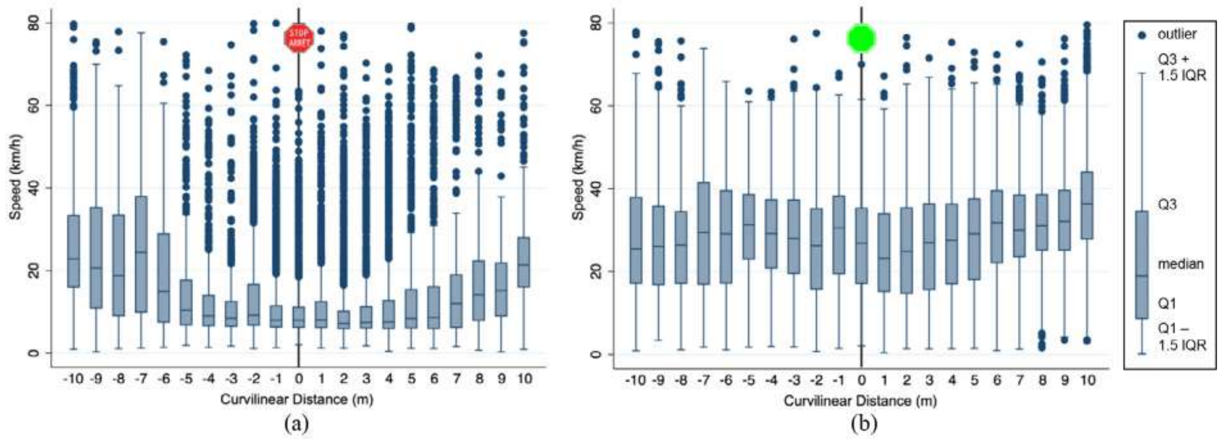


Fig. 6. Distributions of speed observations for stop (a) or uncontrolled (b) approach, independent of location.



Note: Q1 and Q3 are the 25th and 75th percentile values, respectively. IQR is the interquartile range, IQR = Q3 – Q1.

Fig. 7. Distributions of speed along curvilinear stop (a) or uncontrolled (b) approach profile.

Table 2
Data inventory for safety analysis.

Total intersections	66
Partial stop-control intersections	55
Full stop-control intersections	11
Stop-controlled approaches	61
Uncontrolled approaches	65
Motorized vehicles	129,721
Pedestrians	5,392
Total road users	135,113
Total road user pairs	56,815

inferential models, the presented model outputs retain non-significant variables. Model results for $v_{5^{th}}$ and $v_{5^{th}location}$ are presented in Table 3. According to the model constants, motorists on uncontrolled approaches in an unbalanced intersection, without a near-side crosswalk, with no cyclist or pedestrian presence, during the afternoon rush hour, and in an areas with no land use mix, reach an average $v_{5^{th}}$ of 30 km/h at a $v_{5^{th}location}$ 0.4 m after the theoretical stop line location. Stop-controlled approaches in partially stop-controlled intersections are associated with an average decrease in $v_{5^{th}}$ of 17.2 km/h, while full stop control is associated with an average decrease of 20.1 km/h. Full stop-control also affects $v_{5^{th}location}$, moving it 1.50 m downstream, on average, perhaps because motorists at full-stop controlled intersections expect other motorists to stop simultaneously, and can therefore risk entering the intersection prematurely. The centroid of a 4 m long car stopping exactly in front of a stop line should lie at a $v_{5^{th}location}$ of 2 m ahead of the stop line. Thus, this model would suggest that road users on average tend to stop with the front end of the vehicle over the stop line. Balanced intersections tend to have minimum speeds 4.99 km/h higher than unbalanced approaches, while increasing land use mix decreases the minimum approach speed. Demarcated crosswalks and the afternoon rush hour did not have any significant association with either $v_{5^{th}}$ or $v_{5^{th}location}$. It should be noted that the quality of the markings was not considered in the models. In many cases, the markings are deteriorated, and the effect of this should be considered in the future. The presence of cyclists and pedestrians appears to have further effects. 15 s cyclist present was observed to reduce minimum approach speed by 0.74 km/h and shift the location of the minimum speed by 0.16 m. All categories of pedestrian exposure, except for $IEG = 2$ and $IEG = 4$ reduce $v_{5^{th}}$ between 1.50 and 7.49 km/h. Surprisingly, $IEG = 6$ provides a relatively large reduction in speed despite this interaction involving no crossing paths between motorists and pedestrians. Pedestrian interactions had only minor effects on $v_{5^{th}location}$, with many variables found to be non-significant. In both models, the random effects were statistically significant at 95% confidence.

4.3.2. User pairs

For the user pair safety models, demarcated crosswalks were found to be highly correlated with the various stop control configurations and were therefore omitted. Results of the regression models for TTC for vehicle-vehicle and vehicle–pedestrian user pairs is presented in Table 4. First, considering vehicle-vehicle pairs, partial stop-control was observed to increase TTC by 0.18 s or 0.23 s, depending on whether only one or both motorists were required to stop. Although the full stop-control configuration resulted in the greatest improvement in TTC, it was found to be non-significant. Other significant variables included the afternoon rush hour (increased TTC by 0.19 s). User pair configuration was also significant, with rear-end and side collision courses being safer (by increasing TTC) compared to head-on collision courses. Balanced intersections, land use mix, and microscopic exposure variables were also not significant. In the model for vehicle–pedestrian pairs, the only variable found to be significant was the side-collision course, increasing TTC by 0.19 s.

Table 5 presents the results of PET models for vehicle-vehicle and vehicle–pedestrian pairs. The fact that the vehicle-vehicle model has several significant variables appears to support that user pairs with PET values over 5 s are largely useless in studying safety. In the vehicle-vehicle model, partially stop-controlled intersections where one road user must stop increases PET, though PET decreases when both road users must stop: the negative coefficient for "Partially stop-controlled, both stop" is difficult to explain. Perhaps because both road users stop and then proceed simultaneously depending on right-of-way, their paths cross with a shorter PET, compared to when neither road user must stop. Although PET is reduced, this particularly scenario would not have important safety implications given the speeds. Balanced intersections also tend to have lower PETs on average, while the microscopic exposure variables also reduced PET for vehicle-vehicle pairs. No variables were significant in the vehicle–pedestrian model, again likely attributable to the lower number of observed pedestrians. Again, the random effects were found to be significant in all models at 95% confidence. As the R-squared is relatively weak in the TTC model and quite weak in the PET models, it is obvious that these

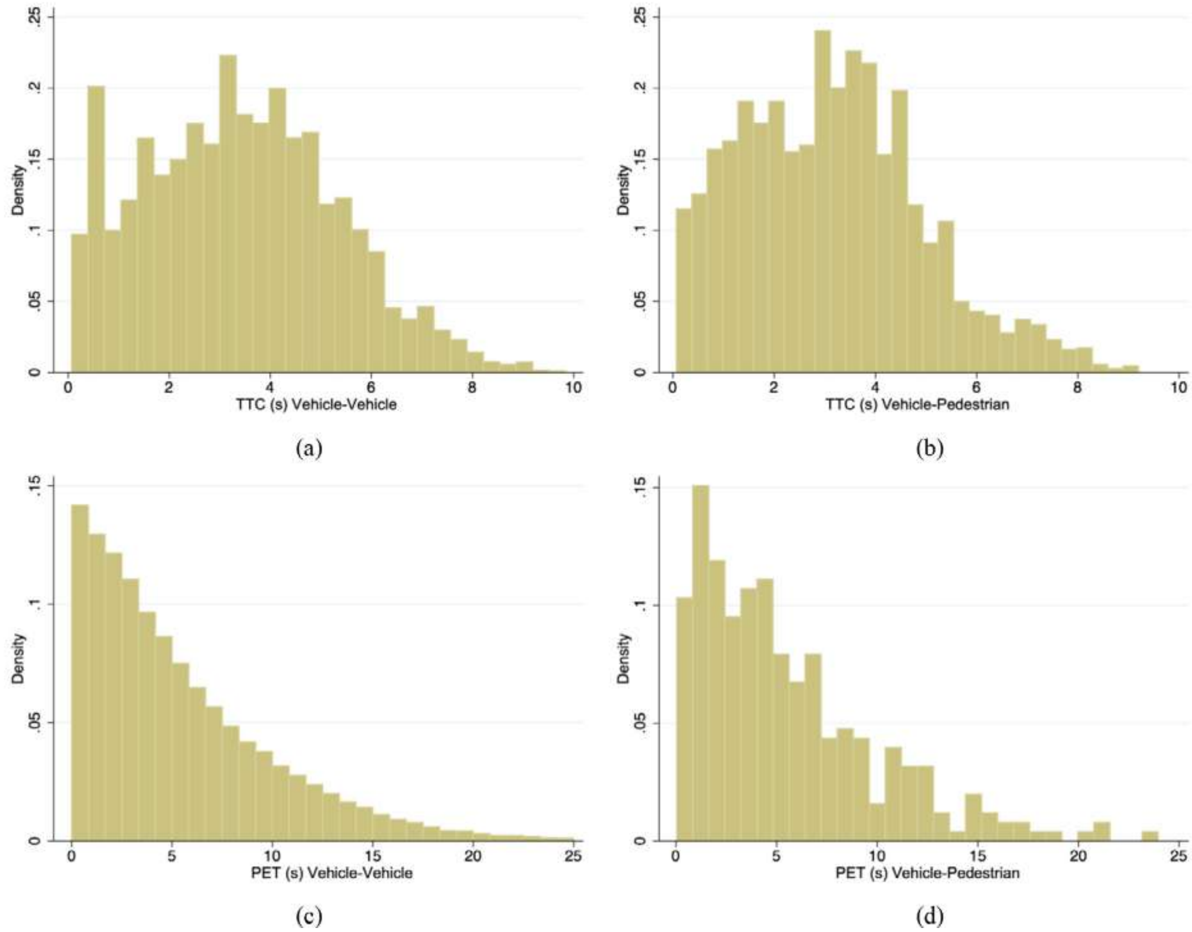


Fig. 8. TTC distributions for vehicle-vehicle (a) and vehicle–pedestrian (b) user pairs and PET distributions for vehicle-vehicle (c) and vehicle–pedestrian (d) user pairs.

Table 3
Model results for 5th percentile speed and location.

	v_{5th} (km/h)		$v_{5th\ location}$ (m)	
	Coefficient	$P > \|t\|$	Coefficient	$P > \|t\|$
Constant	30.2*	0.000*	0.40	0.360
Partially stop-controlled with stop	−17.2*	0.000*	−0.55	0.197
Fully stop controlled	−20.1*	0.000*	−1.50*	0.026*
Balanced	4.99*	0.000*	0.13	0.749
Demarcated crosswalk on approach	−0.47	0.717	0.21	0.642
Land Use Mix	−0.06	0.032	0.02	0.074
Afternoon rush hour	0.07	0.654	−0.07	0.370
15 s cyclist presence	−0.74*	0.000*	−0.16*	0.019*
IEG_1	−1.50*	0.000*	−0.40*	0.000*
IEG_2	0.19	0.412	0.37*	0.016*
IEG_3	−3.46*	0.000*	−0.15	0.331
IEG_4	0.76*	0.000*	0.16	0.107
IEG_5	−7.39*	0.000*	−0.13	0.508
IEG_6	−4.64*	0.000*	−0.05	0.627
R-squared	0.615		0.414	
Observations	70,778		30,970	
Site Groups	97		97	
Approach Groups	336		330	
Intraclass Correlation	0.421		0.385	

* Significant at 95% confidence.

models fail to observe all variables that help to explain user pair safety. However, the models remain sufficient to determine if the considered factors significantly influence safety.

5. Conclusions

The purpose of this study was to investigate the effects of various stop-control configurations at urban intersections on the

Table 4
Model results for TTC for vehicle-vehicle and vehicle-pedestrian pairs.

	Veh.-Veh. Pairs		Veh.-Ped. Pairs	
	Coefficient	$P > \|t\|$	Coefficient	$P > \|t\|$
Constant	2.23*	0.000*	2.22*	0.000*
Partially stop-controlled, one stop	0.18*	0.000*	−0.78	0.087
Partially stop-controlled, both stop	0.23*	0.000*	*N/A*	*N/A*
Fully stop controlled	0.85	0.099	0.04	0.947
Balanced	0.62	0.094	0.31	0.448
Land Use Mix	0.01	0.254	0.01	0.100
Afternoon rush hour	0.19*	0.000*	−0.06	0.586
Rear-end collision-course	0.40*	0.000*	0.01	0.841
Side collision-course	0.70*	0.000*	0.19*	0.003*
15 s cyclist presence	0.03	0.145	−0.05	0.395
15 s pedestrian presence	0.03	0.110	*N/A*	*N/A*
R-squared	0.315		0.222	
Observations	41,415		4925	
Site Groups	49		42	
Intraclass Correlation	0.295		0.278	

* Significant at 95% confidence.

Table 5
Model results for PET for vehicle-vehicle and vehicle-pedestrian pairs.

	Veh.-Veh. Pairs		Veh.-Ped. Pairs	
	Coefficient	$P > \|t\|$	Coefficient	$P > \|t\|$
Constant	1.09*	0.000*	1.12*	0.000*
Partially stop-controlled, one stop	0.06*	0.000*	0.15	0.428
Partially stop-controlled, both stop	−0.07*	0.000*	*N/A*	*N/A*
Fully stop controlled	−0.03	0.392	*0.10*	*0.124*
Balanced	−0.08*	0.007*	−0.05	0.269
Land Use Mix	0.00	0.447	0.00	0.564
Afternoon rush hour	0.00	0.708	0.00	0.961
15 s cyclist presence	−0.02*	0.001*	0.01	0.613
15 s pedestrian presence	−0.02*	0.001*	*N/A*	*N/A*
R-squared	0.037		0.051	
Observations	35,893		3385	
Site Groups	65		56	
Intraclass Correlation	0.028		0.035	

* Significant at 95% confidence.

SMoS of approach speed, and TTC and PET for user pairs, while controlling for other geometric, built-environment, time-of-day, and microscopic exposure factors. Linear random-effects models were estimated on a large sample of video data collected at 97 intersections within the city of Montreal. Using automated video processing and computer vision techniques, direct observations were collected for over 130,000 road users at 336 fully stop-controlled, partially stop-controlled, and uncontrolled intersection approaches.

In terms of approach speed, the presence of stop signs significantly reduced speeds compared to uncontrolled approaches. Speed variability was also much lower on stop-controlled approaches. Balanced intersections had slightly higher approach speeds, while increasing land use mix effectively reduced approach speeds. The presence of cyclists and pedestrians also generally reduced approach speed, including four of the six proposed pedestrian exposure measures. The proposed IEG measure was shown to successfully distinguish various types of pedestrian-vehicle interactions, allowing for the effect of each interaction type to vary in the model. This provides a significant improvement over a simple exposure measure indicating the presence of a pedestrian. Although the location of the minimum speed was also observed to vary between locations and individuals, not nearly as many variables were found to be statistically significant in that model. Only full stop-control and several microscopic exposure variables significantly affected the location of the minimum speed. User pair interactions were quantified using both TTC and PET, and pairs of vehicles and between vehicles and pedestrians were modelled separately. TTC for vehicle-vehicle user pairs was significantly reduced at partially stop-controlled intersections. Additionally, side and rear-end collisions courses and the afternoon rush hour reduced TTC for vehicle-vehicle pairs. For PET of vehicle-vehicle pairs, the effects of stop control were less clear, though balanced intersections and microscopic presence of pedestrians and cyclists were observed to decrease PET values on average. Unfortunately, both vehicle–pedestrian models had very few significant variables and drawing conclusions for in the safety of pedestrians is difficult.

These results have important policy implications, considering that stop signs are often installed to either reduce vehicle speed or improve pedestrian safety. This study clearly demonstrates that stop-control is significantly related to reduced vehicle approach speeds. Therefore, implementing stop signs for this purpose would appear to be effective. This result has important implications for pedestrian safety, because slower vehicles will result in less severe pedestrian injuries. However, a large percentage of vehicles still fail to come to a complete stop. Considering the user pair safety measures, stop signs were generally observed to increase TTC and PET values (improve safety) for vehicle-vehicle pairs. However, the lack of a significant relationship between stop signs and pedestrian-vehicle interactions is equally interesting. This result may indicate that while stop signs reduce vehicle speeds (and therefore crash severity) their effect on crash frequency may not be significant, at least for crashes involving pedestrians. Therefore, policies implementing stop signs with the aim to reduce pedestrian crashes overall may be less effective than other interventions. Enforcement and education efforts, along with geometric design considerations, should accompany any changes in traffic control to ensure effectiveness.

One limitation of this study is that stop-compliance is not recorded in detail. It is difficult to determine pedestrian crossing intentions in an automated way and determine whether or not drivers are reasonably required to yield to them (Fu et al., 2018). The use of video data and current computer vision performance limit the ability to determine if vehicles come to a complete stop, due to the discussed technical limitations. Furthermore, defining stop compliance, from a road safety perspective rather than a legislative one, is also non-trivial. In the future, it may be interesting to estimate the "effective" use of stop signs on yielding behavior, along with other safety benefits of speeding and full-stops and related phenomena of delay and vehicle emissions. The poor fit of the PET models warrants further research, particularly concerning models better suited to the data and into other variable formulations, in particular for the dependent SMoS to improve correlation with the explanatory variables. It is possible that while approach speed and TTC are more strongly influenced by features of the intersection, PET is affected more by the distribution of arrivals and driver features (which are obviously not captured in this study). Future work will also focus on larger datasets, including additional intersections added to the inventory since the undertaking of this project. Additional sites have been monitored both before and after conversion to full stop-control, which yields interesting opportunities for before-and-after studies. Finally, validation of SMoS will be completed by computing correlations with observed historical crash data available for all studied sites. Considering the commonality of stop signs and the advent of SMoS, the results of this study and studies like it are expected to contribute to understanding the relationship between stop control and safety.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

This project was funded by the City of Montreal. Postdoctoral researchers received further financial support from the Institute for Data Valorization (IVADO). The authors thank the City of Montreal and participating boroughs for making this research possible, and the many students who carried out the data collection.

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Joshua Stipancic is a postdoctoral researcher in the Department of Decision Sciences at HEC Montréal and the Institute for Data Valorization (IVADO) in Montreal, Quebec. He completed his BaSc in Civil Engineering at the University of Waterloo in 2013 before obtaining his PhD in Civil Engineering at McGill University in 2018. His research interests include surrogate measures of safety, GPS and other mobile sensors, and innovative statistical models for transportation applications.

Paul St-Aubin is a post-doctoral fellow at the University of Waterloo and the senior product manager for Transoft Solutions (ITS) where he oversees the development of road safety monitoring software. He has over a decade of experience practicing road safety engineering and has been at the forefront of research and development of proactive road safety monitoring and diagnostics, and collision modeling and prediction technologies. He also has expertise in safe road design, traffic data collection technologies, computer vision, and ITS architecture. Paul St-Aubin has taught traffic engineering courses at McGill University and the University of Montreal.

Bismarck Navarro is a doctoral student in Transportation Engineering in the Department of Civil Engineering and Applied Mechanics at McGill University. He is a Civil Engineer with a master's in Highways and Transportation Engineering by the Michoacan University in Mexico. His research objective is to develop a multi-criteria framework to assess bicycle safety and traffic operations efficiency of all modes at intersections under different types of control. He has a particular interest on cyclist safety. He has worked for road safety projects for transportation agencies in Mexico and the city of Montreal.

Aurélie Labbe is a full professor at HEC Montréal in the Department of Decision Sciences and the recipient of the FRQ-IVADO research chair in data science. She received a PhD in Statistics from the University of Waterloo in 2005 and was hired as an associate professor in Université Laval's math and statistics department, where she taught until 2009. In 2009, she joined the faculty of Medicine at McGill University, where she was an associate professor until 2016. In 2016, Ms. Labbe joined the Department of Decision Sciences at HEC Montréal as an associate professor.

Nicolas Saunier has an engineering degree and a Doctorate (Ph.D.) in computer science from Telecom ParisTech (2005). He is a professor in the Civil, Geological and Mining Engineering Department of Polytechnique Montréal. His interests include intelligent transportation, road safety, and data science for transportation. He is a member of IVADO, the Interuniversity Research Centre on Enterprise Networks, Logistics and Transportation (CIRRELT), Interdisciplinary Research Centre on the Implementation of Sustainable Development (CIRODD), the Québec Research Network on Road Safety (RRSR) and the TRB committee on Safety Performance Analysis.

Luis Miranda-Moreno is an Associate Professor in the Department of Civil Engineering at McGill University. His research interests include the development of methods/tools for road safety, ITS, and emerging technologies for sustainable urban mobility. He obtained his PhD in Civil Engineering (transportation) from the University of Waterloo. He has completed projects for agencies including the Inter-American Development Bank, WRI Ross Center for Sustainable Cities, Transport Canada, Ministry of Transportation of Mexico, Quebec, and Ontario, and National Road Cooperative Research Program (NCHRP). Luis is an active member of the Interuniversity Center for Research in Business Networks, Logistics and Transportation (CIRRELT).

Journal of Safety Research 77 (2021) 268–276

Contents lists available at ScienceDirect

Journal of Safety Research

journal homepage: www.elsevier.com/locate/jsr

Evolution of working conditions under the impact of ICTs

Michel Héry *, Marc Malenfer, Stéphanie Devel, Catherine Levert

INRS (Institut national de recherche et de sécurité), France

ARTICLE INFO

Article history:
Received 29 June 2020
Received in revised form 12 January 2021
Accepted 12 March 2021
Available online 10 April 2021

Keywords:
Information and communication technologies
Health and safety
Automation
Robots – Work

ABSTRACT

Introduction: Information and communication technologies (ICTs) play a major role in the current evolution of work. They are both a great tool for emancipating human beings from the most tedious and most dangerous tasks and an effective vector for intensifying work. *Methods*: On the basis of three foresight exercises carried out in recent years and by describing concrete examples of work organizations, the authors highlight the main possible trends for the changes to come. *Conclusions*: They conclude on a few general principles that could allow the establishment of a win–win policy.

1. Introduction

1.1. Changes in work and concerns for employment: An endless story

The debate on the forthcoming changes in work and employment due to the development of automation began with the industrial era. It was also associated with sometimes violent reactions from workers, whose wages were dwindling or who had lost their jobs: Thompson (1963), in "history from below," gave many examples, from poor peasants fighting against the introduction of agricultural machinery to the Luddites. Nevertheless, work has changed profoundly since the beginning of the 19th century, working conditions have improved considerably (even if new risks have emerged) and, with the exception of major economic crises, the volume of employment has not declined, even if the forms of employment (job contracts, unionization, self-employment, etc.) have evolved radically.

However, this permanent concern about job cuts has remained through the ages worldwide. Recently, the debate has been rekindled with the publication of a series of contradictory studies. The most commented paper, and supposedly that which sparked the debate and gave it high level visibility, was published by Frey and Osborne (2013). Examining how vulnerable jobs are to computerization, they estimated that about 47% of total U.S. employment is at risk, with consequences for wages and educational attainment that show a strong negative relationship with the probability of computerization. Since that study, a large number of papers (academic or produced by (inter)governmental economic organizations and management consulting firms) have focused on this issue and provided contrasting answers, either confirming the hypotheses of Frey and Osborne (with often another temporality), or concluding that the figures should be revised downwards. A typical example of these studies that "review the numbers downwards" can be found in the OECD paper by Arntz, Gregory, and Zierahn (2016), in which the same method as that of Frey and Osborne is used, except that it takes into account the influence of automation on single-job tasks rather than on entire occupations. The authors concluded that a significant number of workers (not very different from the figures proposed by Frey and Osborne) will be impacted, but that only 9% of jobs in OECD countries are actually fully automatable.

This debate on automation and its consequences has obvious echoes in a parallel debate devoted to the future influence of artificial intelligence (AI) on work. In the same way, two schools of thought are in competition. The first considers that the productive world and society will adjust to this new resource and that it will create new jobs thanks to the extra wealth produced. On the other hand, researchers such as Brynjolfsson, Rock, and Syverson (2017) consider that we are at the dawn of a technical revolution likely to occur when the production system has adapted to the new possibilities of gains in productivity provided by AI. Following the same idea, Avent (2016) foretells a society in the 21st century where employment will be scarce and reserved for highly qualified workers.

Several ambitious foresight exercises devoted to the future of work increasingly impacted by the development of information and communication technologies (ICTs) have been carried out by

* Corresponding author.
E-mail addresses: michel.hery@inrs.fr (M. Héry), marc.malenfer@inrs.fr (M. Malenfer), stephanie.devel@inrs.fr (S. Devel), levertca@yahoo.fr (C. Levert).

https://doi.org/10.1016/j.jsr.2021.03.009

European and international organizations and researchers such as EU-OSHA (2018), Horton, Cameron, and Devaraj (2018), and the World Economic Forum (2016). Lee (2016) has coordinated a book in which different authors assess the possible influence of ICTs on tomorrow's work. Our exercise is carried out in the same framework but benefits from additional temporal hindsight, allowing us to illustrate a certain number of hypotheses with concrete examples.

These debates clearly stress the growing role of ICTs in the present (and probably future) evolution of production modes, in both industry and services. It is one of the most important elements in any strategic thinking dedicated to work.

1.2. The enormous potential of ICTs

ICTs have already demonstrated that they are a major asset for the emancipation of humankind, in particular at work. They have considerably improved the flow and management of information. They are potentially a powerful means for collecting and discussing all data relevant to an exhaustive analysis of work and its conditions, the preliminary step for the implementation of a good occupational risk policy. They allow comparing production standards and the practices of workers in the field, facilitating the formulation of more realistic (and therefore often more efficient) work procedures that better take into account the health and safety of workers.

ICTs also offer an interesting opportunity to get rid of tedious tasks in both industry and services. If an artificial intelligence (AI) application is given the task of collecting and managing information, then researchers, lawyers, or anyone in charge of compiling bibliographies, will be able to devote more time to more conceptual tasks.

The stakes are probably still higher in industry, where all automation (robotization) is dependent on the use of ICTs. The automation of production represents a means of eliminating dangerous tasks by keeping workers away from risky work situations where they could be injured or intoxicated. Automation can also be a tool for transferring harmful gestures from workers to robots: for example, gestures performed at a high pace and/or likely to damage joints. Robots in the form of cobots, often in the form of robotic and articulated arms, are designed to collaborate with operators: they assist them by performing tasks such as grasping, screwing, welding, sticking, sanding, etc. Operators can stay focused on actions requiring intelligence, adjustment, and dexterity.

Reducing the physical burden of certain tasks makes some jobs accessible to everyone. Inclusiveness can thus be improved for categories such as women, aging workers, and people with disabilities.

1.3. Automation contributes to the polarization of employment

Several studies have documented the rise in wage inequality in developed countries (Autor & Dorn, 2013). This phenomenon has been linked to two major trends since the 1970s:

– The outsourcing of part of production from developed countries to countries with lower wages,
– The automation described above.

Both phenomena have led to the destruction of jobs characterized by the performance of routine tasks for which wages were often situated in the middle of the salary range (because they were often unionized in medium and large companies). Some have also been transferred to contractors or to self-employed workers (mainly in the service sector), often corresponding to a decrease in wages and benefits.

Meanwhile, the growing complexification of production has led to the creation of jobs characterized by abstract, creative, and generally high-level tasks. These jobs are in the higher tail of wage distribution. Service occupations, which are in the lower tail of this distribution, have also been growing during the same period. This growth is in particular linked to a change in modes of consumption, often initiated by the development of ICTs: the rise of the gig economy, and especially of the apps linked to platforms, has created a substantial number of jobs (some of them being "second" jobs). Care services, in particular for aging people at home but also for wealthy consumers, have also grown. They are very difficult to automate because interpersonal communication and direct physical proximity are important components in the expertise developed by the workers who do these jobs, considered as low-skilled (and poorly paid).

This polarization of employment is likely to produce major effects from the perspective of Occupational Safety and Health (OSH). It could profoundly change the need for prevention and the way it is implemented. Since its foundation, the occupational risk prevention system in France has undergone major changes to adapt to the transformations and needs of the working world. These changes are not yet complete and there are still adaptations to be made that we present in a very schematic and simplified manner below:

– After World War II, the French OSH system was built to provide tools for prevention in the most accident-prone sectors (i.e. industry in general, and construction):
– After decades of de-industrialization, priority for action has shifted to prevention in the service sector, with risks similar to those of industry (such as falls on same level, road risks and musculoskeletal disorders [MSDs]), but also with certain disorders more frequent in services, such as psychosocial risks;
– Whatever the case, several hard to reach sectors remain, such as small and medium sized enterprises (SMEs) and, of course, micro-enterprises. Although specific tools have been designed to meet their requirements, the main issues are to find the right vectors to inform them and convince them of the need for prevention.

All these parameters were taken into account when performing the strategic foresight studies quoted previously.

1.4. Why perform a strategic foresight activity in INRS?

It is easy to understand how important it is for an institute such as INRS (French National Institute for Occupational Safety and Health) to foresee future changes in work techniques, work organization, and different forms of employment. In order to implement the most relevant occupational risk prevention studies, research programs must be designed with a long-term vision, along with the hiring and training of experts in evolving areas, etc. As a result, the institute regularly conducts strategic foresight studies for its Management Board (as a Social Security organization, INRS has equal representation on its Management Board: employers and employees on an equal footing). The aim of these studies is to provide information on changes in work and employment that contribute to the design of activity programs. Since 2014, three studies have been carried out:

– *The use of physical assistance robots (exoskeletons, cobots, surgical robots, etc.) in 2030*, designated by the acronym PAR in this article (INRS – Héry and Devel (Eds) 2015);
– *Modes and methods of production in France in 2040: what consequences will they have on occupational safety and health?* here called MMP (INRS – Héry and Levert (Eds) 2017);
– *Platformisation (uberization) 2027: Consequences on occupational safety and health*, called PFM in this paper (INRS - Malenfer and Héry (Eds) 2018).

The aim of the present paper is to present the main results of these studies, whose different themes were obviously interdependent. These studies were conceived and designed by occupational hygiene specialists with the purpose of identifying the drivers of changes in work and employment that are likely to have major importance in terms of occupational risks. In terms of foresight, a driver is a factor of change, affecting or shaping the future.

The design of foresight studies at INRS is governed by two principles:

– It is an opportunity to promote multidisciplinarity within the institute by associating different departments, each of them contributing their different academic specialties and different modes of intervention;
– Since INRS focuses only on occupational risk prevention, it is necessary to set up partnerships with various organizations involved in the subject, but which treat it from other perspectives; INRS's strategic foresight studies are always constructed jointly with universities, trade-unions, professional unions, enterprises, etc.

Whatever the subject and partnership, it is important to state that in all three cases, OSH remains the final goal.

2. Materials and method

2.1. Study design

For the three studies used for this article, the method has been structured in six steps:

a. A dedicated project team was formed whose function was to conduct the project from the beginning until the end. This team associated experts in strategic foresight studies and specialists in the subject considered. The latter came from the different partners of the project. The number of members of the project team ranged from 12 to 17, according to the studies.
b. Basically, the first task of the project team was to identify the main key drivers of the subject. This goal was achieved by pooling the knowledge of the different members of the project team on the subject considered by carrying out interviews (individual or collective) with specialists not directly involved in the works of the project team. The multidisciplinary skills of the actors, both in the project team and among the interviewees, made this step more fruitful. Some of our partners in the project team were specialists in the fields concerned, often having already produced foresight work on the subject. For PAR and PFM, about a dozen experts were thus consulted, but in MMP, the most ambitious work, the number reached 40 people. Regarding the latter work, great emphasis was placed on the retrospective evolution of the subject considered, the interviews mainly being directed on the topic: "What have been the major evolutions in production modes and methods during the last twenty-five years?"
c. Two different methods, according to the studies, were used in the following step of documenting the different key drivers and of determining their future trends and ruptures, including swans[1] of different colors (black, grey, dirty-white, red, etc.) (Masramli, 2017):

[1] In prospective, the events that can possibly occur are designated under the name of swans to which one allots various colors according to the plausibility of their occurrence.

i. For PAR and PFM, the documentation of each key driver was written by one member of the project group. The document was then discussed in a plenary session, with particular attention given to the hypotheses of future evolutions, including potential ruptures.
ii. The context was substantially different for MMP and the method had to be adapted. Due to the ambition of the subject ("What will be produced in France in 2040 and how?"), the number of key drivers identified (several dozen) was too high to allow the same treatment as for PAR and PFM. Consequently, the key drivers were pooled into six thematic groups, each one focused on a topic of main interest for the evolution of the world of manufacturing (see Table 1 for the six specific topics). For each group, a dedicated one-day workshop was organized whose aim was to determine the possible trends for the topic for the next 25 years. The participants (ranging from 10 to 16 according to the sessions, for a total of 79 people) came from very diverse horizons: health and safety specialists, economists, various actors from the business world (from production managers to trade unionists), lawyers, lawmakers, human resources specialists, a novelist, and so forth. One week before each session, each participant was provided with a document of several pages, presenting the topic and the four questions the group would be asked to discuss.

These steps 2 and 3 correspond to a prospective reflection on what NIOSH in a recent article (Tamers, Streit, & Pana-Cryan, 2020) refers to as changes in the workplace, work and workforce (such as demographics, skills, contractual relationships, work organization, work automation, digitalization, robotics, artificial intelligence, etc.). For both NIOSH and INRS, this is not the central object of the prospective study but an indispensable step in defining the possible contexts from which it is possible to conduct reflection on the evolution of occupational risks and their prevention. In this paper, the method of this reflection on risks is described in step 5.

d. On the basis of this material, overall scenarios were developed for PAR and PFM, highlighting in particular the combinations of hypotheses on the drivers most likely to have an effect, producing a significant change in working conditions with impacts on health and safety. Within these scenarios, stress was placed on pathways with profound transformations through gradual evolutions or possible ruptures. Given the multiplicity of the parameters that should have been considered when writing the overall scenarios, this option was not chosen for MMP for reasons of readability. The outputs of this study were then centered mainly on the pathways mentioned above, enriched through "incarnations" describing the modalities of these evolutions in the world of production (industry, services, agriculture, etc.) and their possible consequences on working conditions.
e. As Spaniol and Rowland (2019) have pointed out, the scenario is only a tool for presenting the evolution of a certain number of parameters in perspective. The main objective of strategic foresight for INRS is to help the Management Board to adjust the policy it decides for the institute. Consequently, the data considered in the scenarios and the major pathways were then translated into terms of risks at work in all their complexity, that is to say taking into account the overall environment in which they might be assumed to happen. To do this, and for each of the three exercises, a second group of experts (composed of 10–12 people depending on the exercise) was then set up, composed solely of experts in occupational risk prevention. Its work was, on the basis of the context and the technical and organizational changes

Table 1
Themes of the workshops of the foresight exercise Modes and methods of production in France in 2040 (MMP).

1. Global value chains or local self-production and exchange?
2. Work or jobs? What do we need to be happy?
3. All nomadic entrepreneurs?
4. The zero risk society?
5. In a robotised world, what place for human work?
6. Prescribed or autonomous work? Fulfilling or alienating innovation?

envisaged by the experts of the first group in their construction of scenarios, to diagnose the possible corresponding changes in occupational risks. All occupational hazards (organizational, physical, mechanical, chemical, biological, etc.) are considered.

This overall vision of context is necessary to develop realistic prevention solutions.

f. A results communication phase is systematically organized after each exercise. It aims to reach specialists in occupational risk prevention, but also other functions in the companies: work organization, manufacturing methods, human resources, etc. Professional organizations and workers' unions are also targets. More generally, the aim is also to stimulate wider debate in the world of work and in society.

2.2. Exploitation of the results of these three strategic foresight studies

INRS's foresight activity is accompanied by a bibliographic monitoring activity. In each of the three exercises, key drivers of change have been identified by the experts and a literature watch has been launched for each of them. The target of this monitoring is not the academic literature but the concrete evolutions in the field of production, whether they confirm or contradict the trends announced by these key drivers of change: grey literature, professional and general press, etc. The aim of this monitoring is to identify the key drivers of change in the field. In the same way, this monitoring allows us to orient the choice of new foresight exercises.

On the basis of this combination of foresight and monitoring activities, five key drivers were selected by the authors of the article and are presented in the Results section. This choice was dictated by the radical nature of the changes they can produce from the standpoint of occupational risk prevention. In other words, the major changes they can bring about, identified by the experts of the first working group (specialists in the field studied) and those of the second group (specialists in occupational risk prevention) and confirmed by the results of the bibliographic monitoring. Other key drivers could have been chosen if other effect criteria had been chosen, such as economic weight or technical evolutions in production methods.

This combination of strategic foresight and literature monitoring actions is summarized in Fig. 1 It led to the five key drivers presented in the Results section and the four main issues identified in the Discussion section.

3. Results – five key drivers for working conditions tomorrow

3.1. Exoskeletons

Exoskeletons have been widely considered in PAR. With advances in sensors, actuators and power storage, associated in particular with the possibility of miniaturization, this equipment is likely to encounter massive progress in the coming years. The current "passive" models in which physical constraints are roughly transferred from a part of the body to another one should evolve toward "active" forms where constraints faced by workers will be neutralized by applying opposing forces. Some researchers imagine that these new exoskeletons could be integrated into workwear.

This new type of exoskeleton would be very useful for aging workers, providing them with useful resources to cope with the productivity required, in acceptable working conditions. Furthermore, some firms are already considering the possibility of equipping younger workers in order to avoid the occurrence of MSDs. Given the cost of investment, an increase in work pace could also be considered by firms.

There is a major stake in such an increase in work pace. In the context of fierce competition, this increase could lead to a surge in cases of MSD in the same way as can be seen nowadays, including for equipped workers whose ends of career might be quite similar to those of the previous generation of workers. There are indications that this could constitute a major risk in the years to come. An official of the *Company A*, which has equipped 15 car factories with exoskeletons, said in an interview: "*At Company A, our mission is to augment human capability with wearable technology and robotics that help people rethink current physical limitations and achieve the remarkable*" (Papadopoulos, 2018).

The goal of such equipment would be different from its initial purpose, which was to make workers' tasks less painful. The hypothesis of a surge in psychosocial risks (PSRs) should therefore be considered: what will be the feelings of a worker equipped with an exoskeleton, whose movements are substantially guided and restricted, if they think they are being considered as an instrument?

3.2. Industry: humans in the service of the robot

The fact that automation might become a major parameter in industrial production has already been discussed here. Likewise, the relationship between humans, their work and robots was stressed as a major factor for the health and safety of workers. Based on a recent example, the question of workers' subordination to the robot merits consideration.

Unlike other car manufacturers that design their assembly lines for workers helped by automats, Company B has chosen to completely automate the production of its latest car (Boudette, 2018). No worker was supposed to intervene on the lines. The performance of some robots has been very spectacular: compared to other Company B factories, the use of certain machines has simplified a 14-step process to just five, while at the same time cutting 13 jobs. But overall, unfortunately, things did not happen the way they were supposed to: many production incidents occurred that reduced production to almost nothing. Finally, workers were readmitted on the two lines to compensate for machine failures and a third one was organized in emergency on the car park of the plant, the operation of which combines both workers and robots. However, the two first lines were not redesigned to take into account the new workforce: humans were more or less supposed to replace the robots with only minor technical adjustments to the environment.

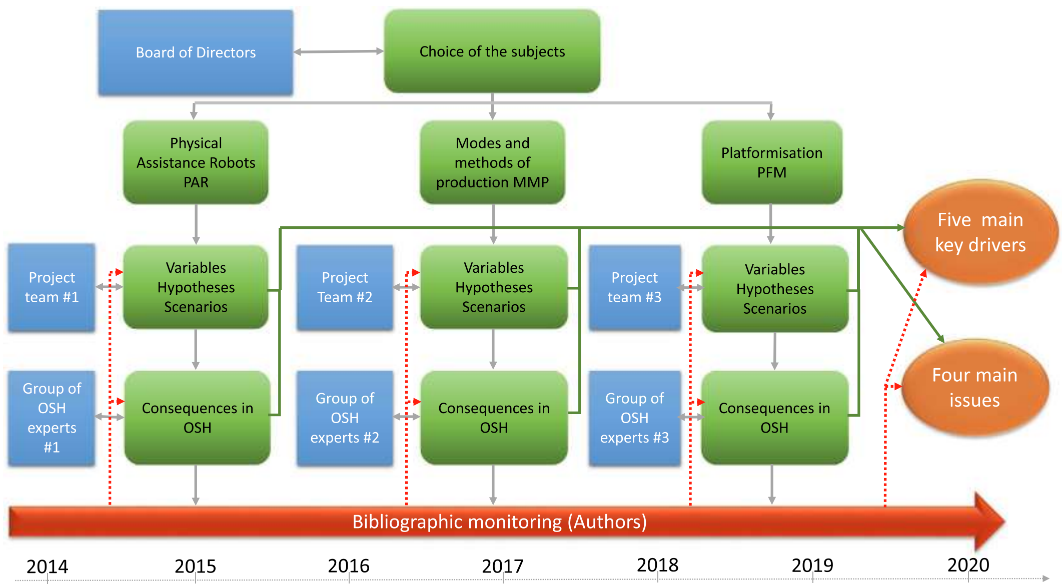

Fig. 1. Synthetic description of the working method.

Harmful consequences have resulted: since humans are not built in exactly the same way as robots, the rate of occupational and professional illnesses has soared (Evans & Perry, 2018). A heavy level of conflict with the workforce and the official services of the state of California dedicated to the implementation of health and safety regulations has resulted from these degraded working conditions. The creation of a clinic on the factory site, the aim of which was not only to treat the injured but also to avoid the automatic declaration of an occupational accident when people are driven to hospital, did not contribute to producing a better climate with the Labor administration (Evans, 2018).

Company B CEO has since acknowledged that human capabilities had been underestimated (Musk, 2018). In any case, one may doubt his desire to maintain the human being as a reference at the center of production systems (as stipulated by European regulations) if, in practice, he considers that work must be defined depending on the capacities of robots. The suspicion that he could be led to consider the workforce as ancillary staff for the robot is therefore legitimate.

3.3. Services: humans in the service of the algorithm

The concept of crowdsourcing covers a wide variety of operating modes, corresponding to very diverse objectives. For example, *Amazon Mechanical Turk*'s activity is part of a commercial rationale, often offering poor pay for tedious microtasks. At the other end of the spectrum, there are projects like Wikipedia (creator of common goods) and alliances of researchers to carry out a common project. Other commercial forms intended for highly skilled workers are currently developing: flash organizations. Their main characteristic is to organize the crowdsourcing of high-level human resources for carrying out complex and open-ended goals, involving dozens or even hundreds of workers.

Company C is an algorithm dedicated to flash organizing, the aim of which is to bring together at any moment the best skills for working in project mode with an optimized capacity of reaction (Valentine, Retelny, & To, 2017). A simplified description of the operating mode of this algorithm should be enough to show how deeply the working conditions of the different actors can be transformed:

- The project manager explains the context and the objectives and determines the skills necessary to carry out the work, they determine the first tasks to be performed;
- From this first analysis, Company C matches the competences needed with profiles on freelancing platforms (such as *Upwork*) and ranks these profiles in order of suitability for the requested task;
- The first person on the list is mailed a description of the task, the time allowed (one to five hours) to perform it and the remuneration offered; they have 10 minutes to accept or refuse; if they refuse, the proposal is forwarded to the next person on the list;
- When the task is performed, the result is sent to the manager; each contributor is urged to comment on the data provided to them, the working method suggested to them, and the results they have obtained;
- From these first results, the manager orders new tasks according to the same method (very likely to different freelancers) and the iteration goes on until the project is completed.

Three different projects have been performed with this algorithm that allows reconfiguring work organization with considerable responsiveness. The median time to complete a task was 3.05 h. The median hiring time for a worker was from 12 to 15 min, depending on the project. This recruitment was worldwide, regardless of time zones. The quality of the final products was judged to be good according to a jury of specialists.

Recently, the *Publicis Groupe* introduced its own internal AI platform called *Company D*. The aim is to make the collaboration of 80,000 employees in 130 countries easier. The app comes in the form of a mobile application and a desktop version. According to the Publicis Groupe's CEO, it is all about "*breaking the barriers between talent and opportunity*." When the platform is available for all the company's staff, 80,000 people will be able to share their expertise and knowledge in a team dedicated to a project, fighting a tendency to work in silos. The staff will also have access to databanks especially designed for their work. It will also be possible to include contractors in the system (Publicis Groupe (2017) (2017), 2017).

These two tools have similarities, but concerning work conditions, there are also significant differences:

– In search of maximal agility, they both tend to reduce the separation between private and professional life: the extreme is reached by *Company C* which imposes immediate answers and work whatever the day and time, but *Company D* can involve online meetings at any moment of the day; the pace of work can also be significantly increased.
– Most contributions to *Company C* are one shot, that is to say that the contractor only intervenes once without having an overall vision of the project to which they contribute, while with *Company D* the aim is to build a specific team for the whole project with a consistent bibliographic background provided by the tool. For most people, the second configuration is more favorable for giving meaning to work, which is often a determining factor to ensure good balance at work.
– During difficult moments, social support inside the specific team set up for the project (or the local team) is possible for *Company D* but unlikely for *Company C*.

Finally, until now, benefits (sick and maternity leaves, pension insurance, etc.) have been provided by *Publicis Groupe*, which is not the case for *Company C*. Given the very short delay before a task is accepted in *Company C*, it can be inferred that the workers involved are satisfied with the work they do (non-taxable). Most of the people who work through *Company C* are currently likely to have another job, probably with benefits such as those described previously, but if their income comes only from *Company C*, it is possible to imagine that their satisfaction might decrease if they have to pay for their social insurance out of their own pocket. The *Publicis Groupe* behaves like an employer that assumes their social responsibilities towards their employees whereas *Company C* remains within the rationale of a commercial contract with subcontractors.

3.4. The stealth company and its network of independent subcontractors

ICTs and outsourcing are perfect ingredients for executing a recipe that turns a company into a brand, thus avoiding many constraints vis-à-vis the State, contracting firms and workers. *Company E* is a fast fashion company that has moved from brick-and-mortar status to an online pure player model (Kitroeff, 2019). Its only production tool is currently an Instagram account (with 17 million followers) on which the company regularly posts pictures of influencers wearing its clothes. The design, manufacture, and sale of its clothing are subcontracted. More than a thousand new styles are produced every week and the delay between a design concept and the first sample must be shorter than one day. With so many models produced to respond to an impulse buying logic, design and manufacturing must be geographically close to the target clientele in order to respond to sudden demand. That is why the vast majority of clothing is made in the United States, especially in California.

Given the very low prices paid by *Company E* to its providers, this system has given birth to a sweatshop network: dozens of small businesses, whose life expectancy does not exceed several weeks. The investigations of the Labor Department have shown a succession of creations and closures after a few weeks of small workshops which move their sewing equipment to another building where they will resume the same activity under another name. This duration of just a few weeks is linked to the minimum time for the Administration to identify a new business. These subcontractors never have any contact with *Company E*, only with go-betweens. Their extreme agility of course goes hand in hand with illegal low wages sometimes paid off-the-books, with unpaid overtime, excessive shift durations, and poor working conditions. Often undocumented, the workers have no way of claiming their due.

This example is caricatural and describes practices bordering on illegality. It is, however, illustrative of the possibilities offered today by ICTs for very rapidly modifying the organization of production to the point that regulations cannot be adapted quickly enough. It is still necessary for states to have the will to do so, which is not always the case: they are sometimes more focused on the number of jobs than on their quality.

3.5. Independent workers and prevention of occupational risks

When an activity is outsourced to a freelancer, the responsibility of OSH no longer resides with the activity provider: the freelancer is supposed to implement measures to ensure their own safety. That is what has happened in France with the arrival of free-floating electric scooter rental. The collection of scooters at the end of the day (from 6:00 pm), their charging and their redeployment in the city at dawn (before 7:00 am) was carried out by contractors called "juicers." Collection and drop-off were guided by global positioning functionalities on smartphone applications.

An analysis of the work, performed from the perspective of OSH, highlights some points of particular concern (Malenfer, 2019):

– operators compete against each other, therefore, there are situations of conflict (sometimes physical violence) to recover the scooters tracked by GPS;
– remuneration varies based on the location of the scooter; if it has been left in a place hard to access, or closed, remuneration is higher; this could encourage juicers to break certain rules, for example, to enter the courtyards of private buildings to pick up scooters;
– work is done at night, involves a lot of driving and handling (each scooter weighs between 12 and 20 kg) with a vehicle that is not necessarily adapted to this activity;
– a juicer can take up to 30 scooters to their home to charge them simultaneously, which obviously poses the question of compatibility with the electrical installation and consequences in terms of a possible overload, which can cause a fire in a private room full of batteries.

In summary, juicers were supposed to organize the prevention of their occupational risks themselves in a context where they had no influence on the organization of their work (entirely dependent on the platform) or on the equipment (scooters and battery chargers). Working properly would mean having a vehicle equipped to transport the scooters safely and a place to charge the batteries, but their income was too low for such investments and they had no visibility on the future of their activity.

In the end, this new activity proved to be quite disruptive to the lives of the city's inhabitants and was subject to fairly strict regulation. In this context, the working conditions of the juicers attracted attention and the companies returned to a more traditional subcontracting model.

4. Discussion: A challenge for tomorrow: humanizing ICTs

On the basis of the different examples described above, it seems obvious that the priority is to make the most of the possibilities offered by ICTs while channeling drifts harmful to workers. In the following sections, the main obstacles to overcome will be detailed more precisely on the basis of the conclusions of the OSH experts involved in the three exercises (PAR, MMP, PFM). Four main issues have been identified.

4.1. Agility as a cardinal virtue

The whole company, from CEO to ordinary workers is summoned to become agile. It must be able to adjust to any change in the demands of its clients: any request (real or virtual) of the consumer should be answered positively. The characteristic at the origin of the companies resulting from the gig economy, this mode of operation is increasingly winning over "traditional" companies thanks to reciprocal takeovers, partnerships and fashion effects.

It can have a stimulus effect for some workers over a varying length of time. But for the experts participating in MMP, this agility appears to be one of the major factors contributing to the expansion of social inequalities. It contributes to widening the gap between workers with poor qualifications and with limited access to ICTs for their work, and high skilled workers for whom ICTs are an efficient working tool. The career of the first are increasingly limited by their shortcomings in the use of these tools, the mastery of which would allow them to adapt to the constraints of ever faster changes in work. Thus, these workers have little to attract employers whose requirements they cannot immediately answer. Over time, they become more and more unemployable. On the other hand, highly skilled workers fully benefit from the possibilities made available by technologies: by eliminating tedious tasks, they can focus on those that require not only a high level of technical knowledge but also the capacity to innovate. Moreover, low-skilled workers are increasingly brought into economic competition with automated processes (except, at present, in the domain of personal services), whereas highly-skilled workers can enhance their competences with the help of ICTs (or AI).

More specifically, work by the ILO and Eurofound has highlighted the health effects of this agility, particularly in the context of distance working (Messenger, Vargas Llave, & Gschwind, 2017; Moore, 2018; Vargas-Llave & Weber, 2020).

4.2. Experimentation facilitated by ICTs

This agility, facilitated by ICTs and characteristic of the gig-economy, has as a corollary: very frequent recourse to experimentation. These innovative companies take a very pragmatic approach to problems and accept the risk of failure. They are confident in their ability to bounce back. The example of the Company B factory's difficult beginnings described above is a good example of this philosophy applied on an industrial scale. It is quite similar to the approach taken by video game designers. The first online version of a video game is never perfectly finished. It contains a certain number of bugs, malfunctions, and areas for improvement. It is the collaboration with the first users that will improve the product through several successive versions. In the same way, the designers of the Company B factory carried out experiments at the start of the operation of the assembly line (such as robots operating at a rate higher than the set point, and the version of work equipment), with the results we know.

Experts participating in MMP and PFM identified several cases (mainly in services, but also in industry) where this logic of experimentation was used. One of their main fears was to see this type of practice increase in the coming years in large companies, but also especially among subcontractors: the workforce thus loses its special status and becomes an adjustment variable like the others.

4.3. Increase in prescription and standardization

The trend towards an increase in prescription at work has been growing throughout the 20th century and at the beginning of the 21st century for many reasons: scientific production management (Taylorism and all its epigones), quality management policies, outsourcing of production on a global scale, the increased importance of legal issues in corporate life, and so forth. For a long time, this trend had been counterbalanced by the remnants of a certain power held by workers: the knowledge acquired and transmitted by long immersion in the entire work ecosystem, the quality of the professional gesture, solidarity inside work teams, and so forth. Many managers were also aware of the potential for innovation contained in workers' knowledge. This knowledge is based on the acquisition of techniques, on the way they were taught, and on their concrete appropriation by workers. This appropriation is the result of successive and complex iterative processes including errors, artifices, the will to improve a technique or a tool concretely, the capacity of workers to innovate, the transmission of the heritage of labor, which is also a cultural and social heritage, etc.

Experts participating in MMP hypothesized that this balance between prescribed work and actual work might be disrupted by the ever-increasing introduction of ICTs in production processes, at the expense of workers' autonomy. From the perspective of strategic foresight, in a context where this influence of ICTs is assumed to continue growing, one may justifiably wonder whether this will not also be at the expense of the capacity to create and innovate. Some studies have, for example, shown that the permanent use of an algorithmic crutch interferes with learning ability (Carr, 2014). Not only would doing one's work become less rewarding and interesting, but an entire segment of the ability to innovate might also vanish or at least weaken. Will the use of AI be able to compensate for this loss? Nobody can foresee this now, of course, but a lower capability to understand and control the tasks that are performed does not help to build health at work. This contributes to the dehumanization of work activity.

This increase in prescription goes with the individualization of careers. Experts participating in MMP have identified this individualization as an important driver (or at least as a significant marker) of the evolution of work organizations during the last 30 years. The increasing use of quality management systems and proceedings, the new possibilities of monitoring workers' activity with processors, sensors, software and connectivity through the Internet of things, and sometimes the desire of employers to bypass trade-unions, are among the factors that have driven the relationship between firms and workers toward a more individualized model.

4.4. ICTs as a tool for developing OSH in hard to reach sectors

The development of platforms can be useful in activities where transmitting risk prevention messages is difficult to implement. Experts in PFM have identified such situations like finishing works in building construction and mostly renovation (i.e., activities such as plumbing, electricity, painting). These jobs are often performed by small craft enterprises that are difficult to reach by the usual means used to encourage firms to improve their occupational safety and health practices. Platforms might be interesting vectors:

- The logic of the approach implies the standardization of the services provided and particular importance given to image: the finishing works industry often suffers from insufficient consideration given to occupational health issues (lack of identification of asbestos, destruction of materials rather than deconstruction that can expose the worker and pollute the private environment, etc.); platforms could be used to introduce best practices;
- This homogenization of professional practices could also lead to the development of new tools (e.g., drills systematically equipped with suction devices) whose use is currently too rare, and which are better designed, cheaper due to wider diffusion, and better used by better trained staff.

5. Conclusion: The need for a new robotics deal

In February 2017, the European Parliament (EP) issued a resolution on "*Civil Law Rules on Robotics*" (Parliament, 2017). Among the several principles it contains, it is written that "(the EP) *stresses that the development of robot technology should focus on complementing human capabilities and not on replacing them.*" The same statements were made for other ICTs derived technology, such as AI, etc. The principle of transparency is also highlighted, particularly through the permanent possibility of identifying "*the rationale behind any decision taken with the aid of AI that can have a substantive impact on one or more persons' lives.*"

This point of view is not exactly shared by several of the largest tech companies (Markoff, 2016). They agree on the fact that the aim of research on AI is to benefit people, but they are very reluctant regarding the concept of preemptive legislation. In a study coordinated by Stanford University [ref], the authors underscored the difficulty of regulating "something" (AI) that has no precise definition and whose risks and considerations are completely different in the different domains in which it is implemented. It would be detrimental for the development of these technologies: certain presently poorly documented fields might be excluded from the research authorized, to the detriment of the future well-being of humanity. Moreover, they consider that governmental bodies do not have sufficient knowledge to make pertinent proposals regarding regulation. The leading tech companies are however interested in exchanges with public authorities and can provide them with elements of reflection.

INRS's foresight work is obviously used to feed the reflections of its Board of Directors and its teams in the elaboration of activity programs in the years to come. But it is also widely disseminated to the various players in the field of occupational risk prevention in France: social security engineers responsible for occupational risks, labor inspectors, occupational physicians, and social partners. These results fuel a debate at different levels (decision-makers, professional branches, workers' unions, etc.): this debate is also an opportunity for the INRS Prospective team to identify new issues, to learn about exemplary achievements, etc.

However, this debate among the actors involved in occupational risk prevention is probably not enough. The recent Covid-19 crisis has shown the growing importance of ICTs in everyday life and in particular in the workplace. Elements from subsequent work on the circular economy have also not been used for the synthesis presented in this article, even though the transition from a linear to a circular economy is likely to significantly modify the context in which ICTs and more generally new technologies will be used (Héry & Malenfer, 2020). Anyway, given the different elements presented in this article, the authors consider it necessary to organize a citizens' debate on the use of ICTs in the world of work. Society must be able to assess its consequences on workers, or even set limits that must not be exceeded. For example, setting up joint committees (employers and employees) at different levels to lay down rules and check their application over time could be considered.

Funding

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

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Michel Héry is an engineer and works in the Foresight department of INRS.

Marc Malenfer is a communication specialist and works in the Foresight department of INRS.

Stéphanie Devel is a documentalist and works in the Training Department of INRS.

Catherine Levert is a political scientist, now retired after working in the Foresight department of INRS.

Journal of Safety Research 77 (2021) 296–310

Contents lists available at ScienceDirect

Journal of Safety Research

journal homepage: www.elsevier.com/locate/jsr

Identifying management practices that drive production-line workers' engagement through qualitative analysis

Franziska Homann [a,*], Caroline Limbert [a], Simon Matthews [b], Darren Castaldi [c], Peter Sykes [a]

[a] Cardiff Metropolitan University, Western Ave, Cardiff CF5 2YB, UK
[b] Pembrokeshire Safety Service, 19 St Peters Rd, Johnston, Haverfordwest SA62 3PP, UK
[c] Ford Bridgend Engine Plant, Waterton Industrial Estate, Cowbridge Rd, Bridgend CF31 3BF, UK

A R T I C L E I N F O

Article history:
Received 19 June 2020
Received in revised form 20 October 2020
Accepted 8 February 2021
Available online 27 February 2021

Keywords:
Work engagement
Safety
Promoting and hindering factors
Manufacturing
Management skills
Qualitative research

A B S T R A C T

Introduction: Engagement research - most often defined by a worker's psychological state of vigor, dedication, and absorption - pays little attention to production-line workers. This study therefore explores factors that drive workers' engagement with health and safety (H&S) in a production-line context as well as their perception of managerial influence Furthermore, the study adds to the body of research by exploring H&S engagement concepts through the use of qualitative research methods. *Method:* 38 semi-structured interviews were conducted and analyzed through template analysis to identify themes that promote and hinder engagement. *Results:* The main engagement drivers were found to be: (a) the displayed safety focus of the company in organizational and social aspects; (b) the quality of the communication approach with respect to quality, consistency and direction; and (c) the environment encompassing the relationship between workers and supervisors and peers as well as the psychological environment. Notably, a trusting relationship between supervisors and workers appeared to be the most influential driver in determining engaged H&S behavior. *Discussion and impact in industry:* The study highlights factors that could be adapted to improve engagement and consequently enhance H&S approaches. *Originality:* The study reported in this paper offers a unique insight into individual production workers' perceived drivers of H&S engagement using Qualitative Analysis. *Practical applications:* The study identified the important role that supervisors play in workers' H&S engagement levels and what skills they need to employ to enhance workers' engagement in general and in the context of H&S behavior and performance. Furthermore, the importance of psychological and sociological factors in safety approaches are highlighted and were found to be key for creating safer workplaces.

1. Introduction

While many managers are knowledgeable about the technicalities of engaging workers to enhance performance and behavior, proactive action to create a positive, trusting environment often falls short. Competing work duties, productivity demands and a lack of consistent communication for example can influence and impact worker's H&S engagement (Conchie, Moon, & Duncan, 2013). This study highlights the consequences of such factors and provides recommendations designed to enhance the workers' engagement with H&S in a production context.

* Corresponding author.
E-mail address: frhomann@cardiffmet.ac.uk (F. Homann).

https://doi.org/10.1016/j.jsr.2021.02.006

2. Literature background

Workers' health and safety (H&S) is of paramount importance to companies, yet often, even in environments with a well-implemented safety management system (SMS), the occurrence of incidents and accidents plateaus, while low-impact incidents still occur regularly and the occasional surprising high-impact accidents seem to be unrelated to the risks monitored (Townsend, 2016). This phenomenon has been described by Dekker and Pitzer (2015), who hypothesized that some safety practices and structures associated with control and compliance may be counterproductive due to reliance on those systems and the restriction of workers taking responsibility and engaging in flexible problem-solving. Despite the United Kingdom (UK) having one of the lowest rates of work-related accidents in Europe, there were still 147 fatalities in 2017/18, of which 26 were in the manufacturing industry with 12,234 manufacturing worker injuries (Health and Safety

Executive (HSE), 2018). Hence, it begs the question, when all necessary structures and systems are in place, how can an environment which actively engages workers with H&S be created?

While the clear outputs of engagement are hard to measure, it has been shown that safety behavior and compliance are positive outcomes of increased engagement (Hansez & Chmiel, 2010; Huang et al., 2016; Wachter & Yorio, 2014).

Most broadly, 'engagement' is defined as a positive psychological state in its own right and is further defined by a worker's "positive, fulfilling, work-related state of mind that is characterized by vigor, dedication, and absorption" (p.74), hence showing (among others) psychological presence and extra-role-behavior (i.e., 'being fully there' and 'going the extra mile;' Schaufeli et al., 2002). However, since the first mention of engagement by Kahn (1990), the term has not been defined specifically; as reported by Macleod and Clarke (2009), there are over 50 different definitions of engagement in use and it is often falsely used synonymously with 'participation' and 'involvement.' Further, Kahn (1990, 1992) found in his research that work engagement (WE) is influenced by three elements: psychological meaningfulness, psychological safety, and psychological availability. Psychological meaningfulness refers to an individual's perceived meaning in one's work and the feeling that there is a return on the investment of the self into the work (Crawford, Rich, Buckman, & Bergeron, 2014). Psychological safety on the other hand involves not fearing negative consequences when immersing and investing one's self into the work (Kahn, 1990). Lastly, psychological availability is said to occur when an individual obtains the personal cognitive, emotional, and physical resources, skills, and confidence from inside, as well as outside the organizational context, to engage and invest in its performance. This makes it more likely that an individual will invest such resources in their performance (Crawford et al., 2014; Kahn, 1990). Although a wide body of research has explored the individual promoters of work engagement to date (such as feedback, autonomy and leader-member exchange; Salanova & Schaufeli, 2008; Vera, Salanova, & Lorente, 2012; Xanthopoulou, Bakker, Demerouti, & Schaufeli, 2009), most promoting factors or precursors fit Kahn's (1990) initial engagement framework based on meaningfulness, safety and availability (Crawford et al., 2014).

3. Engagement in the context of H&S

With respect to H&S, studies show that engaged workers have fewer accidents at work and lower reports of ill-health (Hansez & Chmiel, 2010; Harter, Schmidt, & Hayes, 2002; Nahrgang, Morgeson, & Hofmann, 2011; Wachter & Yorio, 2014). Furthermore, perceived management commitment to safety mediates the relationship between resources and task-related safety noncompliance through work engagement (Hansez & Chmiel, 2010; Laurent, Chmiel, & Hansez, 2018). Laurent and colleagues (2018) proposed that when employees feel cared for by their organization, reciprocal behaviors, such as considering and acting on discretionary safety actions (i.e., extra-role behaviors) are developed (thought to be based on the social exchange theory [SET]; Cropanzano & Mitchell, 2005). Given that most prior research on engagement in the context of safety was conducted in a hospital setting relating to patient safety, there is a gap concerning H&S engagement research in the manufacturing industry, yet they can learn from those results in order to improve their workers' levels of H&S engagement.

Safety culture perceptions have been found to be closely linked with workers' engagement (Nahrgang et al., 2011). Nahrgang et al. (2011) showed that in order to overcome the safety performance plateau in a company, WE is beneficial for workers as well as the company because workers must be motivated to 'go the extra mile' when it comes to their own and their peers' H&S. This is recognized within the concept of Safety-II by Hollnagel (2014) and Hollnagel, Wears, and Braithwaite (2015), which views humans as clever, proactive, flexible resources in safety management, who show their resilience through their performance variability and are considered the reason that things 'go right." Nevertheless, as research around that topic is more focused on processual and system-based factors rather than the psychological implications, it does indicate that H&S engaged workers are a crucial, cooperating part of a Safety-II approach.

In summary, WE research shows potential for the H&S context. The results supporting improved H&S as an output of engagement suggest a need for organizations to implement engagement improvement measures in order to increase H&S (engagement) performance.

In consideration of the vast variety of terms and definitions for WE, and in taking into account the definition presented by Christian, Garza, and Slaughter (2011) in particular, with respect to this research study, the term 'H&S engagement' is defined by the authors as follows:

> *"H&S engagement is defined as a fluid psychological experience influenced by personal and environmental/job resources that result in increased inter and extra-role behavior related to H&S within the context of job performance and contextual performance."*

While the literature indicates the impact of general behavioral characteristics on engagement in a broad context, this study aims to explore H&S engagement as a phenomenon in a production line (PL) context, focusing on evidential behavioral aspects. Hence, the drivers and barriers of workers' engagement and the reasons for workers' compliant or non-compliant behavior with H&S will be identified and analyzed from interviews with employees and their managers within a car manufacturing plant. To date, evidence has largely been drawn from quantitative research, but this novel qualitative study aimed to give workers a direct voice to communicate their perceptions of proactivity, compliance and engagement in the context of H&S leading to practical guidance for organizations.

4. Methods

4.1. Business characteristics

All participants in this research were employees at a UK automotive production plant of a global organization. The UK plant began production of petrol engines in 1980 and during the period of study was operating three production lines (PL) with approximately 1,700 employees on site; 1,350 of which were working in shop floor-close jobs (e.g., assembly and machining lines). The employees were represented by a strong trade union and the plant had a comprehensive Safety Management System (SMS). While the documented safety reports indicated occasional severe safety events, observations by managers and internal H&S professionals also indicated a high level of non-compliant worker behavior (e.g., minor incidents and accidents as well as a generally negative perceptions of H&S topics.)

The plant used both corporate and legislative (e.g., HSE) documents and guidance. In-house safety standards and policies detail how the plant seeks to manage H&S in respect of standards, reporting, responsibilities, and practices. H&S is documented as the number one company value and forms the core principles of an extensive body of safety communication measures (including regular H&S management meetings with H&S professionals, plant department heads, and union representatives).

During the time of the research, the plant faced major economic difficulties that led to forecasted redundancies. Thus, many workers feared for their jobs and the plant's future, which may have influenced responses at times.

With respect to the scope of the analysis, it should be noted that one of the three PL was in the process of being established and particular attention by line managers was paid to empowering and involving workers in the process and decisions. Also, workers at this PL felt that their jobs were secure. To distinguish between these two distinct management styles, workers at the new PL will be referred to as 'WB' while workers at the other two PL will be referred to as 'WA' (the same applies to references to Managers, i.e., 'MA,' 'MB').

4.2. Sampling and participants

Data were gathered over three months between November 2018 and January 2019. The purposive sample for interview consisted entirely of employees directly involved with H&S on the shopfloor (e.g., shopfloor employees, managers of production areas, H&S professionals). Cell sampling was then applied according to hierarchy level, department, and role to gather perceptions from different points of view at the plant as it was assumed that different departments and staff levels may have differing interpretations of H&S behavior.

With regards to sample size, a combined approach was used with the number of interviews determined by saturation of themes, with at least one individual recruited per relevant research area. In total, 38 interviews were completed involving 43 participants. Due to circumstances beyond the researcher's control, two group interviews were necessary; one group consisting of three participants and the other a group of four.

Participants consisted of managers (n = 9), machine workers (n = 8), assembly-line workers (n = 15), specialist department workers (n = 9), and H&S professionals (n = 2) across different PL and departments. Ethical approval was granted through the relevant bodies.

4.3. Procedure and analysis

The research aim was to explore and identify PL workers' perceptions and opinions regarding H&S engagement as well as driving factors. Therefore, the study focused on the experience of the individual worker using qualitative methods. Unlike quantitative methods, deeper insight and meaning can be attributed to the drivers and influencing factors using qualitative approaches (Braun & Clarke, 2013). While the specific focus was workers' perceptions of their individual engagement, managers were also interviewed to ensure a balanced opinion was captured.

For the purposes of the study analysis, the terms 'barriers' 'promoters' and 'driving factors' are defined as follows:

Driving factors: relates to all aspects thought to influence the H&S engagement of the workers;

Promoter: refers to all/any levers that increase and support engaging behavior; and

Barriers: describe antecedents that may harm and hinder engagement.

The analysis presented on the H&S engagement factors was part of a wider study that also investigated aspects impacting workers' perception of H&S climate as they were found to influence the workers' H&S engagement.

Interviews were scheduled for 30 minutes, with flexibility where necessary. The interview guide was developed following the initial literature review, further refined through discussion with H&S practitioners and experts.

In order to demonstrate and ensure the quality of the data collection and analysis, the criteria recommended by Sullivan and Forrester (2019) was followed that considers reflexivity, transparency, coherence, contribution, and trustworthiness (details can be provided by the authors upon request).

A particular type of Thematic Analysis (TA) was applied to interview content called Template Analysis (TemA) (King & Brooks, 2018) as it was best suited to the nature of the data as well as the aim of the study. NVivo Version 12 (NVivo, QSR International, Melbourne, Australia) supported this coding process.

TemA was chosen for multiple reasons. First, coding a number of data items before interpretive themes are structured avoids the premature shaping or directing of research interpretation, complementing the inductive nature of the study (Brooks & King, 2012; King & Brooks, 2018; Saunders, Thornhill, & Lewis, 2019). Secondly, TemA offers a practical and strategic approach to analyzing a large data-set (38 interviews each between 20 and 60 minutes duration), which would otherwise pose a challenge to complete within the given timeframe (Galpin, Meredith, Ure, & Robinson, 2017; King, 2017; Saunders et al., 2019; Shilling, Starkings, Jenkins, Cella, & Fallowfield, 2018; Stead, Fallowfield, Brown, & Selby, 2001).

The common six-step approach (King & Brooks, 2018) was adapted to meet the project's needs (see Fig. 1).

In TemA the data were coded analogue TA, but in contrast to TA, only a sufficient proportion of the data are coded in detail; based on these derived codes and themes, a so-called 'coding template' was developed (King, 2017). This template was then used to analyze the other interview data and was adapted or rearranged according to the data (Saunders et al., 2019). The initial template was designed by analyzing 10 transcripts that were chosen due to their theme density and variation/diversion of perception on the pre-themes as well as their role/hierarchy distribution. The remaining 28 interviews were analyzed audibly from the recordings (i.e., listening and taking notes of accounts relevant to themes and transcribing relevant parts). Hence, the template and themes and their relationships evolved iteratively through input of the subsequent recordings. The final template is presented in Table 2.

In terms of coding, across the whole selected data set, the data were systematically labelled (i.e., coded to a theme on either a semantic or latent level, as the authors were interested in the surface meaning but the study also aims to identify the underlying conceptualizations and assumptions to inform the semantic content). This process is relevant as it aims to create meaning throughout the data set. In general, the TemA was meant to be inductive, exploratory, and naive, as the data were meant to reveal itself to the researchers. In order to make sure that all possible labels or codes were identified, the transcripts were read repeatedly. Some content was labelled from different perspectives and thus, the same text may have been coded to more than one theme.

For example, a sentence along the lines of "My manager doesn't listen to me anyway, why would I even bother." was coded with several different labels. First of all, the general label 'Engagement – voice/feeling heard' was used as the phrase shows how the feeling of not being heard ("My manager doesn't listen to me anyway") leads to disengagement ("why would I even bother"). It also demonstrates that the perception of management (or at least of some managers) from this worker is that they do not listen, therefore it was also labelled as 'Leadership – doesn't listen.' By implication, this also shows that for this worker, being heard is necessary to engage, which led to the label 'Antecedents of pos. safety culture/engagement – voice/feeling heard.' Finally, the sentence could also be construed as a general barrier within the H&S culture that exists for workers in order to engage with H&S. Thus, the label 'safety culture – barrier – not being heard' was created. The researchers acknowledge that some labels might be overlapping, however, this method of labelling allows different perceptions to be taken into account in later analysis. All labels were systematically and logically clustered and translated into codes, sub-themes, and themes.

Phase 1: Familiarising with data set
Initial audio check of records and first collection of themes

To enhance familiarity with the data, the transcribed data was read alongside listening to the audio file twice. Through this critical and analytical process, the first notes, comments and ideas regarding the content were collated.

Phase 2: Generating initial codes/labels of the transcriptions
Systematically and thoroughly labelling of relevant data extracts

Coding was conducted on a semantic or latent level; as the focus was on the explicit and surface meanings and aimed to identify underlying conceptualisations and assumptions to inform the semantic content. In addition, hierarchical (i.e. identifying overarching and more specific themes), as well as parallel coding (i.e. coding the same segment with different codes), were applied.

Once all transcripts were labelled, a total of 192 codes were created. However, due to the detailed and mixed coding approach, it was possible for some labels to be redundant or consider the same topic from different views.

Phase 3: Clustering of codes
Identification of relationships and themes between labels/codes into thematic map

Identified codes and themes were organised in clusters, to identify meaningful coherent patterns and relationships across the whole data set. Thus, not only was the quality and coherence of the themes checked, but also if they suited the collated data. Secondly, to secure quality, the themes were reviewed across the transcribed sub-set of the data set using 'thematic mapping' in order to create a thematic map with differentiated themes, forming clear and coherent patterns that captured the dimensions of data most relevant to the research question.

Phase 4: Development of template
Transformation of thematic map into template showing the connections between themes

Based on the thematic map, the coding template was developed. For this, the thematic list was transformed into a 'big picture' format, which represented the connections and relationships between the themes. This provided a visual answer to the research question.

Phase 5: Modifying and finalising of template
Check of remaining audio records of interviews for codes and additions to the template & revision of template

The development of the final coding template is an iterative process. The remaining twenty-eight interviews were acoustically analysed. After every three interviews the notes and codes were revisited, leading to refining, reorganising and adapting the coding template according to new insights. It was important when adding new codes or themes, that the whole body of data was revisited to ascertain any potential consequences on other themes or codes. Within this iterative process, some of the themes were renamed .

Phase 6: Interpreting the data and writing up
The themes, their connections and interactions were presented and interpreted both systematically and critically in a written report

Finally, the themes, their connections and interactions were presented and interpreted both, systematically and critically in a written report which uses data extracts to support them. A theme-by-theme approach was applied; presenting first an overview of the main theme and then each sub-themes with supporting quotes. The differences between context groups were also highlighted where present. Afterwards, the complete theme was interpreted and discussed with respect to existing empirical research.

Fig. 1. Template analysis process.

Table 1
Final template.

Theme	Sub-theme	Codes
Workers' perception of their H&S engagement	Autonomy of safety/being safe	'Everybody is responsible for their own safety'
	Taking (un)necessary risks	Taking (un)necessary risks
Safety focus	Organisational safety focus	Contextual safety/Context (ir)relevant rules
		Flexibility level/Autonomy
		Autonomy of managers
		Intention
		'Tick-box exercise'
		Hypocrisy and bureaucracy of rules
		Collision between production and safety goals
		Safety as number one value
		Safety system evolution
		Safety department staff proficiency
	'Lived' safety focus	Complacency
		'Work as planned' vs. 'work as done'
		Blame culture
		Feedback and education
		Recognition of positives
		Managers' safety focus
		Managers' focus on safety/production
		H&S policing
		No consequence to in-and noncompliance
		Perception of 'Nothing gets done'
		Management under pressure
		Leading by example/rectifying directly
Communication	Communication quality and consistency	Permeability
		Consistency
		Encouragement
		H&S leadership as H&S consultants
		Positive perceptions
		Events & awareness days
	Communication direction	Level of information sharing and transparency
		Level of explaining
		Directive quality
		Two-way communication
		Communication fair and on equal terms
		Listening and involvement
Environment	Psychological environment	Uncertainty and instability
		Fear of job loss
		Perception of need to be competitive due to plant's financial situation
		Health perception and concerns
		Shift work
		Temperature
		Air quality
	Social environment	Trust
		Relationship between management and shopfloor
		Camaraderie

Only text relevant to the research question was coded, however, information that gave insight into the individual's background or mindset (e.g., their career at the plant) was also noted. Some code names were chosen based on the individual's language concept, while others were based on the researcher's concepts. The codes worked as a label for the researcher as they are descriptive or interpretive, and as such, the codebook and thus the coding template developed and expanded throughout the process. Furthermore, the initial notes, comments, and ideas from the familiarization and coding phase evolved dynamically so that connections and interactions could be noted and mapped in memos and drawings. Once each transcript was coded, the complete body of transcribed data was read once more and compared to the code/label set in order to make sure that no relevant coded section was missing.

5. Results

With respect to the factors affecting H&S engagement at the plant, after careful consideration of all codes, comments fell into three main themes, which were identified as overall categories:

- Safety focus (section 5.2),
- Communication (section 5.3), and
- Environment (section 5.4).

Within the identified themes, several drivers and barriers were identified as sub-themes.

These three broad themes have been identified to aid further analysis of key concepts, but it is recognized that categorization in this way is problematic due to the overlapping nature of these themes and their interdependencies. The categorization was based on the primary and dominant feature of the statement.

In addition, commentary displaying the workers' individual engagement level was collected (section 5.1).

The following presentation of themes will focus on codes deemed most representative to the overall theme. A presentation of all codes is not possible within the scope of this paper due to the extensive body of data.

5.1. Workers' perception of their H&S engagement

This theme contains commentary relating to the workers' perception of themselves and the reasoning for their behavior. Overall, workers indicated that they (1) take responsibility for their own safety and (2) would not take unnecessary risks as they know their jobs (Table 1).

5.1.1. Autonomy of safety/being safe

Most workers agreed that they are *"in charge of [their] own safety"(WA)* and that they *"don't come into work to get hurt"(WA)*, voicing their constant intention of taking care of themselves and others.

Indeed, one worker highlighted that avoiding unnecessary risks and taking care of himself and others comes naturally to him:

> *"I take personal responsibility for myself and I take collective responsibility. I would never leave a machine be unprotected for my colleagues."(WA)*

This quote emphasized the relationship and care-element between workers as well as this worker's intrinsic drive for safety as he takes *"personal responsibility"(WA)* for himself and his peers.

5.1.2. Taking (Un)Necessary risks

For various reasons, such as practicality or contextual relevance, workers' safe working does not necessarily mean compliance with rules, but rather to knowing their jobs *"inside out"(WA)* and *"the best way to do it"(WA)*. Workers perceived that their skill and experience and common sense prevented them from taking unnecessary risks. One worker suggested that a strong H&S mindset was ingrained in his thinking as a consequence of working at the plant:

> *"I find [safety[...]] is embedded [...] into me, I take it outside, I notice the stupidest things, that people won't noticed [...], I'm doing a risk assessment while walking past things without realizing it [...]."(WB)*

He acknowledged that risk assessments and safety calculations are part of his every day thinking and impacted his decision-making inside and outside the plant. While the worker considered this *"H&S standard"(WA)* as a result of the safety trainings and constant communication, it may also indicate that risk assessments that he may have conducted subliminally raised his conscious awareness of risks and potential unsafe situations (e.g., how likely is it that this car will hit me if I cross the street now?).

Overall, workers reported viewing themselves as safety conscious and responsible and displayed a considerate level of H&S engagement, and yet, in their eyes, this did not necessarily equal compliant behavior.

5.2. Safety focus

The safety focus theme contains commentary reflecting the assessment and management of all safety performance. This was impacted by two properties: (1) on an organizational note, the plant's procedures and their perceived quality, and (2) on a social, 'lived' note (i.e., how management behaved regarding H&S aspects and thus how H&S was 'lived' at the plant). Both dimensions were perceived by workers as a demonstration of the company's focus and priorities. An overview of the underlying codes is provided in Table 1.

5.2.1. Organizational safety focus

In general, workers reported satisfaction with the provided H&S standard structures and the *"very good systems [...] to keep everybody safe"(WA)* as well as the personal protective equipment (PPE) provided. While the plant's culture was described as *"evolving"(WA) "in the desire to make it a safer place"(WA)*, managers as well as workers agreed that the safety system and culture were still in many ways *"old school" (WA)* and *"backwards" (WA)*.

Several workers criticized the contextual relevance of certain regulations. Often, rules were implemented top-down from the global parent company into all plants without consideration of local requirements. In addition, the safety department was perceived by some workers as *"unqualified"* since they *"have worked on the line for a minimal point"(WA)* and have *"just read a book"(WA)* and therefore *"don't understand what it's like"(WA)* to work on a PL. Consequently, these workers doubted the safety department members' ability to define relevant and practical safety items. One rule, often mentioned in this context, was the use of headphones on the PL with the explanation that workers wearing them *"can't hear it if people are calling you, you wouldn't know if something has happened"(WA)*. In addition, workers mentioned that they *"don't feel it's an issue wearing headphones on the line, because nothing should be going into you, you shouldn't having a fork truck coming into you"(WA)*. While the aforementioned forklift trucks *"are electric anyway, so you would never hear it"(WA)*, workers perceived the PL environment as protected since they *"have boxes behind [them], you have racks behind you, you have everything on the line, I think it's safe"(WA)*. Nonetheless, the same worker admitted that *"while walking, I would say, headphones out"(WA)*. The worker displayed a general understanding of the necessity and benefits of the policy in a certain environment (e.g., when walking or close to vehicles), however, in other circumstances (e.g., on his workplace) he does not see the relevance in that specific (by him perceived as 'safe') context. Thus, while not questioning the complete policy, the worker identified difficulties and displayed frustration with a 'one-size-fits-all' approach in relation to certain regulations that applied plant-wide. He proceeds by explaining that by *"putting a bit of music in your ears [...] time goes quicker"(WA)* and it *"brightens your day up (WA)* because the work on the PL is otherwise *"monotonous"(WA)* and *"boring"(WA)*. Consequently, certain rules were perceived as *"taking something away from"(WA)* the workers in order to *"mollycoddle"(WA)* them with overprotective rules. This led to workers doubting the genuineness of management's intention and only considering safety as a *"tick-box exercise"(WA)* for the company to appear "*legally safe"(WA)*. For example, one worker questioned the company's trust in his ability and sense of responsibility based on the safety items provided:

> *"It's a checklist, making sure that everything is safe for me to work. You know, if I have to observe a machine if it's actually working [slightly ironic tone]...I understand it, it's to cover it all. But I like to think that I'm a responsible enough person to do all that. Maybe not...[...]We should be trusted to do [our jobs] without the paperwork ((...)) as it comes back to responsibility. [The company] should give us back a bit more responsibility. Let us do our job." (WA)*

While the worker acknowledged the awareness-factor of checklists, he also indicated annoyance and disappointment and slight offence by the controlling, 'parent-child' connotations of them. In his perception, checklists not only reflected management's doubts in his personal responsibility but also questioned his experience and intellect. This was perceived as evidence of H&S leaders' distrust in him as well as an insult and discretization of his skills, and consequently, his pride in his work. Thus, this worker's need for autonomy, feeling valued, and competency recognition may have been unfulfilled. This led to frustration and disregard of the H&S leadership team as well as certain H&S topics. However, the statement also indicates that for this worker, feeling trusted was linked to actively taking responsibility. Hence to increase workers' trust, a distinct transfer of responsibility from management to the workers together with an increase in workers' autonomy must occur regarding safety decisions.

5.2.2. 'Lived' safety focus

In the same way that safety was defined in the official standards and procedure, the way that it was 'lived' and presented through actions was shown to impact workers' H&S engagement.

The perceived focus of the H&S leadership team throughout the organization was primarily on negative events, displaying a punitive and retributional mindset, appearing to promote a disengaging environment, confirmed by management admitting that they *"look for the failures rather than the successes"(MA)*. This resulted in workers' attempts to hide mistakes and enhanced the divide between leadership and workers, with a lack of perceived trust and fair feedback.

In one instance, a worker clearly highlighted his positive intentions and the inner drive to remain safe at work by saying *"[n]o one has accidents on purpose"(WA)* and yet he admitted that *"[. . .] if you drop something you may not come forward because it's a black mark on your record"(WA),* identifying that the retributional mindset at the plant led him to be careful to disclaim negative events. This also implies that this worker feels he cannot speak up about potential safety issues or improvement opportunities in fear of punishment. The commentary also suggests a certain level of frustration with how the worker feels he is treated, despite the first part of the comment indicating that he takes pride in - and aims to do - a good and safe job. Hence, the comment demonstrates how the *"blaming culture"(WA)* at the plant suppressed workers' involvement and voice in H&S, as well as reducing the meaning they get from their work. Most workers agreed that a constructive approach was needed in order to learn from incidents. Consequently, providing balanced feedback that acknowledged both positive and negative events, *"to educate rather than dictate"(WB)* would provide workers with an opportunity to learn from mistakes without the fear of discipline. This was linked positively to an open and positive safety climate, supporting worker engagement, and enabling workers to *"develop together"(WB).*

This notion was particularly evident at PL-B, with workers reporting feeling empowered as a result of additional training and a stronger integration into decision-making processes. Here, workers *"have been educated"* and when they are *"making a decision on something", "[management] listen to what [they] gotta say and they go along with what [the workers] suggesting"(WB).* The worker who described the approach at PL-B continued by saying that *"[i]t's nice to have an opinion that people actually appreciate and use" (WB) and "[t]hat's been a massive positive for [him] in this launch [of the new PL], the biggest thing to be honest"(WB).* This demonstrates how increased levels of involvement and recognition of his positive effort is valued by him, giving meaning and pride to his job and driving his engagement.

On another note, workers' commentary suggested that their interpretation of management's behavior in relation to H&S was directly translated into how management prioritized H&S. When *"people got concerns"(WA)* and *"they report it to [the managers]" (WA)* they had the feeling that *"[management does] nothing"(WA)*. Despite actions possibly taking place in the background, but often with no feedback to the issue-raising person (e.g., something was being done, but it was not directly perceivable), this led to frustration about the lack of recognition of their voices and concerns. The lack of action was also often interpreted as management's lack of commitment to H&S and care towards the workforce, since *"[management doesn't] listen until an accident happens"(WA).*

While most workers agreed that the production line would be stopped in the case of a very serious issue, aspects that management identify as 'minor' (e.g., lighting situation or roof leaks) would be ignored or unresolved for 'production sake.' Workers consequently perceived that *"production is king"(WA)* with one worker emphasizing the perceived collusion between safety and production as the number one value, noting that *"[the workers] tend to have that safety culture mindset anyway, but I think probably the hierarchy they are probably more concerned about money first" (WA).* This insinuates that management are prioritizing production over safety and stating that *"if [the workers] do it the way, [the safety department] want [them] to do it, [the workers] not gonna have any chance on hitting that [production] target"(WA).* Also, the same worker (and some of his peers) explained that *"[they are] working on 20-year old machines that are basically falling apart"(WA),* which leads to the workers' perceived need to *"firefight"(WA)* constantly which in turn was reported to *"[have] an effect on how [the workers] conduct [themselves]* cos *[they] have to cut corners to keep the machines running"(WA).* The perception of *"production is king"* appears to derive from the perceived lack of consequences for noncompliance, which they interpreted as an encouragement to continue; *"Basically, they know that we know what we are doing and they leave us alone to do it"(WA).* While the workers seemed to agree they would never put themselves in what they would perceive as a dangerous situation, they admit that *"there is a disparity between what the safety department asks from us and what we actually do"(WA).* Workers also perceived that H&S leadership was aware of the variations in procedures and thus the breach of protocol appeared as acceptable to them. Hence, the workers perceived they had autonomy through neglect of H&S leadership in enforcing the rules in favor of production and subsequently acknowledged policies as impractical. While the management may not have intended this, the perception as outlined resulted in the respective H&S behavior.

5.3. Communication

In discussing engagement and H&S, the workers perceived: (a) quality and consistency and (b) direction of communication efforts regarding H&S policies, procedures and behavior as recurring themes (Table 1).

5.3.1. Quality and consistency of communication

In terms of quality, one important factor was identified: the subliminal messages perceived as being communicated (intentionally or not). By way of example, in discussing a task, one manager admitted that often, despite the supervisor highlighting that "*obviously*" safety comes first, they were *"sending [the] wrong message by asking wrong questions like 'when will you be done?"(MA).* This was confirmed by workers reporting that the *"the pressure is already there,* cos *you don't want [PL] to go on stop. You feel obligated to try and rush"(WA)* or that managers criticized the worker later for taking more time to complete a task safely and in compliance with the rules. As a result, this was identified as adding pressure to the workers and undermining the safety message, leading to workers feeling obliged to prioritize pace over safety. Also, it could be suggested that supervisors' behavior and communication regarding the prioritization of safety may influence subjective norms. Thus, behavior in which safety was displayed as secondary in comparison to production (with or without respective intentions) might be perceived as favorable in the context of the perceived norms.

Regarding safety messages, management and workers described issues with the permeability of messages, since *"[. . .] the information is [not] passed on well enough to the [. . .]shopfloor [. . .]"(MA).* Generally, safety messages were cascaded from top-management to managers who were in charge of ensuring that the messages were communicated via the supervisors to the shopfloor. Concerning regulations or rules, several workers reported that management would give none or very limited explanations with managers admitting that some workers *"have never been told why"(MA).* This led to workers not understanding and/or accepting these policies, as one worker reported that *"[s]ome foremen are on a power trip and don't explain tasks or things and just scream at you" (WA).* This remark emphasizes the importance of communication, as well as education and training for supervisors and managers, to ensure they are aware that they are considered as role models by the workforce and therefore must always lead positively in the topic of safety.

Most workers and managers agreed that *"taking the time to talk and explain to people" (MA)* was paramount to getting support from the shopfloor. Similarly, workers highlighted the importance of personal communication to the manager and safety department on a regular basis to explain safety issues and rules. For example, taking five minutes every day with each shift team to raise and discuss (safety) issues would be beneficial. Otherwise, the commentary suggests that messages were diluted; they were perceived as *"tick-box exercises"(WA)* resulting in a loss of significance and meaning, or, they did not reach the workforce at all leaving workers feeling disrespected and ignored by management.

In addition, it was considered important that the safety focus was aligned between the different departments since it is currently perceived as *"[e]ach area manager pretty much runs his own area the way he wants"(WA)* with no *"collective aligned strategy"(WA)* leading to unequal handling of H&S in each area and a regarded lack of stability and justice. Hence, not only is the communication frequency and quality important, but also consistency in the safety messages in terms of workers' H&S engagement.

5.3.2. Communication direction

As indicated above, workers often felt *"annoy[ed]"(WA)* and as if *"[the company] is completely ignoring the feelings of the workforce" (WA)* with management perceived as neither listening to them nor taking their thoughts into account (e.g., ignoring their input). As it was reported that *"[s]afety rules always come down"(WA)* and *"never come from the shopfloor"(WA),* workers criticized their lack of involvement in decision-making or managers' attempts at taking their ideas on board. Also, the commentary suggested that the approach did not fit the workers' values or that they did not agree with it. This disengaged workers from H&S as they felt that they were made to take orders as opposed to being part of the process and supporting something they believed was right.

As an example, one worker illustrated this point by reporting that after he and his colleagues had completed a training course on rescuing, they proactively came up with the idea to *"give a map to everybody in the plant so everybody knows where they are" (WA)* and where the nearest defibrillator was, but he felt that he was *"not taken serious"(WA).* The manager did not listen to their suggestion and directly disregarded it since the plant already had an established approach. The worker clearly showed a feeling of disappointment in the lack of appreciation of his creativity and proactivity. His frustration at the disregard of his input was since demonstrated towards the manager by pointing out every time he sees him that he would probably be *"dead now"(WA)*, since the company's *"way doesn't work"(WA)*. While this may or may not be true, it depicts how the lack of involvement and the perceived disregard of workers' proactive improvement ideas may lead to resentment and disrespect.

Similarly, many workers communicated frustration with the level of information flow, as feedback on certain processes, concerns, or issues (e.g., roof leaks, status plant future) were not reported back to them and they felt like they *"were kept in the dark"(WA).* In light of the plant's uncertain future, many felt that *"if something happens to the plant [they] should be the first to hear about it"(WA)* instead of receiving news through the media, which was perceived as disrespectful.

In contrast, fair communication on equal terms as well as *"listen[ing] to the workforce"(WA)* and *"hold[ing] meeting[s] with people from every area"(WA)* to include them as part of the safety discussions and decision-making processes was thought to improve workers' H&S engagement by creating a feeling of trust and appreciation. A good example can be found in the commentary of a worker from empowered PL-B. Here, workers reported feeling trusted and valued as if *"[management] want you to succeed."* At this PL, since they were *"all a team, so [they] share information"(WB),* workers reported feeling *"part of the process"(WB)* and consequently respected by management. They felt PL-B had a cooperative environment since it was *"a two-way street over here"(WB),* in which everyone could speak up and (positively) challenge as no one was left to their own devices.

5.4. Environment

This theme entails commentary regarding the environment of the workers: (1) from a psychological perspective, such as their concerns and fears regarding the economic climate as well as issues impacting their wellbeing and health (such as shift work); and (2) their social environments reflecting on interpersonal factors such as trust, camaraderie, and the leader-member relationship (see Table 1).

5.4.1. Psychological environment

The biggest concern affecting workers' psychological availability, and therefore engagement, was the economic situation of the plant and the resulting job insecurity with workers' biggest wish being *"to have future work"(WA)* and them being *"afraid to just live"(WA)*. One worker reported that this is now *"in the forefront" (WA)* of their minds and continues by using the situation of a peer as a visualization:

"I know one boy who has taken on a mortgage. He just bought a house. And he is one of the junior men in the plant. Within two years, he's gonna lose his job and he has a three hundred thousand pound mortgage. That's gonna be a distraction. He is gonna be thinking 'What the hell am I gonna do in two years' time?' rather than 'Am I working safely'."(WA).

This remark shows how fears and worries are taking up the younger workers' thoughts due to prior financial commitments, taking psychological availability away from concentrating on the task in hand, highlighting the importance of a secure working environment for (H&S) engagement. At the same time, the worker reporting this case also displays empathy for the colleague and therefore evidences a certain level of camaraderie and care for their peers at the plant.

In addition, the overall commentary suggested that even though the workers understand that shift work is *"part of the parcel"(WA)* of working at the plant, it negatively influences workers' health and wellbeing (e.g., the changes in shift patterns). This especially affected workers who had longer commuting times, with reports of sleep deprivation and thus concentration issues both inside and outside the plant (e.g., while driving home). Hence, the commentary displaying psycho-social consequences of environmental factors impacted their willingness and availability to engage with H&S.

5.4.2. Social environment

The relationship between the workforce and management was reported as impacting almost all interpretations and decisions regarding safety behavior, even if not directly stated. Throughout many conversations, remarks made suggested a distrusting environment with a "*they [management] against us [workers]"(WA)* attitude indicating a distinct divide between the leadership team and shopfloor preventing positive H&S engagement. As the relationship between workers influenced the individual worker's behavior and mindset, the relationship (or its absence) between the H&S Leadership team and shop floor significantly influenced workers' perceptions of feeling cared for and their engagement willingness. Demonstrating the full gravity of consequences that the sum of perceived negative events and behavior by leadership had on the workers, one worker stated:

"I know that sounds a bit mercenary and when it comes to safety, our attitude should be different, but the company has worn us down from keeping us in the dark about things and our mentality towards [the plant] has altered.[...] I'm not saying I resent the company, but I'm resenting, the way the company is treating us at the moment. ((... ...)) Whereas before I would have gone the extra mile, but now if this is how the company is treating me then this is how I'm going to treat the company."(WA)

This quote displayed the strong impact the perceived leadership's lack of camaraderie had on engagement (i.e., 'going the extra mile') when workers felt poorly treated and uncared for. Interestingly, the relationship between workers and managers was often measured in their willingness to share information. Hence, this theme is closely linked to the prior theme 'Communication' (at section 5.3). Workers reported that *'before,'* a former manager who had a better relationship with them had made a concerted effort to build relationships with each worker (e.g., by making an effort to get to know them and *"speak[ing] to you every day"(WA)).* Since his departure, several workers reported that they felt like they were *"just a number"(WA)* to management. Thus, an open environment where people feel heard, respected, involved and recognized was mentioned in terms of feeling engaged with H&S since *"a happy worker is a safe worker"(WA).* One manager, supervising PL-B, an area in which workers reported more positive engagement and contentment levels, mentioned introducing measures to promote workers' feelings of being cared for and valued (i.e., writing congratulations and sympathy cards and having personal chats with workers). He also highlighted the importance of *'fun'* in work to create a positive environment and workforce. After all, since workers *"spent more time [in the plant] than you spent with your family"(WA)* a positive environment was crucial for someone's wellbeing. Additionally, the manager mentioned, in his experience, that people were more willing to listen when a relationship was established. Also, in assuming this as a sign of respect and interest in the person, it can be perceived as 'caring' for the other individuals. These observations and opinions by the manager were supported by his team who reported higher levels of engagement and a positive and proactive attitude towards H&S.

Similarly, the relationship between workers impacted the workers' H&S behavior. One worker reported he would not challenge anyone else on the shopfloor because he would get *"a nasty reply"(WA).* Another worker described the culture in the plant as an *"' I'm alright, Jack'-culture"(WA),* in which departments act against departments and individuals act *'selfishly'*. In addition, a *"bad morale"(WA)* with people not *"taking any responsibility and ownership"(WA)* due to pressure from senior workers who feel *"entitled" (WA)* was reported as a barrier to speaking up about H&S and in general, the fear of being mocked or bullied for being forward and proactive. Hence, this atmosphere may influence workers' willingness to participate in different initiatives or speak up and raise issues or ideas. Thus relationship-building initiatives, such as *"teambuilding between shifts"(WA)* was thought to have the potential to positively increase the cooperation between workers.

6. Discussion

The commentary suggests that the workers' level of engagement cannot be determined by monitoring compliance with H&S rules and procedures alone. For example, while management indicate that some workers exhibit *"childish behavior" (MA)* putting *"themselves at risk" (MA)*, this does not necessarily mean that workers are disengaged with H&S. Indeed, Kahn in Daisley's (2019) podcast 'Eat Sleep Work Repeat' suggested that 'H&S engagement' – be it non-compliant or compliant – is still an outward reflection of levels of engagement. Voicing and displaying a negative perception of certain H&S aspects, such as the safety department staff or rules, did not equal disengagement either. Indicating and voicing anger and frustration may actually be considered as engagement, as workers are demonstrating that they care about the topic (Kahn & Daisley, 2019). In fact, these polar perceptions may reveal a general meaning-gap between shopfloor and leaders. Therefore, these comments highlight the workers' intrinsic drive to keep themselves and their peers safe. Furthermore, the different standards the two groups use to measure 'engagement' and 'working safely' need to be addressed, so that a common understanding between management and workers can be created. Otherwise workers may experience irritation and feel attacked when micro-monitored by supervisors or not feel appreciated for their experience and proactiveness in regards to H&S engagement (Andersen, Karlsen, Kines, & Nielsen, 2015; Hollnagel et al., 2015). The strong link between workers expressing themselves in, and bonding emotionally with, one's role and work and engagement with H&S was shown (Kahn, 1990; Macey & Schneider, 2008). This was displayed during the interviews whenever the interviewee showed a dissonance between personal values and identity and the perceived company values or company representative behavior. For example, this occurred when workers viewed themselves as specialists and with many skills but felt the company did not take them and their expertise seriously, or in having to comply with rules when workers considered themselves as already working safely. Consequently, when workers felt they had invested themselves in work, yet the outcome was not acknowledged as important, this may lead to disengagement (Kahn, 1990; Macey & Schneider, 2008). This, in turn, highlighted the relevance for companies to add meaningfulness to employees' work and role performance (e.g., through autonomy, feedback, task variety, input or recognition of expertise and outcome).

Furthermore, the commentary indicated the importance of workers' feeling heard, involved, appreciated, and especially cared for by the company in order to increase their sense of psychological meaningfulness, safety, and availability regarding their work. As such, the organizational, as well as social factors, need to reflect this. Therefore, company-wide, the safety system as well as all individuals' behavior have to encompass the safety culture that the company aspires to. This will facilitate a united, multi-faceted and consistent approach to H&S, which is established to encourage and support greater worker investment in their daily tasks, thereby creating a thriving H&S engagement culture (Kahn, 1992; May, Gilson, & Harter, 2004). Thus, measures should be applied that support fair, accurate, respectful, and balanced feedback in order to help workers find solutions to challenges, support their personal development as well as creating a trusting and honest relationship between workers and the leadership team. Similarly, an environment in which the contextual complexity of working is acknowledged and workers' insights are appreciated and encouraged has to be created (Catteeuw, Flynn, & Vonderhorst, 2007). While some rules may not be open to discussion and non-compliant behavior needs to be addressed accordingly, non-compliance should be approached as a learning opportunity for the person conducting the mishap and the company. Weaknesses or areas of improvement (e.g., training, communication, or work instructions) may quickly become apparent and so contextually relevant rules can be created. For this, education of workers and supervisors is essential as they will benefit both from learning how to make educated decisions and conduct relevant risk assessments.

Hence, focusing on employee growth instead of weaknesses can create accountability, prompting engagement in both workers and managers by making them responsible for not only the quality of work, but also the quality of work relations and their employees' development (Shuck & Rocco, 2013).

The commentary on the safety focus demonstrates that the (perceived) intention of rules and procedures also needs to be considered as the workers' H&S engagement seems to be reduced when procedures are not perceived as relevant or discourage proactivity. Creating psychological safety was found to be key to engagement through establishing a blame-free, trusting environment (Kahn, 1990), whilst a 'blame culture' reduced trust between workers and supervisors and is detrimental for workers' self-image and consequently engagement (Brandis, Rice, & Schleimer, 2017; Dekker, 2012; Rich, Lepine, & Crawford, 2010). In terms of performance, workers who felt supported by their leaders demonstrated higher levels of engagement as it moderated psychological safety (May et al., 2004; Saks, 2006).

Concerning communication, commentary suggested that one-way communication, where workers felt talked at and ordered to do things that did not fit their values or that they did not agree with, disengaged workers from H&S as they felt that they were made to do things instead of being included as part of the process to support something they believed was right. Similarly, workers' and managers' commentary highlighted the association between regulations where the benefits were not fully understood and a lack of consistency in safety messages, directions and the synchronization between what was said and what was being done. Two-way communication, as well as helping workers to feel listened to and cared for promoted worker engagement, as those communication strategies prompted meaning in the individual's jobs and consequently enhanced engagement (Shuck & Rocco, 2013).

Regarding psychological safety, the current economic situation at the plant naturally took a toll on workers and their engagement level. However, the strongest influencers were the leadership style as well as the leader-member exchange (LMX), which directly impacted the perceived work climate and organizational justice in the plant. The perception of mixed messages as well as reported variability in H&S gravity formed workers' H&S mindset and sense of psychological safety. In this respect, the trust gap between workers and management also influenced workers' engagement, since an environment of trust and security were reported to be paramount. In order to create an environment that facilitated a dialogue and exchange between hierarchies and departments, communication channels must be employed, respective structures must be implemented and H&S leaders must adjust their behavior and genuinely listen, discuss and take workers' opinions on board, thus, promoting psychological safety through non-threatening contexts where there is consistency, predictability, and respect (Kahn, 1990).

In addition, a bilateral trusting relationship between workers and management was shown to be paramount for workers' engagement. Showing trust and appreciation in workers' through autonomy and having open conversations where workers are part of the decision-making and solution-design processes allow workers to bring themselves into their work, take responsibility, and have pride in their work. Similarly, workers' trust in management must be established. Rees et al. (2013) found that trust, as well as the LMX, had a mediating effect on workers' engagement, hence, those elements also constituted the organizational climate that determined if engagement could flourish or not (Purcell, 2014). Thus, the interpersonal dynamics not only between leaders and workers, but also across workers were reported to predict levels of engagement (Crawford et al., 2014; Schneider, Macey, Barbera, & Young, 2010). LMX was also found to have an effect on the relationships between employees and leaders and were based on trust, mutual respect and liking, yet differed in quality from follower to follower (Soane, 2014). This could be explained through workers having a trusting relationship with their supervisors and feeling 'attached' to them, which would extend their meaning and purpose in work through deeper connection (Kahn & Heaphy, 2014). Additionally, this added to the psychological safety of workers since trusting relationships established through authenticity were found to be enablers of engagement (Stephens, Heaphy, Carmeli, Spreitzer, & Dutton, 2013). Again, receiving trust as well as perceiving an effort made to establish a connection may be perceived as an exchange relationship (based on SET) due to feeling empowered,

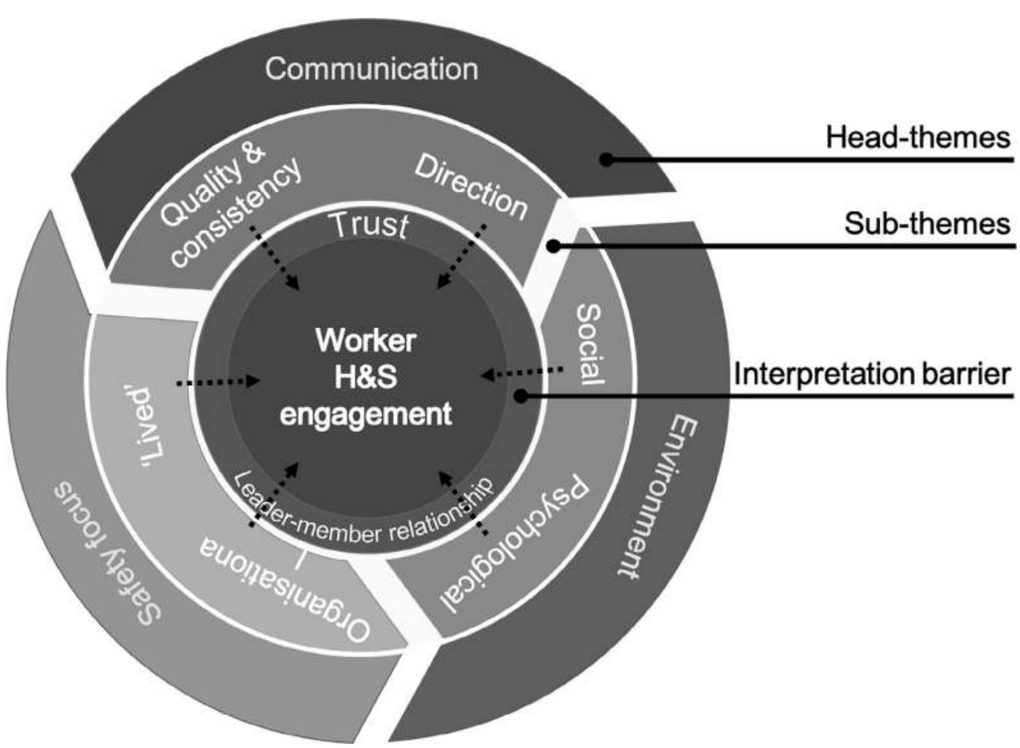

Fig. 2. Derived H&S engagement factor framework.

Table 2
Overview of engagement themes and sub-themes.

Sub-themes	Barriers	Example Quotes	Promoters	Example Quotes
Theme: Workers' perception of their H&S engagement				
Description: Relating to the workers' reasoning about their H&S behavior and safety perception, thus their engagement with H&S.				
Autonomy of safety/ being safe	Colliding perception of what means 'safety' between management and workers	"But then again I'm skill so I know what I'm doing it's always done right [. . .] but the manager doesn't know what I do [. . .] so how can they make it safe for me?"	Intrinsic drive and personal ambition to keep themselves and peers safe	"You look after your own safety anyway you've just got to be sensible" "I'm in charge of my own safety."
Taking (un)necessary risks	Personal convenience Not being aware of risks	"No one here does something deliberately wrong. [The workers] cut corners and by trying to do the right thing, they do the wrong thing."	Confidence in skills and experience	"Safety-wise I would like to think that I don't cut corners because I would put myself at risk." "as an individual, you should know what line you shouldn't cross. So, ya, we hold back on certain things. . .. . . we wouldn't put ourselves in danger if we know an area."
Theme: Safety focus				
Description: Reflecting on the negative (barriers) and positive (promoters) aspects of the safety focus and the behavioral and performance characteristics displayed during communication (including how feedback was given and received in order to effect a change in safety behavior) as well as the organization aspects that support and reflect that safety focus.				
Sub-themes	Barriers	Example Quotes	Promoters	Example Quotes
Organizational safety focus	Contextual irrelevant rules Rules perceived to be a 'tick-box exercise' Production goals collide with safety goals	"Safety is just a tick box for [the] company, they put you on a training course, tick the box, done, forget about it." "[. . .] we have to cut corners to keep the machines running."	Context relevant rules Involvement in decision-making Safety as number one value Autonomy and responsibility	"[. . .] because you have been educated, when you're making a decision on something, they accept it and go along with it rather than stopping it and saying 'this is how it's gonna be done'. They listen to what you gotta say and they go along with what you're suggesting"
'Lived' safety focus	Focusing on negatives (a 'blame culture') A perceived retributive or punitive mindset Feeling underappreciated for positive work efforts H&S leadership perceived as policing Management prioritizing production	"We look for the failures rather than the successes" "[The safety department and managers] will find everything that's wrong" "[. . .] the company's motto is 'noting is more important than our people, there can't be no compromise', but there always is, we say it but we don't deliver it" "I think they take us for granted or maybe they don't trust what we're saying, I don't know." " [. . .] sending wrong message by asking wrong questions like 'when will you be done?'"	Receiving balanced feedback Recognition for a 'job well done' Educating and sharing knowledge Focusing on 'learning' from mistakes (constructively) Safety always comes first – managers walk the talk Involvement in decision-making	"I say, rather educate first rather then, you know, discipline people, sometimes it's just down purely that they don't realise the danger that is involved you know they can't foresee it." "[. . .] being more positive when we're sharing information, you know, not just focusing on the negatives" "You develop together"
Theme: Communication				
Description: Reflecting on the perceived quality, direction and intention of communication in relation to H&S in relation to the workers.				
Sub-themes	Barriers	Example Quotes	Promoters	Example Quotes
Communication quality & consistency	Lack of consistency in communication No consequences to non-compliance Hypocrisy and bureaucracy of rules Subliminal pressure Lack of explaining	"They [management] have led a few things go, but historically if you stepped out and don't follow the plant policy nothing is done about it. . . " "When someone takes something away from you it's not nice, is it. It doesn't matter what it is. [. . .] Well, they are not trying to make your life more difficult, they're trying to make it safer. safeER! Are you safe or do you need to be safer?"	Constant encouragement of safe working and a safety mindset Managers and safety professionals as H&S consultants	"I know there are the posters up about the lost time accident information that sort of stuff, but it's just more than hands-on, you know, more feedback often, I suppose." "They did [. . .] like a safety day. Maybe they could do more of that, because that was quite good" "It's all about encouragement and [communication], to do a bit further I guess."
Communication	One-way communication	"Safety rules always come down, they	Two-way communication	"We are all a team, so we share information."

direction	Top-down approach Disregard of workers' insights and ideas	never come from the shop floor"	Fair and on equal terms Listening and involvement	"[H&S Leadership team] could possibly take people from the line and have a sit down then with them I guess and say: "Let's have a meeting. These are what we want to implement. What do you think?". "Listen to the people of the shop floor, who work in this environment, cos H&S people, they don't work daily in this environment, and managers, they don't work daily in this environment.[...] But I would like to have them listen to us a little more in regards what we are talking [...]."
Theme: Environment				
Description: Reflecting discussions around psychological, i.e. concerns and fears that workers displayed with respect to the current economical and physical climate, and social, i.e. the relationship between workers and managers and between workers, factors perceived to have an impact or influence on the level of H&S engagement among workers.				
Sub-themes	Barriers	Example Quotes	Promoters	Example Quotes
Psychological environment	Job insecurity Uncomfortable environment Health worries Negative impact on social life outside the plant	"we are on the precipice of the plant shutting. We ((...)) ...we have been in this situation for four years and it has affected our mindset, we gotta get the engines out and we gotta get the out, get them out. And it does affect our attitude towards safety [...]" "I'm working shifts so I'm all over the place, ((...)) I don't wanna blame it on shift but it's half the time, I guess. Most of the time you eat dinner on irregular times, nightshift is no good..."	Clarity of future of jobs Trust in healthy environment	"I do enjoy coming here, certainly hope that I'm gonna be here for some time after as well. Obviously, there is a bit of uncertainty at the moment, but fingers crossed, that there is a future there for us." "[...]my only one wishes is to have future work. But that really is........ At the moment we're in uncertain times, but if there is anything, I can change it would be to know that the plant has got a future."
Social environment	Perception that workers are "just numbers" to managers Negative management/shop floor relationship 'us vs. them' Lack of trust in management's intention Lack of camaraderie on certain PLs	"The company's motto is 'nothing is more important than our people, there can't be no compromise', but there always is, we say it but we don't deliver it [...]." "[...] I'm resenting, the way the company is treating us at the moment. [...] Whereas before I would have gone the extra mile, but now if this is how the company is treating me then this is how I'm going to treat the company." "Managers do what they wanna do"	An open environment where workers feel heard and valued Feeling supported by management Management perceived as prioritising workers' H&S Building trust Teamwork between shifts	"I think I have changed massively [since working at Dragon [...] we have been told a lot of information [...] you go to the lines, they [workers] are all happy, they are all energetic." "We are all a team, so we share information." "I felt they [management] were on my side. I could make a mistake and generally they were on my side." "I think I have changed massively [...] we have been told a lot of information [...] you go to the lines they are all happy they are all energetic they all wanna work" "We need more collaboration between safety department, managers and the shopfloor"

Table 3
Exemplary practical implications drawn from reported behavior and consequences.

Theme	Consequential recommendation
Workers' perception of their H&S engagement	Uniform definition of 'safety': Open discussion and understanding between managers and workers of what 'safety' and 'safe work' means to them and why. Clarify a shared definition and consequently, specific meaningful reporting measures and performance indicators can then be developed (Dekker, 2018b).
Safety focus	Balanced feedback: Train supervisors and managers on how to give positive constructive feedback and acknowledge work well done as well as making efforts to understand drivers and reasoning behind incompliant behavior (e.g. to learn from 'work-as-done'). Also, train on transformative leadership style and the importance of 'leading by example'. Move from punitive safety to restorative safety such as use of Dekker's (2018a) 'Restorative Just Culture Checklist' in case of incidents to acknowledge all victims of incidents (Dekker, 2012). Contextual safety: Implement participatory measures to address 'global' rules to ensure local relevance and fit (Knight et al., 2017; Nielsen, 2013; Punnett et al., 2013; Rasmussen et al., 2006).
Communication	Integration of workers in decision-making: Promote cooperative design of H&S measures through participatory action design processes, where workers are a valued inclusive part of the design and decision-making process of interventions (Knight et al., 2017; Nielsen, 2013; Punnett et al., 2013; Rasmussen et al., 2006). Shared information: Share information through integration of (representative) workers in management and decision-making meetings.
Environment	Teambuilding: Build trusting relationships between shifts and between workers and management through designated training and events (e.g. (H&S) trainings between shifts with formulation of handover processes). LMX: Designate resources (especially time) for managers to be spend on the shopfloor in dialogue with workers.

making workers feel obliged to reciprocate the trust and repay the effort by caring for the organization and their work (Cropanzano & Mitchell, 2005; Saks, 2006, 2008). An increasing gap was identified in trust between the shop floor and higher levels of management, which Saks called the 'engagement gap' (Saks, 2006). This was reported to exist at the plant where workers' comments showed that every element concerning H&S and all the workers directly (e.g., communication, safety focus, environment incl. management behavior, rule intentions) is interpreted through a relationship/trust barrier. The quality of this barrier determines how the input is being decoded (i.e., confirmation bias): insinuating good intentions if the quality of the barrier is positive and in reverse (see Fig. 2). Therefore, it is recommended to initially concentrate on fixing the identified trust gap before changes regarding the other dimensions can show improvement. Workers and managers could benefit from working together to come up with solutions and measures to address these issues in order to take into account the different perspectives and their requirements, for example, by using participatory measures (Dollard & Karasek, 2010; Knight, Patterson, Dawson, & Brown, 2017; Nielsen, 2013; Punnett, Warren, Henning, Nobrega, & Cherniack, 2013).

7. Summary

Whereas much research has been conducted in other industries, this study is the first of its kind to the authors' knowledge that has analyzed the factors influencing engagement of PL workers in particular in a H&S context from a qualitative angle.

By using template analysis, three main themes were identified as overall categories affecting the H&S engagement climate in the plant:

- Safety focus,
- Communication, and
- Environment.

All themes were found to be strongly linked to each other. Thus, they must be seen as a whole and not individual areas that stand alone from each other. An overview of all themes and the respective barriers and antecedents they represent can be seen in Table 2.

Not surprisingly, the interviews displayed the importance of leadership's influence on workers' engagement and disengagement. Building on existing engagement antecedent research (Conchie et al., 2013), this research found that supervisors' behavior had a stronger influence on workers than co-workers' behavior. Leadership's responsibility for fostering a safe and supportive environment in which workers felt that their needs and opinions were being taken seriously and developmental feedback was given for them to grow and develop were found to be the main promoters of worker engagement. However, for that to be achieved, an environment of trust between both groups must be established.

Generally, the interviews showed that the workers in the plant appeared to be fundamentally, intrinsically self-motivated to keep themselves and others safe and their comments indicated that personal protection (i.e., keeping themselves safe) and human empathy (i.e., keeping others safe) were general values that the workers followed, and which formed their identity ('we keep ourselves and others safe'). Yet, there were limitations to this protection need that appeared the moment that workers perceived disagreement between their own perceptions of what was safe and the company's proposed measures in order to keep a worker safe. Consequently, when workers felt that they invested themselves in work, yet the outcome was not acknowledged as important or when they felt these values were not reflected by the organization, this led to disengagement (Macey & Schneider, 2008). This, in turn, highlighted the relevance for companies to first establish trust and secondly to add meaningfulness to the employees' work and role performance (e.g., through autonomy, task variety, and recognition of expertise and outcome).

8. Limitations

Although this research has meaningful findings and offers contributions to the H&S as well as engagement literature, due to the context and nature of the research some limitations may apply. During the time when the interviews took place, the plant went through a phase of negative media where potential job losses were revealed before management had talked to staff about them, which may have introduced bias. Thus, this polarization was acknowledged and it was recognized that while the internal validity of the data was assured, the external validity might be compromised/limited. On a positive note, this may have motivated certain workers to take part or talk more freely than they would have under more stable circumstances. Furthermore, social desirability bias was acknowledged to be a general threat within this study, since the interviews may have tackled personally challenging topics (i.e., admitting rule-breaking or personal shortcomings) which might have influenced workers' responses.

Moreover, observer bias might have appeared since the transcription and analysis were done only by the researcher in order to honor the anonymity of participants. With respect to the quality of transcription, coding, and theme development, after each step in the process, the results were discussed in detail with the research team in order to identify blind-spots or inconsistencies. Further, the researcher critically and repetitively sample checked the results at each stage in a test–retest format. While this process may not have eliminated all bias, on the positive side, internal consistency can be assumed.

9. Practical implications and future research directions

Based on the findings, exemplary recommendations for manufacturing environments to enhance H&S engagement were derived (see Table 3). It also became clear that a one-size-fits-all-solution will not be possible and that companies must make individual efforts to understand their workers' drivers and barriers in terms of H&S engagement.

Whilst this study provides a meaningful insight into the drivers and barriers of engagement in one case-study plant, the findings are considered a snapshot of this particular organization and so generalization to the whole industry should be considered with caution. Thus, it would be interesting to see how the factors identified match up with qualitative results from other manufacturing environments and whether there are distinct differences between industries. So far, a previous literature review has indicated that there does not appear to be a vast amount of academic research focusing on engagement in (automotive) blue-collar industry settings. In comparison to the striking amount of research conducted in hospital settings, it may be beneficial to see how those particular industries differ in terms of individualistic H&S engagement. In addition, given the vastly different working environments, future research may benefit from taking a more specific look at the differences aspects of H&S engagement within industries.

In addition, in the accompanying literature review, it was found that engagement research was mainly dominated by quantitative findings. Hence, the body of knowledge might benefit from increased use of qualitative measures, taking a stronger account of individual and more in-depth insights (Bailey, Madden, Alfes, & Fletcher, 2017).

Moreover, the research highlights the impact of management upon workers' engagement levels. While this is not a new point, the major influence of the trust level between management and workers on workers' engagement, as identified in this research, was a less explored factor that may deserve more consideration in future research.

Finally, the workers' commentary showed that the directive, distrusting, and often nannying quality of H&S leadership and management was perceived to not only eliminate the feeling of responsibility for H&S but also the feeling of meaningfulness in, and appreciation of, one's work. Therefore, on a trusting base, a cooperative and balanced approach to H&S on equal terms is recommended. To conclude, interventions must ensure that workers feel they gain psychological meaning, safety and availability through their work and working environment in order to be engaged (with H&S) by being:

- heard and taken seriously (e.g. for their insights, concerns, ideas),
- involved and part of decision-making processes,
- recognized and appreciated (e.g. for their expertise and work), and
- cared for by the company and by management.

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Franziska Homann, MSc, is a doctoral candidate in Health Science and Psychology at Cardiff Metropolitan University with the research aim to develop a tool kit containing recommendations for change which can be applied within blue-collar organisations to enhance engagement in health and safety practice via a focus on employee engagement. On the side of her PhD, she works as a business consultant and is a certified business coach and trainer.

Dr. Caroline Limbert, PhD, CPsychol AFBPsS SFHEA, is a HCPC Registered Health and Occupational Psychologist based at Cardiff Metropolitan University. She completed a PhD working for University of Oxford PGMDE exploring the use of evidence-based medicine by doctors. Her more recent research focuses on health and wellbeing, predominantly in a work-place setting. Much of her work involves conducting systematic reviews and service evaluations, as well as training the health psychologists of the future.

Simon Matthews, PhD, IOSH, IEMA, is a chartered safety and environmental professional with 20 years of experience within the oil & gas, manufacturing, food, and power generation industries. Simon is passionate about sensible safety processes and is a firm believer in culture and it's impact in the safety performance across all levels of a business.

Darren Castaldi, DipNEBOSH, Grad.IOSH, is a Safety Engineer at the Ford Motor Company's engine manufacturing facility at Bridgend, South Wales. Darren has worked at the facility for 23 yrs, and most notably employed as a Safety Technician between 2011-16 and then as a Safety Engineer/Site Lead from 2016 to present. Amongst other qualifications, Darren has a Nebosh Diploma in Occupational Health and Safety, has 1st Class degree in History, and is presently working towards his MSc in Safety, Health and Environmental Management. Darren is a very experienced safety professional and classified as the plant's subject matter expert on all health and safety related matters.

Dr. Peter Sykes, PhD, is a Principal Lecturer and the Associate Dean (enterprise) at the Cardiff School of Health Sciences, Cardiff Metropolitan University. Peter is actively involved in occupational health and safety research, primarily in the waste management sector. In addition to his teaching duties at undergraduate and post graduate levels, Peter is actively involved in supervising doctoral work in Occupational Health and Safety.

Journal of Safety Research 77 (2021) 170–181

Contents lists available at ScienceDirect

Journal of Safety Research

journal homepage: www.elsevier.com/locate/jsr

Improving the safety of distracted pedestrians with in-ground flashing lights. A railway crossing field study

Grégoire S. Larue [a,b,*], Christopher N. Watling [a], Alexander Black [c], Joanne M. Wood [c]

[a] Queensland University of Technology (QUT), Centre for Accident Research and Road Safety-Queensland, Australia
[b] Australasian Centre for Rail Innovation, Australia
[c] Queensland University of Technology (QUT), School of Optometry and Vision Science, Australia

A R T I C L E I N F O

Article history:
Received 27 July 2020
Received in revised form 23 October 2020
Accepted 24 February 2021
Available online 30 March 2021

Keywords:
Distraction
Vulnerable road user
Mobile device
Road intervention
Crossing

A B S T R A C T

Introduction: Current signage at intersections is designed for attentive pedestrians who are looking ahead. Such signage may not be sufficient when distracted by smartphones. Illuminated in-ground LED lights at crossings are an innovative solution to alert distracted pedestrians. *Method:* We conducted a field study at a railway crossing equipped with in-ground lights to assess whether distracted pedestrians ($N = 34$, Mean age 33.6 ± 8.6 years) could detect these lights and how this impacted on their visual scanning and crossing behaviour. This involved a 2×3 repeated measures design exploring the impact of the presence (treatment) or absence (control) of in-ground lights (treatment) at a crossing, and a distractor task presented through a mobile device (none, visual, and audio) on eye movements recorded using an eye tracker, and verbal reporting of when participants detected the lights. *Results:* Participants engaged in the distraction tasks as evidenced by their accuracy and reaction times in all conditions. With both the audio and visual distraction tasks, participants looked at the in-ground LEDs and detected their activation as accurately as when not distracted (95%). While most participants detected the lights at their activation, visual distraction resulted in 10% of the detections occurring as participants entered the rail corridor, suggesting effectiveness in gaining pedestrians' attention. Further, participants were significantly less likely to check for trains when visually distracted (70%), a 10% reduction compared to the no or audio distractor conditions (80% and 78% respectively). The introduction of the in-ground lights resulted in appropriate scanning of the rail tracks (77% and 78% for the visual and auditory distractor tasks respectively) similar to that of non-distracted participants for the crossing without lights (80%). *Conclusions:* Our findings indicate that illuminated in-ground lights could be useful in attracting the attention of distracted pedestrians at railway level crossings, and possibly at other road intersections. *Practical Applications:* Illuminated in-ground lights can be installed at rail and road intersections with known pedestrian distraction as a countermeasure. Further research is necessary to understand their long-term effects.

1. Introduction

1.1. Pedestrian distraction at intersections

Distraction is a growing road safety concern worldwide for all road users. Extending the definition of driver distraction (National Highway Traffic Safety Administration, 2010) to pedestrians, suggests a specific type of inattention that occurs when pedestrians divert some of their attention from the walking task to focus on an alternative activity. Distracted walking has become more prevalent as the use of smartphones has become more widespread in everyday-life (Basch, Ethan, Rajan, & Basch, 2016; Solah et al., 2016).

Pedestrian distraction has, however, not been widely researched, despite numerous observational studies and anecdotal reports that report large numbers of pedestrians being distracted, especially while crossing roads, as shown by Mwakalonge, Siuhi, and White (2015)'s review of the literature. Distractions include talking on a mobile phone, looking at a mobile phone screen, or wearing headphones (Basch et al., 2016).

Pedestrian distraction is associated with poor decision-making such as crossing at non-designated areas (Pešić, Antić, Glavic, & Milenković, 2016), as well as inattentional blindness (Coleman & Scopatz, 2016; Solah et al., 2016). At intersections, pedestrians distracted by their smartphones are less likely to scan their

* Corresponding author at: Queensland University of Technology (QUT), Centre for Accident Research and Road Safety-Queensland, 130 Victoria Park Road, Kelvin Grove 4059 QLD, Australia.

E-mail address: g.larue@qut.edu.au (G.S. Larue).

https://doi.org/10.1016/j.jsr.2021.02.014
0022-4375/

environment while approaching and entering the intersection (Lin & Huang, 2017). They also exhibit increased levels of unsafe behaviors while crossing, such as failing to stop (Lin & Huang, 2017; Pešić et al., 2016) and being unable to follow a straight path (Sammy, Robynne, Miranda, & Conrad, 2015; Solah et al., 2016).

1.2. The case of railway crossings

Railway level crossings are an example of intersections where pedestrian distraction can result in catastrophic consequences. One major contributor to the risk of pedestrians being involved in collisions with trains at railway level crossings is when pedestrians are complacent, distracted, or inattentive (Edquist, Stephan, & Wigglesworth, 2009; Larue, Naweed, & Rodwell, 2018). Distraction and inattention also become more prevalent at this type of intersection with increased use of mobile phones and headsets (Goodman, 2018; Larue, Naweed, et al., 2018).

The current form of pedestrian protection at railway level crossings comprises a warning sign when passively protected, or warning sign signals, sometimes associated with bells and gates, when the crossing is actively protected. The effectiveness of such warning devices is likely to be reduced by pedestrians diverting their attention towards their mobile devices or by using their headphones. Despite the rarity of train collisions with pedestrians at railway crossings, the contribution of pedestrian distraction to these collisions has been highlighted by the number of rail incident investigations of collisions involving pedestrians (and even cyclists) that report distraction as being a contributing factor. This has been identified in the United Kingdom and in New Zealand for pedestrians using a mobile phone (Transport Accident Investigation Commission, 2016), when wearing earphones, which reduce the ability to hear warning sounds (e.g., train horn; Rail Accident Investigation Branch, 2009, 2013), or more general distraction in the rail environment (Rail Accident Investigation Branch, 2010), and at railway stations (Transport Accident Investigation Commission, 2011).

1.3. Advanced warnings

An innovative solution to address the issue of distracted pedestrians is the use of visual warning lights installed in the ground. Such devices have been trialed in some locations around the world at road intersections (Potts, 2016; Sulleyman, 2017; Timson, 2016). These warning lights can be used at signalized or unsignalized intersections. At signalized intersections, the lights are activated concurrently with the standard crossing signals provided to pedestrians, and inform pedestrians that they should not proceed through the crossing. At unsignalized intersections, the lights are activated when a motion sensor detects the approach of pedestrians. At such intersections, the aim of the lights is to remind pedestrians that they are approaching an intersection.

Railway level crossings represent one type of intersection where such interventions could be useful, given their design leads to complex interactions between road and rail users and that the consequences of a collision are significant and often fatal. Railway crossing design often leads to human errors, deliberate non-compliance with signals and road rules (Larue, Blackman, & Freeman, 2020; Larue & Naweed, 2018), and inaccurate perceptions of risks by road users (Larue, Filtness, et al., 2018). In-ground lights have been installed to try and circumvent these problems and have been tested in New Zealand at selected railway level crossings, first for road vehicles (Larue, Watling, Black, & Wood, 2019) and more recently for pedestrians (Hirsch, Mackie, & Cook, 2017).

In a laboratory study conducted by Larue, Watling, Black, Wood, and Khakzar (2020), lights placed at ground level were effective in attracting the attention of distracted pedestrians, regardless of whether they were engaging visually or auditorily with their mobile device. Pedestrians are likely to have detected the activation of the lights through the use of their peripheral vision while performing the distractor task on a smartphone (Larue, Watling, et al., 2020). While showing promising effects in laboratory conditions, there have currently been no field-based evaluations regarding the potential safety benefits obtained from such interventions.

1.4. Study aim

This research aimed to evaluate whether the addition of in-ground LEDs located at ground level at railway level crossings is useful in attracting the attention of pedestrians when performing a visual or auditory distractor task on a smartphone. We focused on evaluating pedestrians' accuracy in detecting the illuminated in-ground LEDs and in their scanning behavior toward railway crossings, while performing a distractor task (visual or auditory) compared to when not distracted.

2. Method

2.1. Study design

In this field-based study, a 2 $\times$ 3 repeated measures design was used to evaluate the safety effects of in-ground LEDs during the daytime. Two within-subject factors were considered:

1) Level crossing protection type: standard passive pedestrian crossing (control), and passive pedestrian level crossing with the illuminated in-ground LEDs (treatment); and
2) Distraction condition: no distraction (control); visual distraction; and auditory distraction.

The order of conditions was counterbalanced between participants to mitigate order effects.

For each testing condition (in-ground LED lights present or absent (2), for each given distraction condition (3)), participants walked toward the level crossing (from 30 m before the crossing), traversed the crossing and continued walking for another 30 m after the crossing. They then walked back to their original position. They repeated this walking task three times for each of the six conditions, resulting in the participants crossing the level crossing a total of 18 times. The key outcome measures were the participants' ability to detect the activation of the illuminated in-ground LEDs, the gaze behavior of participants, and their crossing behaviors.

2.1.1. Trial site and signage

The trial site was one of the passive pedestrian level crossings in New Plymouth where KiwiRail had installed in-ground LEDs. Level crossings in the vicinity were investigated to find a comparison site. This required comparable characteristics in terms of protection (passive), standard signage ('Look for Trains'), and enclosed maze (enclosure forcing pedestrians to make at least one 180 degrees turn when approaching the rail tracks, to elicit alternative scanning toward both the left and right rail tracks, see Fig. 1), as well as similar low traffic both in terms of trains ($\sim$4 per day) and pedestrians ($\sim$130 per day). No other level crossings in the vicinity matched the characteristics of the site selected for treatment, so the selected crossing was used as its own control.

The illuminated pedestrian warning devices (treatment) consisted of in-ground LEDs, and the reiteration of the standard 'Look for Trains' signage that is displayed vertically on the fence positioned in the middle of the maze at passive pedestrians level crossings in New Zealand. This combination of in-ground LEDs and

Fig. 1. View of the Cutfield level crossing (Left: Control configuration; Right: Treatment configuration (LEDs) with the protection officer in position for monitoring the rail tracks).

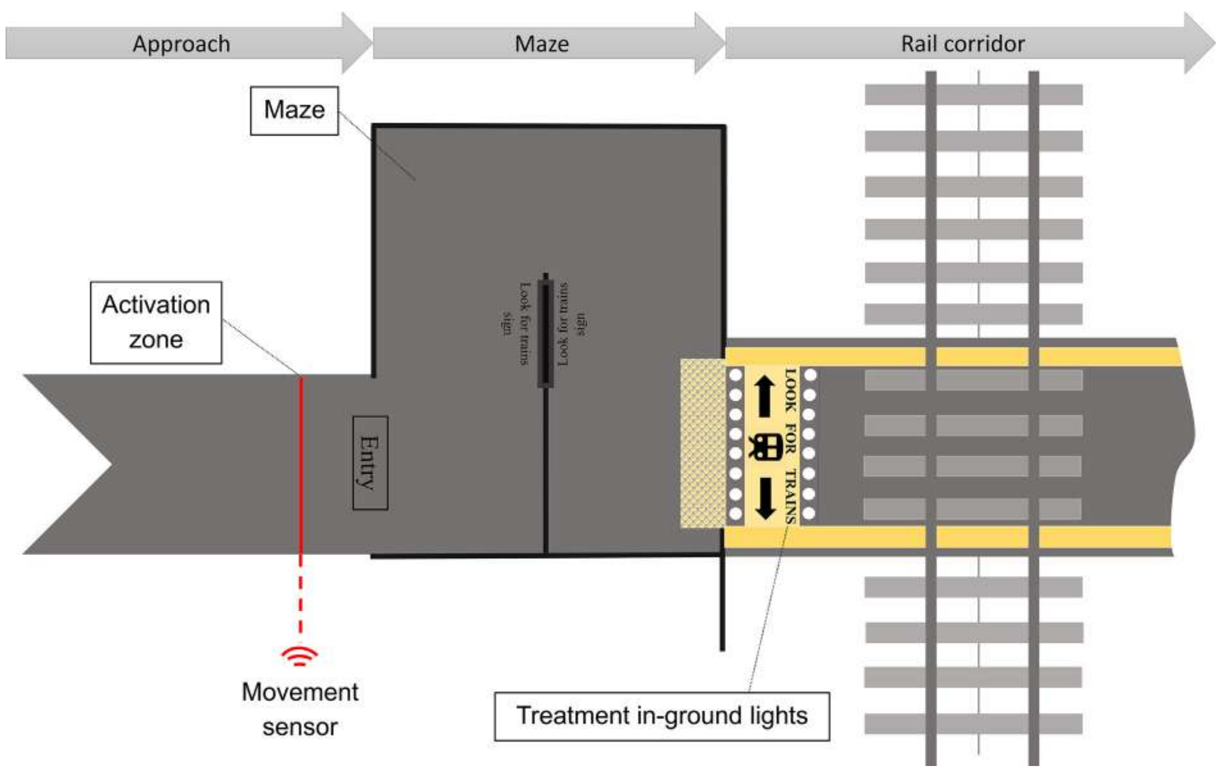

Fig. 2. Signage and its placement (showing only one side of the level crossing; grey area: pedestrian footpath; black lines: fence).

warning sign was installed on both sides of the rail corridor, after the maze when travelling towards the rail tracks (see Fig. 2) and were installed two months prior to commencement of the study.

The in-ground LEDs comprised yellow flashing lights, which were activated on both sides of the crossing simultaneously by the movement of pedestrians just before their entrance into the maze of the level crossing (around a meter and a half away from the maze). Once activated, the lights flashed for 10 seconds, alternating every second. LEDs were only activated on movement of the pedestrian towards the level crossing. The activation of the LEDs was independent of the presence of trains and aimed to alert pedestrians regarding the presence of the crossing and the need to look for trains when crossing.

For the control configuration, mats were placed over the in-ground lights and hid their activation, as it was not possible to control whether the lights were activated or not at the site (see Fig. 1-Left).

2.1.2. Distractor tasks

A simple reaction time task was developed to create a distractor task that sufficiently engaged the participants, provided an analogue for either texting on a phone or engaging in an active listening task using a headset, and increased their cognitive workload without overloading them and jeopardizing their safety while walking. The distractor tasks were similar to those used by Larue, Watling, et al. (2020).

The visual distractor task was performed on a smartphone. Every 1.5 seconds, a word was randomly selected from a list of 6 words (cat, box, pen, desk, note, switch), and displayed on the screen for 1.0 s. One of these words (cat) was the target word and appeared 25% of the time, while the other five words were equally likely to appear. Participants were instructed to touch the screen as quickly as possible only when the target word appeared. The 'Screen' text changed to red when the screen was touched, independent of the word (or lack of) displayed on the screen, to provide feedback to participants.

The auditory task was similar to the visual task, where rather than displaying the words on the screen, it was played as a sound by the smartphone equipped with earphones. Participants were provided with the same red 'Screen' feedback when they touched the screen. This approach ensured that only the task modality was investigated, rather than a combination of modality and task difficulty.

2.1.3. Detection task

A detection task was also performed when the level crossing was in its treatment configuration (with the in-ground LEDs illuminated, see Fig. 3). Participants were instructed to verbally report the word 'LIGHT' as soon as they noticed that the in-ground LEDs were illuminated as they approached the level crossing.

2.1.4. Questionnaires

A demographic questionnaire was administered. Self-reported pedestrian behavior was also assessed, using the Pedestrian Behaviour Scale (PBS: Granié, Pannetier, & Guého, 2013). Problematic mobile phone use was quantified via self-report on the Mobile Phone Problem Use Scale (MPPUS: Bianchi & Phillips, 2005).

2.2. Participants

A sample of 34 participants completed the study. Participants were healthy adults between the ages of 18 and 45 years who identified as regular users of mobile devices while they are walking (three times or more per week). Participants were screened to ensure that their visual acuity would not affect the results of the study: all participants were required to meet the visual requirements (with or without correction) for holding a private driving license. Participants were also required to have normal hearing, and no physical impairments that affected walking (which were derived through self-report).

Participants were recruited from the general public in the New Plymouth area. Recruitment strategies included local flyer distributions, as well as through local community or volunteer groups who circulated email or paper flyers. A snowballing approach was also used with participants who completed the study. Ethical clearance was obtained from the university's Ethics Committee (clearance number 1800000417).

2.3. Materials

2.3.1. Eye-tracking system

The SensoMotoric Instruments (SMI Instruments, Teltow, Germany) eye-tracking system was used to record scanning patterns and is specifically designed for active users in the field. It is fully wireless, compact, and allows the use of unconstrained eye, head, and hand movements under variable lighting conditions. The system comprises lightweight eyeglasses with high-resolution cameras and records natural gaze behavior in real-time at a 60 Hz sampling rate. It provides point of gaze with audio capability to record what participants are saying as they are walking.

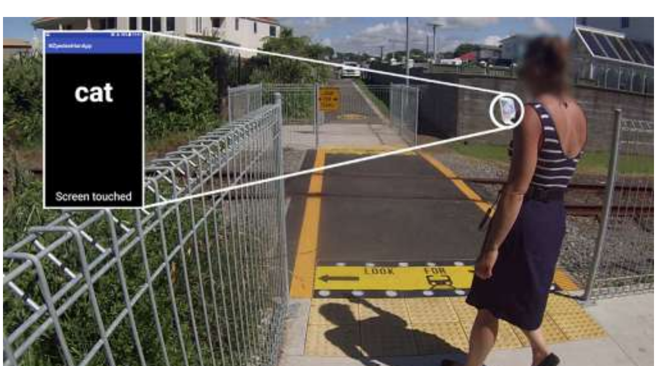

Fig. 3. Illuminated in-ground LEDs; participant equipped with eye-tracking glasses and performing the visual distractor task.

2.3.2. Smartphone

A Samsung S6 smartphone was used to run the visual and auditory distractor tasks. An app was developed to implement the distractor task and record participants performance on the task, using AndroidStudio version 3.2.1.

2.4. Procedure

Participants attended a pre-testing screening session at a local library. During this initial session, each participant signed the consent form. They had their vision tested under photopic conditions to ensure that they met normal limits for visual acuity using a high contrast letter chart (logMAR) and contrast sensitivity using a Pelli-Robson chart and met the visual acuity requirements for driving. They also familiarized themselves with the eye-tracking equipment, and completed the demographic survey, as well as the questionnaires including the Pedestrian Behaviour Scale and the Mobile Phone Problem Use Scale.

At the start of each testing session, researchers met participants near the level crossing used in the study. Each testing session took up to 2 h, and started at either 9 a.m., 11 a.m., 1 p.m., or 3 p.m. Participants were then equipped with the eye tracker, which recorded their scanning behavior and their oral comments. After the eye tracker was calibrated, the rail protection officer provided a safety briefing to each participant. The protection officer then positioned themselves in a strategic and unobtrusive position in the maze (see Fig. 1 right image), in order to detect any approaching trains and inform participants of the need to stop walking in a safe location if a train was approaching.

Participants were instructed to walk to the other side of the rail crossing and continue until they reached a given location and then turn and walk back three times consecutively under each distraction condition. Each walking task took up to five minutes. Participants were requested to complete these tasks to the best of their ability. Participants were informed that the mobile phone task was a reaction time task and involved tapping on the phone screen (using their thumb) as quickly and accurately as possible. They then practiced walking with and without completing the mobile phone task, until they felt confident to proceed with the experiment. Prior to the walking tasks, participants were instructed to say the word "LIGHT" whenever they perceived the in-ground lights flashing on approach to the level crossing (note that the in-ground LEDs were covered for the walking tasks using large mats for the control configuration). Participants were also told to maintain their safety at all times during the study, to be aware of their surroundings and other pedestrians or cyclists, and to be aware that trains did run from time to time through the rail crossings that they were approaching. After each testing conditions, participants completed a quick questionnaire (outside the scope of this study) and were given the opportunity to take a rest. At the end of their session, participants were thanked and provided with their incentive payment.

2.5. Data analysis

2.5.1. Coding of eye tracker videos

Videos recorded with the eye tracker provided information on where participants fixated their gaze while completing the study.

Table 1
Participants' demographics.

Demographic variable and Proportion/Frequency[a] (%)			
Gender		Highest education	
Male	12 (35.3)	High school	10 (29.4)
Female	22 (64.7)	Diploma	9 (26.5)
		Undergraduate	9 (26.5)
		Post-graduate	4 (11.8)
		Other	2 (5.9)
Activities mobile phone used for			
Phone calls	34 (100.0)	Navigation	29 (85.3)
Texting	33 (97.1)	Banking	29 (85.3)
Emailing	30 (88.2)	Shopping	19 (55.9)
Social networking/Facebook	33 (97.1)	Exercising	9 (26.5)
Entertaining	29 (85.3)		
Yes, had a 'close call' meaning you were almost hit, by a vehicle while walking and using your mobile phone[b]			27 (79.4)
Yes, hit by a vehicle while walking and using your mobile phone			1 (2.9)

[a] Gender, Highest education are proportions (add to 100%), while Activities mobile phone used for is reported as frequency (adds up to more than 100% given the multiple usages of the phone one participant can have).

Participants' gaze during their approach to the crossing (10 s before entering the maze) to the exit of the rail corridor were coded with the software Interact (version 9). The following coding scheme was used to record gaze position:

- Forward: Gazes that were directed straight ahead or towards the 'Look for trains' sign;
- Down: Gazes towards the ground, looking at the phone or looking at the in-ground LEDs; and
- Rail tracks: Gazes towards rail tracks, to both the left or right of the participant.

The video recordings were further coded in order to record the times when participants:

- Approached the crossing (10 s prior to the entrance of the maze);
- Entered the maze;
- Arrived at the entrance of the rail corridor;
- Entered the rail corridor;
- Exited the rail corridor; and, in the case of the level crossing with flashing lights
- Reported "LIGHT" To indicate that they had detected an in-ground LED light at the crossing.

These times were also used to estimate participants' walking duration (as a proxy for speed), in conjunction with measurements of the level crossing and their position ('Approach,' 'Maze,' and 'Rail corridor' as in Fig. 2) as they progressed through their tasks.

2.5.2. Statistical analyses

Data analysis evaluated the effect of (1) the level crossing type (two levels: control or treatment including in-ground LEDs), and (2) the distraction condition (three levels: no, visual, or auditory distraction) on the following dependent variables:

- Engagement with the distractor task, evaluated through the percentage of target words correctly detected, reaction times (time taken by the participant to tap the screen of the smartphone after the word was displayed or played by the smartphone), effects on gaze directions (looking down), and effect on walking speed when navigating the maze and traversing the rail tracks (measured as time);
- Ability to detect the activation of the flashing in-ground LEDs, evaluated through the percentage of correct detections, and the location where the lights were detected (approach, maze or once in the rail corridor);
- Gaze behavior while navigating the level crossing, evaluated as whether participants looked for trains before entering the crossing (three categories: cases when participants looked for trains in both direction, cases when participants only looked one way, and cases when participants did not look at all for trains) and the total time spent looking for trains.

Variables related to engagement with the distractor task were obtained from the data log of the app, as well as the coding of the eye tracker videos. Variables relating to the detection of the LEDs were obtained from the audio recording of the eye tracker, and gaze behavior were obtained from the coding of the eye tracker videos.

Statistical tests were run using Generalized Linear Mixed Models (GLMMs) to take into consideration the repeated measures design of this study. Software R version 3.4.2 was used with the MCMCglmm library. The level of significance chosen for the study was set at $\alpha = 0.05$. The participant sample size was chosen to reach a 0.9 power for medium to large effect sizes.

Specifically, the outcome measures were modelled using GLMMs from a Gaussian (for continuous variables) or Binomial (dichotomous variables) families, while considering the effects of the level crossing configuration (control or treatment including in-ground LEDs), distractor task (no, visual or auditory distraction), as well as their interactions.

3. Results

3.1. Demographics

Thirty-four participants completed the study protocol; however, visual acuity measures were not available for one of the participants (the participant was not able to attend the visual acuity testing session). The mean age of participants was 33.6 years

Table 2
Self-reported measures of pedestrian behaviour, and mobile phone problematic use.

Construct	Mean	SD	Actual range	Number of items	Cronbach's alpha
Pedestrian Behaviour Scale (PBS)[a]					
PBS Violation Subscale	3.20	1.02	1.00–6.00	4	0.69
PBS Error Subscale	3.39	0.89	1.75–5.50	4	0.61
PBS Lapse Subscale	1.70	0.76	1.00–5.00	4	0.80
PBS Aggressive Subscale	1.55	0.64	1.00–4.67	4	0.26
PBS Positive Subscale	3.41	1.07	1.75–6.00	4	0.66
Mobile Phone Problematic Use Scale[b]	107.06	33.74	46.00–191.00	27	0.91

[a] Possible range: 1–6.
[b] Possible range: 27–270.

Table 3
Statistically significant effects of factors considered on the variables of interest in this study.

	B	SE B	*β*	*t*	df	*p*
Distractor tasks						
Target word detection accuracy						
Intercept	3.14	0.22	2.89	14.6	147	<0.001
LEDs	−0.64	0.18	−0.61	−3.47	147	<0.001
Reaction times (ms)						
Intercept	655	14.3	0.56	69.19	3780	<0.001
Visual task	−350	8.3	−1.10	−42.28	3780	<0.001
Walking duration (s)						
Intercept	8.96	0.2	−0.13	47.19	1049	<0.001
Visual distractor	0.79	0.06	0.36	7.94	1049	<0.001
Audio distractor	0.28	0.06	0.2	4.37	1049	<0.001
LEDs	0.18	0.05	0.13	3.34	1049	<0.001
Down gazes (s)						
Intercept	2.71	0.32	−0.66	8.57	945	<0.001
Visual distractor	6.13	0.22	1.46	28.38	945	<0.001
LEDs	0.63	0.18	0.15	3.53	945	<0.001
Detection of flashing lights						
Accuracy						
Intercept	3.51	0.3	3.51	11.67	513	<0.001
Location where detected						
During approach						
Visual distractor	−0.58	0.19	−0.24	−3.00	488	0.003
In maze						
Intercept	3.65	0.42	3.08	8.8	275	<0.001
Visual distractor	−1.53	0.39	−0.74	−3.96	275	<0.001
Checking for train behaviour						
Appropriately checked						
Intercept	4.12	0.74	3.9	5.6	1188	<0.001
Visual distractor	−1.08	0.22	−0.60	−4.96	1188	<0.001
LEDs:Visual distractor	0.56	0.27	0.44	2.07	1188	0.038
Duration (s)						
Intercept	2.92	0.13	0.15	21.92	923	<0.001
Visual distractor	−1.24	0.12	−0.37	−9.90	923	<0.001
LEDs	−0.62	0.1	−0.35	−6.50	923	<0.001
LEDs:Visual distractor	0.36	0.18	0.11	2.03	923	0.042

(SD = 8.6; range = 18–51; 65% female). A summary of the demographic details is presented in Table 1.

The Pedestrian Behaviour Scale (Table 2) indicated that participants performed several positive pedestrian behaviors as well as frequent pedestrian violations and errors. The Mobile Phone Problematic Use Scale (Table 2) mean score was below the mid-point of 121.5 and well below the 160 cut-off mark indicating that participants were dependent on mobile phone use (Kalhori et al., 2015).

3.2. Visual acuity

Participants who usually wore corrective lenses or spectacles were asked to wear them for the vision testing and during the study. The mean visual acuity for participants was −0.08 (SD = 0.07) logMAR for their better eye, −0.02 (SD = 0.11) logMAR for their worse eye and −0.11 (SD = 0.07) logMAR with both eyes (better than 6/6 Snellen equivalent). Contrast sensitivity was also assessed and was shown to be normal for all participants, with a mean score of 1.96 (SD = 0.12) logCS.

3.3. Engagement with the distractor tasks

3.3.1. Performance

While navigating the control level crossing, participants correctly detected 94.4% of the target words in the visual and 95.3% in the auditory distractor condition. Statistical analyses (see Table 3) showed that accuracy on the distractor task was significantly reduced when walking through the crossing in the presence of the in-ground LEDs ($t = -3.47$, d.f. = 147, $p < .001$), independent of the modality of the distractor task (91.0% for the visual and 90.2% for the auditory condition). This decrement was on average 3.4%, which is likely to be due to participants attending more to navigation of the level crossing in the presence of the in-ground LEDs, resulting in reduced performance on the secondary task. However, the magnitude of this reduction was relatively small and is not the primary outcome of interest, which was scanning of and navigation of the crossing.

The reaction time to the distractor tasks was not significantly affected by the presence or absence of the flashing in-ground LED lights for either the visual (639 vs 644; $p = 0.962$) or auditory distractor tasks (992 vs 969 ms; $p = 0.525$). Participants were, however, 350 ms slower when performing the auditory distractor task compared to the visual distractor task (t = 42.3, d.f. = 3,780, $p < .001$; see Table 3).

3.3.2. Walking duration

Participants took an average of 8.9 seconds (SD = 1.2) to navigate through the control crossing and traverse the rail corridor while not distracted. Participants reduced their walking pace while performing the distractor task, as highlighted by the longer time taken to navigate the maze and the crossing (see Table 3). This increase in duration was more pronounced for the visual distractor task (0.79 s; $t = 7.94$, d.f. = 1,049, $p < .001$) than the auditory distractor task (0.28 s; $t = 4.37$, d.f. = 1,049, $p < .001$). Participants also walked more slowly to perform the task when the crossing was equipped with LEDs, with an increase in time of 0.18 s ($t = 3.34$, d.f. = 1,049, $p < .001$) compared to when traversing the crossing in its control condition (without in-ground lights).

3.3.3. "Down" gaze behaviors

The gaze analysis revealed that participants spent on average 2.9 s (SD = 2.0) looking down when approaching the control

Table 4
Count and frequency of when the activation of the LEDs was first detected by condition and location.

Distractor task	Location where in-ground LED activation detected		
	Approach	Maze	In the rail corridor
None	75 (45.2%)	85 (51.2%)	6 (3.6%)
Auditory	76 (45.8%)	87 (52.4%)	3 (1.8%)
Visual	61 (36.1%)	92 (54.4%)	16 (9.5%)

crossing while not distracted. Performing the auditory task did not significantly affect the "down" gaze behavior (p = 0.217), given that participants did not need to look at the mobile device to perform the task. In the presence of the visual distractor task, participants increased their "down" gazes to view the mobile phone screen (see Table 3). Under this visual distractor condition, participants spent on average 6.13 s longer looking down (t = 28.38, d.f. = 945, p < .001). The presence of the in-ground LEDs further increased the duration of "down" gazes by 0.63 s (t = 3.53, d.f. = 945, p < .001), most probably due to the need to look down at the LEDs. There were no significant first-order interactions.

3.4. Detection of flashing lights

3.4.1. Accuracy

Participants detected almost all in-ground LED light activations. On average, they detected the activation of the LEDs 95.2% of the time. There were no significant differences in LED detection as a function of distractor task.

3.4.2. Position where light activation is detected

For each detection of the activation of the in-ground lights, the relative position of the participant (approach, maze, or rail corridor) was determined (Table 4). There were no significant differences in detection position between the auditory task and the non-distraction condition (p = 0.764), showing that the auditory task did not have any effect on the location away from the crossing where participants' detected the LEDs. Participants were less likely to detect the activation of the LEDs in the 'Approach' section when visually distracted (t = −3.00, d.f. = 488, p = .003; see Table 3). Detection of the in-ground lights reduced from 45.5% (no and auditory distractor tasks combined) to 36.1% during the approach when performing the visual distractor task. This suggests that they detected the activation of the lights later in their approach to the level crossing compared to the no distractor or auditory distractor tasks. Participants were also more likely to detect the LED activation after they entered the rail corridor when they were visually distracted, as compared to the two other conditions (t = −3.96, d.f. = 275, p < .001).

Further analysis was conducted to determine more precisely when the in-ground LEDs were first detected within the participant's navigation path. Heat maps of the location where participants reported detecting the LEDs are presented in Fig. 4 for each distractor condition. The heat maps revealed that participants detected the activation of the LEDs either during the approach or at the start of the maze, with most participants detecting the in-ground lights as soon as they activated. When completing the visual distractor task, a second peak in the probability distribution was observed in the vicinity of the in-ground LEDs. This suggests that participants who did not detect the LEDs when first activated (because of looking down at the visual distractor task), detected them as they got closer to them. Importantly, detections of the LEDs reported while in the rail corridor (i.e. while traversing the crossing) occurred as they reached the entry to the rail corridor, before reaching the danger zone, thus well in time for acting on such detection.

3.5. Eye gaze behavior at the crossing

3.5.1. Checking for presence of trains

Fig. 5 reports the proportion of participants who searched for trains or not. Analyses revealed that for most traversals (79.9%) of the control crossing, participants looked at least once in both directions when not distracted, and this was statistically similar when performing the auditory task (77.9%). However, participants were less likely to check for trains when performing the visual distractor task (see Table 3), with a reduction to 70.1% (t = −4.96, d.f. = 1,188, p < .001). For the treatment condition, participants performing the visual distractor task checked both sides of the crossing 77.0% of the time, which was a significant increase compared to visual distraction when navigating the control crossing (t = 2.07, d.f. = 1,188, p = .038). This level of performance was close to that found when not distracted at the control crossing.

Furthermore, the detection of the in-ground lights was followed by gazes toward the rail tracks 42.9% of the time. This suggests that the in-ground LEDs were effective at reminding participants to look for trains, and may explain the improvement in checking behavior when visually distracted relative to the visual distractor condition when crossing the control site.

3.5.2. Amount of time spent looking for trains

On average, participants spent 2.92 s searching for trains when they navigated through the maze and traversed the control level crossing. The auditory distractor task did not significantly affect this duration, however the visual task resulted in a reduction of this checking behavior by 1.24 s (t = −9.90, d.f. = 923, p < .001, see Table 3). In the presence of the in-ground LEDs, this duration decreased by 0.62 s (t = −6.50, d.f. = 923, p < .001) when participant were not distracted, which may be related to the fact that participant spent some time looking at the LEDs when in the maze, which is often the location where most participants looked for trains. This reduction in the treatment condition was not as pronounced for the visual distraction condition. Indeed, the reduction was 0.36 s less than what would have been expected when combining the reduction from the visual distractor and the presence of LEDs (t = 2.03, d.f. = 923, p = .042). However, this checking duration remained the shortest of all conditions (1.42 s) and is likely to be due to participants checking for trains just as they entered the crossing (see Section 3.4.1).

4. Discussion

In this field-based study, the effects of in-ground LEDs at a passively protected level crossing equipped with a maze were evaluated, with the LEDs being activated by the approach of the pedestrian just prior to them entering the maze. Participants were regular users of mobile devices when walking, as confirmed by the Mobile Phone Problematic Use questionnaire.

4.1. Engagement with distractor tasks

The findings showed that the participants were actively engaged in the visual and auditory distractor tasks. Both tasks were performed at a high level of accuracy, with rapid response times. Participants' performance was similar to the performance levels reported in a laboratory study using a similar task (Larue, Watling, et al., 2020). We can therefore be confident that participants were allocating sufficient attention towards the distractor tasks. Participants compensated for performing the distractor tasks

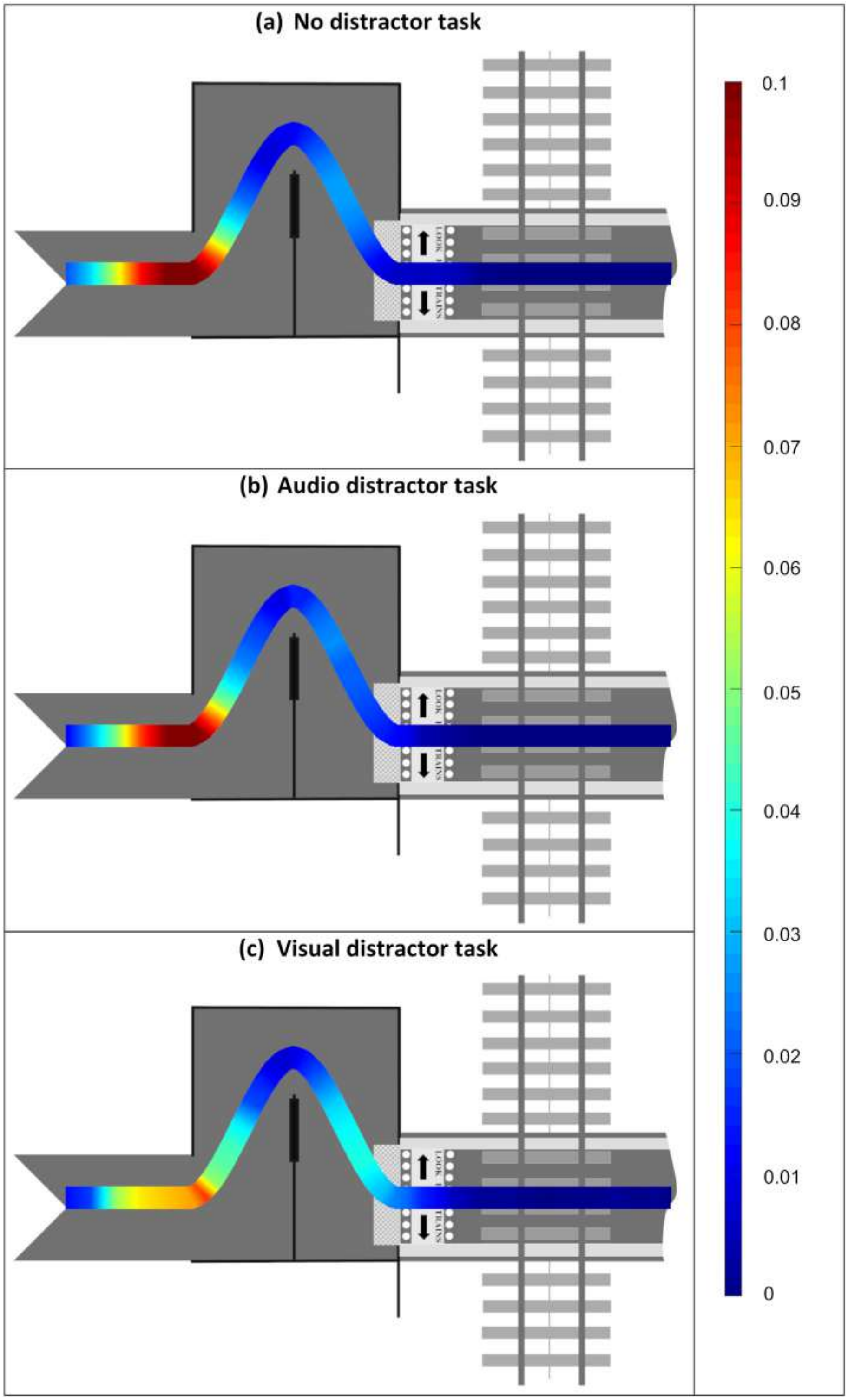

Fig. 4. Probability density function (displayed as a heat map) of the location where the activation of the LEDs was detected by participants.

while walking through the crossing (a dual task) by reducing their walking pace. Such behavior has also been observed in other research concerning distracted drivers reducing their vehicle's speed (Alsaleh, Sayed, & Zaki, 2018) as well as pedestrian behaviors (Kim, Park, Cha, & Song, 2014). Reducing walking speed was more pronounced for the visual distraction condition, suggesting that the visual task was more difficult to perform while walking through the crossing and undertaking the other tasks. This is also supported by the fact that pedestrians looked down three times longer when performing the visual task, potentially to look at the phone, or at the path just in front of them. This behavior was different in the absence of the visual distractor task, where participants were looking ahead most of the time during the no distractor and auditory distractor conditions. This suggests that the audio distractor task was less distracting compared to the visual task, likely due to participants being able to perform the

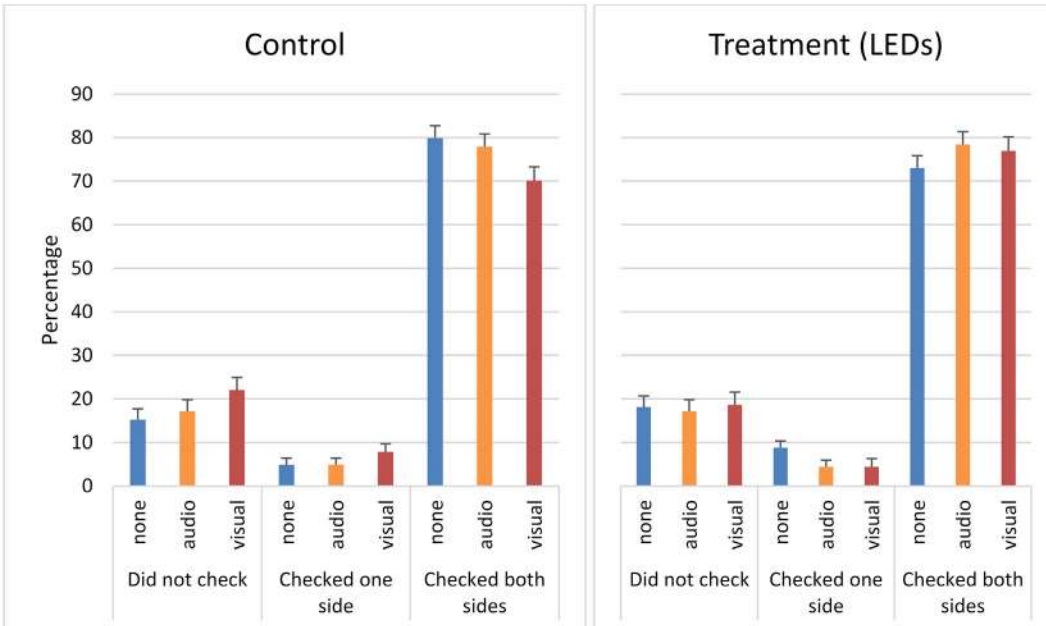

Fig. 5. Gazes at the rail tracks when looking for trains.

audio secondary task while looking ahead. Overall, this highlights that participants were distracted while navigating the crossing, and that we can be confident that our findings reflect the effects of in-ground LEDs at passive level crossings while distracted. However, the effects of the audio distractor task were less pronounced than the visual distractor task.

4.2. Behaviour at the control pedestrian level crossing

The observed behavior of pedestrians navigating through the crossing in the absence of in-ground lights (control) was to enter the maze and to look for trains while going through the maze. The mazes are designed to make pedestrians look for trains in both directions prior to entering the rail corridor without stopping. In the current study, participants did check for trains in both directions of the rail corridor 79% of the time, collapsed across distractor conditions. Searching for trains took, on average, 4.5 seconds to complete in the absence of any distractors.

Performing the auditory distractor task did not result in any significant change in behavior while navigating through the crossing. On the other hand, the visual distractor task was found to reduce performance: checking for trains in both directions was reduced by 10%. Participants also spent less time looking for trains when visually distracted, as the results showed they had to keep looking down at their phone while performing the task, even though they reduced their walking pace (a compensatory behavior). These outcomes are consistent with several studies examining the effect of distracted pedestrians when crossing roadways and failing to check their surroundings for danger (e.g., Pharo, 2019; Simmons, Caird, Ta, Sterzer, & Hagel, 2020). In the current study, participants' compensation (slower walking) was sufficient to maintain similar performance when performing the auditory task relative to the no-distractor condition and the audio distractor may have not been sufficiently distractive to be representative of a realistic listening task. Yet, slower walking was not sufficient to maintain performance when visually distracted, and this resulted in more risky crossing behaviors occurring (such as not checking for trains before crossing when visually distracted).

4.3. Detection of activations of LED lights

The activation of in-ground LEDs with the approach of a pedestrian was found to be an effective way to attract their attention. Indeed, participants almost always detected the activation of the flashing lights, even when distracted. However, distraction affected the location at which the flashing LEDs were first detected. The auditory distraction resulted in the activation of the LEDs being detected slightly later than when not distracted, as pedestrians entered the maze. This highlights that the audio distractor task, while simpler, had nonetheless a distractive effect on participants, slowing their response to the activation of the lights. When participants were visually distracted, the typical pattern of detection of the LEDs consisted of either detection at the entrance of the maze (similar to the non-distraction and auditory distraction conditions), or when they were almost walking on top of the LEDs, as they approached and entered the rail corridor. This suggests that while participants were looking down at the phone, they were less likely to detect the activation of the LEDs when they approached or entered the maze, which would likely have been out of their field of view.

As the participants traversed through the maze, they were able to detect the LEDs as they looked down at the phone and were almost on top or next to the LEDs. The current findings are consistent with outcomes reported from a laboratory study, where visually distracted participants were effective at detecting the activation of lights only when they were close to them (Larue, Watling, et al., 2020). It should also be noted that in the present study when traversing the crossing with in-ground LEDs, participants spent more time (0.7 s) looking down, which suggests that they were looking down at the activated LEDs. Gazes toward the in-ground LEDs may increase the chance for pedestrians noticing the "Look for Trains" signage. This is a positive finding, given participants tended not to look at the 'Look for Trains' sign placed vertically in the middle of the maze. But more thorough investigations are necessary to confirm this and ensure that this is not due to a novelty effect (e.g., Schomaker & Meeter, 2012). Together, these findings support the efficacy of in-ground LEDs for attracting distracted pedestrians' attention and facilitating safer crossing behaviors. Moreover, this also suggests that the placement (at the entrance of the rail corridor, on both sides of the crossing, and around 2 meters away from the rail tracks) and time of activation of the LEDs (around the entrance of the maze) are important and appropriate for their intended use, being effective at attracting pedestrians' attention, even when visually distracted.

4.4. Effects of the lights on behavior

In addition to attracting the participants' attention, in-ground LEDs resulted in safer environment scanning behaviors at the crossing, particularly when visually distracted, compared to the control condition. Participants who were visually distracted by the phone task but detected the activation of the LEDs, were found to check for trains on both sides of the crossing 77% of the time. This behavior is similar to that observed in the absence of distraction. It should be noted that 43% of the time, the first gaze following the detection of the LEDs when visually distracted was on the rail tracks, suggesting that participants made the link between detecting the lights and the need to look for trains. This suggests that in-ground LEDs can act to remind distracted participants to perform checking behaviors when approaching rail tracks, in a similar manner to when they are not distracted. Previous research has determined that road signage and road perceptual treatments can lead to safer driving behaviors, despite signage not being explicitly comprehended but rather at an implicit awareness level (Auberlet et al., 2012; Charlton, 2004; Montella et al., 2011). However, it did not appear to induce an increase in the time checking for trains in this study, which could be due to participants perceiving that their visual scanning of the tracks was sufficient and no further checking was required, however, the motivation for these behaviors needs to be explored further. Alternatively, given the sample was generally effective at checking for trains in the control condition, the LEDs may act as a reminder for them to perform visual checking that they would have performed anyway if they were not distracted. Further investigations should be conducted to better understand the positive effects found here, especially since the installation of in-ground lights at road intersections has been reported to heighten pedestrians' level of caution (Transport for New South Wales, 2014).

When visually distracted, pedestrians not only tended to check for trains less often, but they also checked for trains for a shorter duration. Importantly, this reduction was less pronounced in the presence of the in-ground LEDs. While no literature is available to provide a minimum duration for checking for trains appropriately, it is likely that such time (2.8 s) is sufficient to safely assess the situation on both sides of the crossing.

Finally, participants were found to spend less time looking for trains when the LEDs were installed. The duration reduced by 0.7 s, such that they spent 3.8 s looking for trains. This is linked to the 0.7 s increase in looking down behavior, which is the time participants spent looking at the in-ground LEDs.

4.5. Strengths, limitations and future directions

This study is the first to evaluate the potential benefits of in-ground LEDs for attracting the attention of pedestrians distracted while using mobile devices. However, there are a number of limitations that need to be acknowledged when interpreting the results. Only one site was evaluated, and only one type of pedestrian level crossing: passive level crossings with a maze. The sample size also does not allow generalization of the findings outside the current circumstances and tasks performed. Further research is therefore necessary to confirm whether the observed effects of in-ground flashing LEDs are also observed at other level crossing configurations, (such as active crossings, or crossing without mazes), and also for road intersections and other populations.

The distractor tasks were designed to increase cognitive workload without being overly challenging. This approach was selected to ensure the safety of participants at a site where trains could traverse the crossing, due to the current lack of evidence around the effectiveness of the treatment. In particular, the auditory distractor task focused solely on listening and had a limited effect on participant's performance while navigating through the level crossing. The distractor task difficulty level, while sufficient for the visual modality, may have been not sufficient as a distractor in the audio modality. Further research should investigate whether the positive effects found in this study remain for other types of distractions (e.g., phone discussion) and for more challenging and realistic distractor tasks, particularly when presented in an auditory mode.

The observed behavior may also not be fully representative of participants' habitual behavior at level crossings. Indeed, participation while wearing an eye tracker and the presence of the safety officer are likely to have increased people's awareness of looking for trains. However, the safety officer tried to be as inconspicuous as possible and intervene on only limited occasions.

Effects over longer periods of time were not investigated in this study. The positive changes in behavior at the crossing may reduce with habituation, and further research should aim at assessing whether behavior changes remain after pedestrians get used to this warning, and when not involved in a study. Indeed, longer exposure to such added warning could lead to complacency, which is a known issue at railway crossings for road vehicles (Landry, Jeon, & Lautala, 2016), particularly at passive level crossings with low train traffic volumes (Larue, Wullems, Sheldrake, & Rakotonirainy, 2018; Rudin-Brown, George, & Stuart, 2014).

The effects of the in-ground flashing lights were not investigated at night. However, their conspicuity at night is likely to be higher and effects on attracting pedestrians' attention are likely to be even stronger than during daytime. It would be useful to determine if this were the case by conducting further research at night.

While the results suggest that the behavior of participants improved with the LEDs, with increased attention toward the rail tracks when distracted, further research should aim to understand whether such an intervention is likely to be effective for all types of users of level crossings, or whether it will attract pedestrians' attention without resulting in a change in behavior. This understanding is critical in determining whether it would be beneficial to install in-ground LEDs more generally at level crossings. If the presence of LEDs changes behavior, they would be effective generally, however, if they are only effective at attracting attention, they may only be effective with pedestrians who are generally compliant with signage and fail to realize they were approaching a crossing when distracted. Such information would be useful for conducting cost-benefit analyses, which are critical to ensure the viability of the approach as an intervention. Future research should also investigate the effects of in-ground LEDs at other types of intersections, such as road intersections.

5. Conclusion

The use of in-ground illuminated lights installed in the footpath demonstrate a range of positive effects at passive rail crossings with a maze, in terms of attracting attention and checking for trains. Performance at the control level crossing decreased when distracted, particularly with the visual distractor task. With these flashing in-ground LEDs, performance at the level crossing while distracted was similar to that when not distracted. These benefits were found for a cohort of pedestrians who regularly use their mobile device while walking and are largely compliant with level crossings. Further research could focus on whether such signage is effective for pedestrians who would not normally comply with the crossing (due to habituation to low train traffic which can lead to complacency, for instance through not looking for trains) and for other types of intersections, such as road intersections. Evaluation over longer periods would also be valuable to ensure that any positive effects are sustained following pedestrians becoming familiar with these warning devices.

Acknowledgements

The research team would like to acknowledge the assistance of KiwiRail and financial support from the Australasian Centre for Rail Innovation (ACRI) project LC18 – Pedestrian LED visual warning device.

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Dr Gregoire Larue received his Master of Science (mathematics) from the University of Queensland (Australia) and a Master of Engineering from the Ecole Centrale de Lyon (France). He joined the Centre for Accident Research and Road Safety – Queensland at the Queensland University of Technology in 2006. He is currently a

senior research fellow in road safety and Intelligent Transport Systems, and he has worked on a range of industrial and government projects focusing on evaluating how road users react to new technologies.

Dr Christopher Watling is a Research Fellow with the Centre for Accident Research and Road Safety – Queensland, Australia, and is the principal researcher for sleepiness and fatigue at the Centre. His main research focus is the impact of sleepiness and arousal on neurobehavioural and driving performance as well as attitudinal and behavioural precursors and facilitators involved with sleepy driving. Christopher has a strong background in the assessment and interpretation of psychophysiological data (i.e., NIRS, EEG, ECG, EOG, EMG, EDA/GSR, actigraphy, eye tracking) in the contexts of driving behaviours, human factors, and human-computer interaction. He also has extensive experience with conducting experimental research designs in driving simulators, hazard perception tests, and with field-based studies, evaluations of the effectiveness of a number of driver sleepiness countermeasures (naps, rest breaks, rumble strips) as well as conducting surveys of drivers' attitudinal and behavioural outcomes.

Dr Alexander Black is a Lecturer in the School of Optometry & Vision Science at Queensland University of Technology (QUT) in Brisbane, Australia. He received his PhD in Vision Science (QUT) in 2010, and completed a Masters of Public Health (University of Queensland) in 2012. Dr Black is engaged in the clinical training of optometry students. Dr Black is an optometrist and injury epidemiologist whose research focuses on the impact of vision impairment on everyday activities, such as walking and driving, especially older adults with age-related ocular conditions. Current active research interests include gaze behaviour when driving, night-time driving difficulties and pedestrian visibility. He is a member of the Association for Research in Vision and Ophthalmology (ARVO) and the American Academy of Optometry.

Dr Joanne Wood is a Professor in the School of Optometry and Vision Science at QUT, and has extensive research experience in a number of areas: vision and driving, vision and falls, children's functional vision and clinical psychophysics (including visual field testing and development of techniques for the early detection of ocular disease). Her research experience, spanning over a period of 25 years, includes a PhD in Visual Sciences at Aston University, UK, followed by a Post Doctoral Fellowship in Clinical Psychophysics at Oxford University. Since 1989 she has been at QUT, and she has also had roles as Director of Research in Optometry and leader of the Vision Improvement Domain of the Institute of Health and Biomedical Innovation. In recognition of her achievements she was awarded an Honorary Doctor of Science (DSc honoris causa) from Aston University in Birmingham, UK.

Journal of Safety Research 77 (2021) 56–60

Contents lists available at ScienceDirect

Journal of Safety Research

journal homepage: www.elsevier.com/locate/jsr

Incidence of injury in children and adolescents with intellectual and developmental disability

Jen Calver, Robert Balogh, David Rudoler *

Ontario Tech University, 2000 Simcoe St. N., Oshawa, ON L1G 0C5, Canada

ARTICLE INFO

Article history:
Received 13 March 2020
Received in revised form 26 September 2020
Accepted 2 February 2021
Available online 2 March 2021

Keywords:
Hospitalizations
Injury
Accidents
Fractures
Wounds
Disability

ABSTRACT

Introduction: Children and adolescents living with intellectual and developmental disability (IDD) have a higher risk of experiencing morbidities and premature death when compared to children and adolescents living without IDD. Childhood injuries are a leading cause of morbidity and death, yet there are limited studies that explore the prevalence of childhood injuries for individuals living with IDD. The purpose of this study was to analyze Ontario health administrative data to identify and compare rates of injury resulting in hospitalization in children and adolescents living with and without IDD. *Methods:* This is a cross-sectional study of all Ontarians aged 0–19 years with and without IDD. The outcome of interest was the rate of injury resulting in hospitalization. *Results:* This study found that children and adolescents with IDD had 1.79 (CI 1.66, 1.92) times higher rates of both intentional and unintentional injuries that resulted in hospitalization when compared to children and adolescents without IDD. Hospitalizations for self-harm related injuries were 3.16 (CI 3.09, 3.23) times higher in the IDD group. *Conclusion*: Children and adolescents with IDD have a higher risk of sustaining serious injuries, particularly injuries resulting from self-harm. *Practical Applications:* This study provides evidence of increased injury related hospitalizations for children and adolescents with IDD when compared to their peers without IDD.

1. Introduction

Injury is a predominant driver of morbidity and mortality in children and adolescents (Brameld, Spilsbury, Rosenwax, Leonard, & Semmens, 2018; Brenner et al., 2013; Canadian Institute for Health Information (CIHI), 2010; Wada et al., 2018; White, McPherson, Lennox, & Ware, 2018). The serious and often irremediable implications of childhood injuries place a heavy burden on social and economic systems. In 2015, there were more than 10,000 Ontarian children hospitalized for reported injuries and over 280,000 visits to the emergency department (Cowle, 2016). The economic burden of injury costs Canadians more than $26 billion dollars a year and is expected to double over the next 15 years (Parachute, 2015).

The focus of this research is on injuries among youth with intellectual and developmental disabilities (IDD). We use a definition for IDD that is consistent with the one used by the Government of Ontario to determine eligibility for services for people with developmental disabilities. Accordingly, a person with IDD has limitations in cognitive and adaptive functioning that originates before the age of 18 (Lunsky, Klein-Geltink, & Yates, 2013). Cognitive function refers to an individuals ability to reason, organize, and make judgments while adaptive behavior refers to the ability to perform practical skills in daily activities in an effort to gain independence (Ministry of Children Community and Social Services, 2014).

Previous studies have suggested that children with disabilities are more susceptible to injuries and have a higher risk of sustaining unintentional injuries (Shi et al., 2015; Yung, Haagsma, & Polinder, 2014). Unintentional injuries include burns, falls, motor-vehicle accidents, and environmental injuries, while intentional injuries include assault and self-harm (Association of Public Health Epidemiologist in Ontario [APHEO], 2012). Existing research has examined injury in children living with disorders related to IDD such as autism spectrum disorder; however, few studies could be found that investigated injuries among youth with IDD, and specifically intentional injuries have been identified as an important gap in existing research (White, McPherson, Lennox, & Ware, 2018). This gap exists despite the known health inequities identified between those with and without IDD for a number of health and health care related outcomes (Krahn, Hammond, & Turner, 2006). The limited availability of evidence to inform injury prevention experts of the potentially unique considerations specific to

* Corresponding author.
E-mail address: david.rudoler@ontariotechu.ca (D. Rudoler).

https://doi.org/10.1016/j.jsr.2021.02.003
0022-4375/

children and adolescents with IDD suggests a need to prioritize research in this area.

This study addresses data and information gaps in the research by determining the rates of unintended and intended injuries resulting in hospitalization in the youth IDD population through the use of health administrative data. Moreover, this study provides valuable information for social and healthcare practitioners, injury prevention experts, and provides a foundation for future research in injury prevention in children with disabilities.

2. Materials and methods

2.1. Study design

This was a cross-sectional study of injury rates resulting in hospitalization (between January 1, 2014 and December 31, 2016) for youth and adolescents living in Ontario, aged 0 to 19 with IDD compared to those without IDD. This research study was approved by the University of Ontario Institute of Technology Research Ethics Board. File number 15337.

2.2. Data sources and identification of study groups

This study used administrative health data obtained from IntelliHealth Ontario (Ontario Ministry of Health and Long-Term Care, n.d.). The IntelliHealth Ontario data contains information on all persons registered with the Ontario Health Insurance Plan (OHIP). This includes all people who are Canadian citizens, landed immigrants or convention refugees, who make their permanent residence in Ontario, and who are physically present in Ontario for 153 days of any 12-month period. This information is linked with data on all inpatient hospitalizations (Discharge Abstract Database), psychiatric hospitalizations (Ontario Mental Health Reporting System), emergency department visits (National Ambulatory Care Reporting System), and physician visits (Medical Services) through an anonymized identifier. The data also include information on resident characteristics, including age and sex.

Youth and adolescents with IDD were identified by adapting an algorithm developed by Lunsky et al. (2013). We assigned an IDD diagnosis to anyone who met one or more of the following criteria: (a) at least one inpatient hospitalization or emergency department visit where the main diagnosis was an IDD code; (b) at least one psychiatric hospitalization where the Axis-I or Axis-II diagnosis was an IDD code (299 to 299.80 and 317 to 319.99); or (c) at least two physician visits with an IDD diagnosis code (299 or 319). International Statistical Classification of Diseases (ICD) codes for diseases and conditions consistent with our definition for IDD described earlier were included in the analysis; the original list of codes was developed in consultation with clinicians and policy makers (Lunsky et al., 2013). This included codes for diseases and conditions such as intellectual disability, autism spectrum disorder, Down syndrome, fragile x, fetal alcohol syndrome, and other conditions. A list of ICD-10 and ICD-9 codes used to identify persons with IDD is provided in the supplementary materials.

To identify records of people with IDD, we used the longest lookback period that the data would allow. This included all inpatient hospitalizations from 1996 to 2016, all physician visits from 2000 to 2016, all emergency department visits from 2002 to 2016, and all psychiatric hospitalizations from 2005 to 2016. We limited our study population to youth and adolescents between the ages of 0 and 19 years, with an IDD diagnosis who were eligible for provincial health insurance between January 1, 2014 and December 31, 2016. Our comparison group included all Ontario youth and adolescents between the ages of 0 and 19 years, without an IDD diagnosis who were eligible for provincial health insurance during the same time period.

Our outcome of interest was captured using an algorithm developed by the Association of Public Health Epidemiologists of Ontario (2012). The algorithm identified external cause ICD-10 codes in the National Ambulatory Care Reporting system for all unintentional (ICD-10: V01-X59 and Y85-Y89) and intentional (ICD-10: X60-Y09) injuries that resulted in hospitalization. We captured all reported injuries resulting in hospitalization between January 1, 2014 and December 31, 2016. We reported our main results as crude, sex and age stratified, and sex and age adjusted incidence rates for injuries in the IDD and no-IDD groups over the three-year study period. We also generated incidence rate ratios for all comparisons. In addition, we generated incidence rates by different external causes of injury: vehicle-related (ICD-10: V01-V99), falls (ICD-10: W00-W19), mechanical forces (ICD-10: W20-W64), and self-harm (ICD-10: X60-X84). Due to small numbers of observations in each of the remaining categories, we combined them into a general category that we called "Other Causes." Since each hospitalization could have been associated with several external causes, the number of injury events aggregated across all of these categories was greater than the total number of injuries resulting in hospitalization.

3. Results

The study population (Table 1) included all Ontario residents between ages 0 and 19 captured in the Registered Persons Database from January 1, 2014 to December 31, 2016 (n = 10,095,328 person years). We excluded those who were ineligible for public health insurance in Ontario (n = 635 person years), and those with missing health insurance eligibility information (n = 359 person years). We identified 144,737 person years in the IDD group (aged 0–19 years) and 9,949,587 in the general Ontario population (aged 0–19 years).

The incidence rates, ratios and 95% CIs for the study population are described in Table 1. During the study period, there were 730 and 28,064 injuries that resulted in hospitalization in the IDD group and general population, respectively. Overall, the crude incidence of injury was higher in the IDD population (5.04 per 1,000 population; 95% CI 4.68–5.42) than the non-IDD population (2.82 per 1,000 population; 95% CI 2.79–2.85).

The incidence rate of injury was 1.36 (95% CI 1.24–1.49) and 3.15 (CI 95% 2.80–3.55) times higher for males and females with IDD, respectively (Table 2). Meanwhile, the incidence rates were 1.45 (95% CI 1.30–1.61) times higher for children (aged 0–12) with IDD, and 2.22 (95% CI 2.01–2.45) times higher for adolescents (aged 13–19) with IDD (Table 2).

The crude rate for vehicular accidents was 0.27 for the IDD population and 0.35 for the non-IDD group. The crude rate for falls was 1.02 for the IDD population and 0.92 for the non-IDD group (Table 3). Self-harm was the leading mechanism of injury for the IDD population. The IDD population had 3.16 (95% CI 3.09–3.23) times the incidence rate of hospitalizations for injuries caused by self-harm (Table 3).

Comparing different groups within the IDD group, we also find differing levels of risk. The incidence rate for injury resulting in hospitalization was twice as high for girls with IDD than boys with IDD (IRR = 2.05; 95% CI 1.77–2.38), and half as high for children aged 0 to 12 compared to adolescents aged 13 to 19 (IRR = 0.48; 95% CI 0.41–0.55). Also, the incidence rate for hospitalized injuries resulting from self-harm was over six times higher in girls with IDD compared to boys with IDD (IRR = 6.36; 95% CI 4.83–8.36), and dramatically lower for children compared to adolescents (IRR = 0.04; 95% CI 0.02–0.07).

Table 1
Injury incidence rates (per 1,000 population) and incidence rate ratios (2014–2016).

Group	At Risk (person years)	Cases	Crude Rate (95% CI)	IRR (95% CI)	Sex Std. Rate (95% CI)	Sex Std. IRR (95% CI)	Age Std. Rate (95% CI)	Age Std. IRR (95% CI)
IDD	144,737	730	5.04 (4.69, 5.42)	1.79 (1.66, 1.92)	6.13 (5.69, 6.58)	2.17 (2.14, 2.20)	5.06 (4.69, 5.43)	1.83 (1.81, 1.86)
No IDD	9,949,587	28,064	2.82 (2.79, 2.85)		2.82 (2.79, 2.85)		2.76 (2.73, 2.79)	

Table abbreviations: IDD = intellectual developmental disability; IRR = incidence rate ratio; 95% CI = 95% confidence interval; Std = standardized.

Table 2
Injury incidence rates (per 1,000 population) and incidence rate ratios by sex and by age group (2014–2016).

Group	At Risk (person years)	Cases	Crude Rate (95% CI)	IRR (95% CI)
IDD Male	111,638	454	4.07 (3.70, 4.46)	1.36 (1.24, 1.49)
No IDD Male	5,066,737	15,140	2.99 (2.94, 3.04)	
IDD Female	33,099	276	8.34 (7.38, 9.38)	3.15 (2.80, 3.55)
No IDD Female	4,882,850	12,924	2.65 (2.60, 2.69)	
IDD Age (0–12)	92,324	334	3.62 (3.24, 4.03)	1.45 (1.30, 1.61)
No IDD Age (0–12)	6,398,936	15,968	2.50 (2.46, 2.53)	
IDD Age (13–19)	52,413	396	7.56 (6.83, 8.34)	2.22 (2.01, 2.45)
No IDD Age (13–19)	3,550,651	12,096	3.41 (3.35, 3.47)	

Table abbreviations: IDD = intellectual developmental disability; IRR = incidence rate ratio; 95% CI = 95% confidence interval.

Table 3
Incidence rates (per 1,000 population) and incidence rate ratios by mechanism of injury (2014–2016).

Group	At Risk (person years)	Cases	Crude Rate (95% CI)	IRR (95% CI)	Sex Std. Rate (95% CI)	Sex. Std. IRR (95% CI)	Age Std. Rate (95% CI)	Age. Std. IRR (95% CI)
IDD Vehicular	144,737	39	0.27 (0.19, 0.37)	0.76 (0.55, 1.04)	0.21 (0.14, 0.28)	0.59 (0.56, 0.62)	0.27 (0.18, 0.35)	0.78 (0.74, 0.82)
No IDD Vehicular	9,949,587	3,529	0.35 (0.34, 0.37)		0.36 (0.34, 0.37)		0.34 (0.33, 0.35)	
IDD Mechanical	144,737	157	1.08 (0.92, 1.27)	2.01 (1.94, 2.09)	1.25 (1.05, 1.44)	2.31 (2.24, 2.38)	1.09 (0.92, 1.26)	2.05 (1.99, 2.12)
No IDD Mechanical	9,949,587	5,364	0.54 (0.52, 0.55)		0.54 (0.53, 0.55)		0.53 (0.52, 0.54)	
IDD Falls	144,737	147	1.02 (0.86, 1.19)	1.10 (1.03, 1.18)	1.00 (0.84, 1.16)	1.09 (1.06, 1.12)	1.08 (0.91, 1.26)	1.19 (1.16, 1.22)
No IDD Falls	9,949,587	9,145	0.92 (0.90, 0.94)		0.92 (0.90, 0.94)		0.91 (0.89, 0.93)	
IDD Self-harm	144,737	225	1.55 (1.36, 1.77)	3.16 (3.09, 3.23)	2.51 (2.18, 2.83)	5.12 (4.97, 5.28)	1.40 (1.22, 1.58)	2.96 (2.87, 3.06)
No IDD Self-harm	9,949,587	4,897	0.49 (0.48, 0.51)		0.49 (0.48, 0.51)		0.47 (0.46, 0.49)	
IDD Other	144,737	168	1.16 (0.99, 1.35)	2.24 (2.17, 2.31)	1.20 (1.02, 1.38)	2.30 (2.23, 2.38)	1.26 (1.07, 1.45)	2.49 (2.41, 2.57)
No IDD Other	9,949,587	5,167	0.52 (0.51, 0.53)		0.52 (0.51, 0.53)		0.50 (0.49, 0.52)	

Table abbreviations: IDD = intellectual developmental disability; IRR = incidence rate ratio; 95% CI = 95% confidence interval; Std. = Standardized. Note: "other" injuries include the following ICD 10 codes: W65-W79, X00-X59, Y00-Y09.

4. Discussion

Using health administrative data, this study demonstrates a higher incidence rate of injury reported hospitalizations for children and adolescents living with IDD compared to those living without IDD. We also found that, among those with IDD, adolescents were at higher risk than children, and girls were at higher risk than boys, particularly for injuries resulting from self-harm. This study is distinct from existing publications as it includes data pertaining to both unintentional and intentional injury reports.

Health administrative data have not been commonly used to explore childhood injury in the IDD population. While preserving anonymity, health administrative data contains specific information making it possible to identify individuals living with IDD and utilization of health services (Lin et al., 2013; Wada et al., 2018). The individualized identifiers available through health administrative data provides useful individual level diagnostic information (Lunsky et al., 2013).

Although previous studies have suggested the risk of injury is greater for children living with disabilities than without disabilities (Bonander, Beckman, Janson, & Jernbro, 2016; Shi et al., 2015; White et al., 2018), this is the first study to measure the actual rate of injury reported hospitalizations for children and adolescents with and without IDD. Overall, this study found a consistently higher incidence rate of hospitalizations for injuries in the IDD population for both males and females, and in both children and adolescent groups when compared to their peers without IDD (Table 2). As the injuries observed in this study required hospital treatment and interventions, the injuries should be considered more severe.

It is well documented that the IDD population generally experience greater health disparities and poorer health status when compared to non-IDD groups (Brameld et al, 2018; Lunsky et al, 2013; Weise, Pollack, Britt, & Trollor, 2017). The higher rate of injuries for persons with IDD reported in this study are consistent with this literature. In contrast, a study by Brenner et al. (2013) suggested there is no difference in injury rates between youth with and without developmental disabilities. The authors found that medically reported injury rates were comparable between the two groups. We speculate that this inconsistency can be explained by the difference in how disability was defined in each study, and the methodology used to identify children and adolescents with a disability. In Brenner et al. (2013), parents of children who suffered an unintentional injury were asked if they had ever been told by a medical professional that their child had: a learning disability, autism, blindness, cerebral palsy, deafness or trouble hearing, mental retardation, attention deficit disorder (ADD) or attention deficit hyperactivity disorder (ADHD). In our study, parents were not interviewed. Instead, we identified children and adolescents with IDD in health databases using diagnostic codes from a list of conditions that were different from the list in Brenner et al. (2013) (see supplementary material). Additionally, Brenner et al. (2013) concentrated on unintentional injuries, where we also observed rates of hospitalization both unintentional and intentional injuries. Our findings suggest intentional injuries are a larger driver of hospitalizations for the IDD population. Using a longitudinal design, future research should investigate the reasons for the higher rates of injuries and identify potentially modifiable factors.

Our study found that self-harm was the most common mechanism of injury among those with IDD (31% of injuries), while only 17% of injuries among those without IDD were related to self-harm. This finding is not surprising considering the high prevalence of mental illness and behaviors that challenge exhibited by those with IDD (Fodstad, Kirsch, Faidley, & Bauer, 2018; Richards, Oliver, Nelson, & Moss, 2012). Identifying and developing effective interventions that address self harm and the injuries they cause are a priority for youth with IDD.

Our study had some limitations. Due to data restrictions we were unable to perfectly recreate the IDD cohort generated by the algorithm developed in Lunsky et al. (2013), which was used to generate a cohort of adults. It is possible that we underestimated the number of children with IDD in the study period. However, the size of our IDD cohort represents about 1% of the Ontario population aged 0–19, which is line with the size of the IDD cohorts found in previous studies (Bizier, Fawcett, Gilbert, & Marshall, 2015; Kohen, Uppal, Guevremont, & Cartwright, 2006; Shi et al., 2015; White et al., 2018). While there is no specific reliability or validity of data on how to identify persons with IDD, researchers have found that creating cohorts of persons with IDD created from multiple databases are representative of the population. In addition large health administrative data have proved useful when making population level comparisons (Lin et al., 2013). Using health administrative data to identify individuals with IDD, our study is unlikely to miss more serious disability cases, since they are likely to need the health services provided by a physician or at a hospital. With regards to the outcome, the accuracy of external cause codes has been evaluated in some studies and synthesized in a systematic review (McKenzie, Enraght-Moony, Walker, McClure, & Harrison, 2009). The review found that the accuracy of broader groups of injuries could be used with some confidence.

Although we found that females with IDD are hospitalized for injury at a higher rate than males, we suggest this result be interpreted with caution as it is possible that females with IDD may be underdiagnosed and there is no way for us to know if they would increase or decrease the rate of injury. A recent study on females and autism spectrum disorder suggests that females have a greater ability to adapt coping strategies and often mask difficulties as they have a greater disposition for social interactions when compared to their male counterparts (Green, Travers, Howe, & McDougle, 2019).

The rates of assaults found in the health administrative were too low to report independently. Although children with disability are reported to more likely be victims of violence (Jones et al., 2012), it is possible that many assaults do not lead to hospitalization or are underreported in administrative data. It is also possible that we misclassify a greater proportion of younger children with IDD as they have less opportunity to access health care services that would lead to identification in the administrative health data. However, the difference in incidence of injury between the IDD and non-IDD groups are more pronounced at older ages, which is a greater driver of overall differences in injury rates between the two groups.

5. Conclusion

The use of health administrative data was a reliable and effective means to extract population characteristics and identify children and adolescents with and without intellectual and developmental disabilities (IDD). Furthermore, this study identified a higher rate of both intentional and accidental injury reported hospitalizations in children and adolescents with IDD when compared to the non-IDD group. The rate of self-harm hospitalizations in the IDD group was significantly greater. Prospective studies could further explore the high rate of intentional injuries in the IDD population. Future research could also examine physical, social, and environmental factors that have led to the higher rates of serious childhood injuries for the IDD population.

6. Practical applications

This study identifies the magnitude of the frequency for injury related hospitalizations for children and adolescents with IDD in the Canadian context and is the first step on the path toward developing targeted health and safety interventions. This research highlights the need for further research on causes of injury in children and adolescents with IDD in order to develop future injury prevention strategies and safety interventions.

Conflict of interest

The authors declare no conflict of interest. This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

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Jen Calver, RPN, BAHSc, GPN(c) has a background of experiences in clinical practice, education, and research roles across health care and academic institutions. She has a special interest in populations with complex and chronic care needs, aging, policy, health service research, and interdisciplinary collaboration. Jen is currently pursuing her graduate studies in the Master of Health Science concentrated in Community, Public, and Population Health at Ontario Tech University in Oshawa.

Dr. Robert Balogh graduated with a Physiotherapy degree from McMaster University in Hamilton, Ontario in 1993 and has used his health professional background in clinical, research and teaching environments. He received a Master of Science in Epidemiology from Queen's University in Kingston, Ontario in 2003 and a PhD from the University of Toronto in 2008.

Dr. David Rudoler is an applied health services researcher with expertise in health policy, health economics, econometrics, health economic evaluation, administrative data analysis, mixed methods and health policy analysis.

Journal of Safety Research 77 (2021) 151–160

Contents lists available at ScienceDirect

Journal of Safety Research

journal homepage: www.elsevier.com/locate/jsr

Investigating factors affecting severity of large truck-involved crashes: Comparison of the SVM and random parameter logit model

Aryan Hosseinzadeh [a,*], Amin Moeinaddini [b], Ali Ghasemzadeh [c]

[a] Department of Civil and Environmental Engineering, University of Louisville, Louisville, KY 40292, United States
[b] Department of Civil and Environmental Engineering, Amirkabir University of Technology, Tehran, Iran
[c] Department of Civil and Architectural Engineering, University of Wyoming, Laramie, WY 82071, United States

ARTICLE INFO

Article history:
Received 20 March 2020
Received in revised form 8 December 2020
Accepted 22 February 2021
Available online 24 March 2021

Keywords:
Crash injury severity
Large truck crashes
Support Vector Machine
Random parameter logit model
At-fault party
Unobserved heterogeneity

ABSTRACT

Introduction: Reducing the severity of crashes is a top priority for safety researchers due to its impact on saving human lives. Because of safety concerns posed by large trucks and the high rate of fatal large truck-involved crashes, an exploration into large truck-involved crashes could help determine factors that are influential in crash severity. The current study focuses on large truck-involved crashes to predict influencing factors on crash injury severity. *Method:* Two techniques have been utilized: Random Parameter Binary Logit (RPBL) and Support Vector Machine (SVM). Models have been developed to estimate: (1) multivehicle (MV) truck-involved crashes, in which large truck drivers are at fault, (2) MV track-involved crashes, in which large truck drivers are not at fault and (3) and single-vehicle (SV) large truck crashes. *Results:* Fatigue and deviation to the left were found as the most important contributing factors that lead to fatal crashes when the large truck-driver is at fault. Outcomes show that there are differences among significant factors between RPBL and SVM. For instance, unsafe lane-changing was significant in all three categories in RPBL, but only SV large truck crashes in SVM. *Conclusions:* The outcomes showed the importance of the complementary approaches to incorporate both parametric RPBL and non-parametric SVM to identify the main contributing factors affecting the severity of large truck-involved crashes. Also, the results highlighted the importance of categorization based on the at-fault party. *Practical Applications:* Unrealistic schedules and expectations of trucking companies can cause excessive stress for the large truck drivers, which could leads to further neglect of their fatigue. Enacting and enforcing comprehensive regulations regarding large truck drivers' working schedules and direct and constant surveillance by authorities would significantly decrease large truck-involved crashes.

1. Introduction

Road traffic crashes have become a serious menace to public health worldwide, specially in developing countries, in which about 90% of all crash fatalities take place. As a developing country with about 18,000 road fatalities, Iran has one of the highest rates of road casualties per capita in the world (Ainy, Soori, Ganjali, Le, & Baghfalaki, 2014). Statistics show there is a growing rate of fatal crashes involving large trucks in Iran. Although large trucks may lead to more severe crashes, their role in freight transportation, as an eminent part of the world economy, is undeniable (Ariannezhad, Karimpour, & Wu, 2020; Karimpour, Ariannezhad, & Wu, 2019; Rahimi, Shamshiripour, Samimi, & Mohammadian, 2020; Zou, Wang, & Wang, 2016). Therefore, the current study elaborates on large truck-involved crashes to identify significant crash injury severity factors. In the rest of the paper, for the sake of simplicity, instead of the term "large trucks," which means large semi-trailer trucks above 10,000 pounds gross vehicle weight rating (GVWR), the word "truck" has been used.

While some studies focused on truck-involved crashes in the literature, at-fault parties in these types of crashes have largely been ignored. Truck drivers are believed to have decent driving proficiency levels and busier driving schedules than non-professional drivers during an ordinary day. However, long hours of driving and fatigue could adversely affect their performance (Habibian, Avaz, & Hosseinzadeh, 2015; Hosseinzadeh, Karimpour, Kluger, & Orthober, 2020; Karimpour, Kluger, Liu, & Wu, 2021; Li, Yamamoto, & Zhang, 2018; Stern et al., 2019). To address this issue, this study considered three different categories: (1) multivehicle (MV) truck-involved crashes, in which the truck driver is at fault; (2) MV truck-involved crashes, in which the non-truck driver party

* Corresponding author.
E-mail address: Aryan.hosseinzadeh@louisville.edu (A. Hosseinzadeh).

https://doi.org/10.1016/j.jsr.2021.02.012

is at fault; and (3) single-vehicle (SV) truck crashes. In most previous studies, crashes are only classified into two categories: MV and SV. The three categories used in this study could add insight into safety literature by highlighting the at-fault party's role on contributing factors in crash severity (Adanu, Hainen, & Jones, 2018; Behnood & Mannering, 2017; Bogue, Paleti, & Balan, 2017).

In this study, Support Vector Machine (SVM) and Random Parameter Binary Logit (RPBL) were applied to explore how explanatory factors, such as drivers' characteristics, road situations, crash-contributing factors, weather conditions, etc., affect the severity of truck-related collisions. The current study used four years (2011–2014) of crash data in eight Iranian provinces.

This research has three major goals: (1) investigating the contributing factors affecting fatal versus non-fatal crashes by developing SVM and RPBL methods; (2) evaluating and comparing the prediction power of the developed models; and (3) exploring the necessity of categorizing crashes based on the at-fault party.

The next section is an overview of different models used to predict influencing factors in crash injury severity literature by focusing on truck-involved crashes. The area of study and data description are provided in the third section. The fourth section provides on a brief explanation of the RPBL and SVM. Results and discussion are presented in the next part. The conclusion is the seventh section, and the empirical implication is the final section of the paper.

2. Literature review

Identifying factors affecting injury severity through various modeling frameworks is a common approach in the literature (Lord & Mannering, 2010; Mannering & Bhat, 2014; Savolainen, Mannering, Lord, & Quddus, 2011; Khoda Bakhshi & Ahmed, 2020). A typical method in these studies is using a statistical modeling approach with crash severity as a dependent variable and characteristics of the crash, driver, roadway, weather, etc., as independent variables (Adomah, Bakhshi, & Ahmed, 2021; Iranitalab & Khattak, 2017; Mahdinia, Mohammadnazar, Arvin, & Khattak, 2021). A wide range of modeling approaches has been used in crash severity studies. The rest of this section elaborates on a summary of models applied in the crash injury severity studies.

2.1. Injury severity modeling approaches

Since the outcome of crash severity is mostly categorized by discrete severity levels, discrete choice models such as binary logit and binary probit models (Kononen, Flannagan, & Wang, 2011), Multinomial Logit (MNL) model (Khorashadi, Niemeier, Shankar, & Mannering, 2005), ordered response model (Zou, Wang, & Zhang, 2017), and mixed variants of these models have been applied to develop crash severity prediction models as functions of contributing factors (Al-Bdairi, 2020; Ghasemzadeh & Ahmed, 2017).

In recent years, accounting for heterogeneity in crash safety modeling has gained significant attention. Accounting for heterogeneity is based on the assumption that some unobserved drivers' characteristics and roadway/vehicle attributes affect the severity of crashes (Anastasopoulos & Mannering, 2011; Hosseinzadeh & Kluger, 2021; Yu & Abdel-Aty, 2014). Several studies found statistical superiority of random-parameter models over traditional fixed-parameter models (Anastasopoulos & Mannering, 2011; Boggs, Arvin, & Khattak, 2020; Khoda Bakhshi & Ahmed, 2021a). For a more detailed exploration of the parametric injury severity modeling approaches, please see (Savolainen et al., 2011).

Machine learning (ML) techniques applied in safety research have received a growing interest in the past years. The accuracy of ML techniques is comparable to the conventional statistical and econometric models. For instance, a study employed three models (fixed parameter logit model, random parameter logit model and SVM), and the SVM model outperform the others (Yu & Abdel-Aty, 2014). Iranitalab and Khattak (2017) utilized Multinomial Logit (MNL), nearest neighborhood classification (NNC), SVM and Random Forest (RF) for crash severity prediction purposes. They concluded that ML models are more successful than the parametric model (Iranitalab & Khattak, 2017). Moreover, Li, Lord, Zhang, and Xie (2008) applied both SVM and ordered probit models in predicting injury severity based on crash data collected at 326 freeway divergence areas. Comparing the two models' results revealed that SVM produced better prediction performance for injury severity than the ordered probit model (Li et al., 2008).

Several studies were also conducted to compare the performance of ML methods (Li, Liu, Wang, & Xu, 2012; Yuan & Cheu, 2003; Hosseinzadeh, Haghani, & Kluger, 2021). For instance, a study compared the SVM results with a multi-layer, feed-forward neural network and probabilistic neural network. The results showed that SVM has a lower misclassification and false alarm rates than the two other methods (Yuan & Cheu, 2003). Another study evaluated the application of SVM models for predicting motor vehicle crashes. The results show that the SVM model predicts crash data more effectively and more accurately than the Back-Propagation Neural Network (BPNN) and Negative Binomial (NB) models (Li et al., 2012).

Utilizing a two-layer stacking framework, Tang, Liang, Han, Li, and Huang (2019) combined RF, AdaBoost, and Gradient Boosting Decision Tree in the first layer and logistic regression in the second layer to predict crash injury severity. The outcomes were compared with SVM, multi-layer perceptron (MLP) and RF. The results show the proposed two-layer stacking framework was slightly better than both SVM and RF and considerably better than MLP (Tang et al., 2019).

Several other examples of ML approaches in evaluating and predicting injury severity include Artificial Neural Networks (ANN) (Abdelwahab & Abdel-Aty, 2001; Zeng & Huang, 2014), Decision Tree (DT) (Abellán, López, & De OñA, 2013; de Oña, López, & Abellán, 2013), RF (Das, Abdel-Aty, & Pande, 2009; Harb, Yan, Radwan, & Su, 2009) and K-means clustering (Anderson, 2009; Mauro, De Luca, & Dell'Acqua, 2013) exist in the literature. However, most of the ML approaches perform as a black box, which restricts insight into the significant variables and their influences.

2.2. Injury severity modeling in truck-involved crashes

According to Table 1, since the studies were conducted mostly in developed countries, the findings from a developing country that explore the influencing factors on the severity of crashes would highlight the differences in these types of countries. Moreover, the role of the at-fault party has been explored very limited in previous studies, none of them in developing part of the world. Summing up the previous studies' findings, the SVM approach and a parametric model that accounts for heterogeneity would perform comparatively better among non-parametric and parametric approaches (Savolainen et al., 2011; Yuan & Cheu, 2003).

3. Data

3.1. Area of study

The data used in this study was extracted from suburban crash data between 2011 and 2014 in eight provinces of Iran: Isfahan, Qom, Qazvin, South Khorasan, Kerman, Mazandaran, Khuzestan,

Table 1
summarizes the truck-involved crash literature.

Study	Number of records	Model structure	Research highlights	Analyzing based on the faulty part?	Geographical context
Chang and Mannering (1999)	17,473	NL	by comparing truck-involved vs. non-truck-involved crashes, risk factors specifically associated with large trucks were identified as well as the relative importance of such factors	No	Washington, U.S.
Khorashadi et al. (2005)	17,372	MNL	the significant differences found between rural and urban injury severities in truck-involved crashes. 13 variables significantly influenced driver-injury severity in rural areas but not urban ones, and 17 variables significantly influenced driver-injury severity in urban areas but not rural ones.	No	California, U.S.
Zhu and Srinivasan (2011)	953	OP	driver distraction (truck drivers), alcohol use (car drivers), and emotional factors (car drivers) were found to be associated with higher severity crashes.	No	U.S.
Islam and Hernandez (2013)	8363	RPOP	several complex interactions between factors highly influence the level of injury severity, and the effects of some factors can vary across observations	No	U.S.
Cerwick, Gkritza, Shaheed, and Hans (2014)	23,538	RPOL/LC	comparison between LC and RPOL; a slight superiority of the LC in terms of model fit, slightly better prediction power in RPOL	No	Iowa, U.S.
Islam, Jones, and Dye (2014)	8328	RPOL	important factors that significantly impact the injury severity resulting from SV and MV large truck at-fault accidents in urban and rural locations have been identified	Yes	Alabama, U.S.
Naik, Tung, Zhao, and Khattak (2016)	1721	RPOL/MNL	Wind speed, rain, humidity, and air temperature were linked with SV truck crash injury severity.	-	Nebraska, U.S.
Osman, Paleti, Mishra, and Golias (2016)	2881	GOL/MNL/NL/OL	The GORL model provided superior data fit as compared to MNL, NL, and OL. Results showed a risk propensity of sustaining severe crashes in a work zone, including crashes in the daytime, higher speed limits, and crashes occurring on rural principal arterials.	No	Minnesota, U.S.
Zou et al. (2017)	–	RPOP, spatial GOP	The results showed that a substantial difference between factors influencing SV and MV truck crash severity was found. The results also suggested that heterogeneity does exist in the truck weight, and it behaved differently in SV and MV truck crashes.	No	New York, U.S.
Al-Bdairi and Hernandez (2017)	2486	RPOP	five parameter estimates were found to be random and normally distributed and varied across run-off-road crash observations.	No	Oregon, U.S.
Uddin and Huynh (2017)	41,461	RPOL	various lighting conditions and area types did have different effects on injury severity of truck-involved crashes. Age and gender of the occupant, truck types, annual average daily traffic, speed, and weather condition were found to be significant	No	Ohio, U.S.
Uddin and Huynh (2018)	1173	RPOP, OP	at-fault party being a male truck driver and crashes occurring in rural locations, under dark-unlighted conditions, under dark-lighted conditions and on weekdays were associated with an increased probability of major injuries.	No	California, U.S.
Taylor, Russo, and James (2018)	14,148	RPOL, RPNB	geometric characteristics such as median width, shoulder width, and number of lanes were generally less significant for freight-involved crashes than non-freight crashes	No	Arizona, U.S.
Wang and Prato (2019)	2695	Partial proportional odds model	uncovers the effects of geometric, driver, crash, truck, and environmental characteristics on crash injury severity	No	China
Behnood and Mannering (2019)	5737	RPOL	instability in the effects of factors that influence injury severities in large-truck vehicle crashes across daily time periods and year to year.	No	California, U.S.
Azimi et al. (2020)	3418	RPOP	impacts of lighting conditions and driving speed on crash severity had significant variation across observations	No	Florida, U.S.
Rahimi et al. (2020)	4359	random parameters hierarchical ordered probit	factors including driver age, driver education, collision types, truck weight, ABS deployment, vehicle malfunction, surface conditions, roadway classification, roadway geometry, number of lanes, speed limit, and seasons with adverse weather conditions significantly affected the severity of SV truck crashes.	No	Iran

NL: Nested Logit, MNL: Multinomial Logit, OP: Ordered Probit, RPOP: Random Parameter Ordered Probit, LC: Latent Class, GOP: Generalized Ordered Probit, RPOL: Random Parameter Ordered Logit, GOL: Generalized Ordered Logit, Random Parameter Negative Binomial.

and the eastern district of Tehran. Fig. 1 shows the study area of this research.

3.2. Data description

Data used in this study is obtained from police-reported crash data. There are some differences between crash data in Iran and popular crash data available in developed countries. In Iran, records of crashes do not follow common KABCO scales, and there is not one standardized method of recording injury severity in crash data. The current data is classified into two categories: non-fatal crashes and fatal crashes. Based on police officers' interpretations and information provided by witnesses of the crash, the at-fault party is recorded, as well as the main contributing factors. Crash type is not available in the reports, except for rollover crashes. Many individuals involved in property-damage-only crashes prefer not to report them. Therefore, these crashes are not recorded in the crash database (i.e., under-reporting) due to "safe driver discounts" from insurance companies.

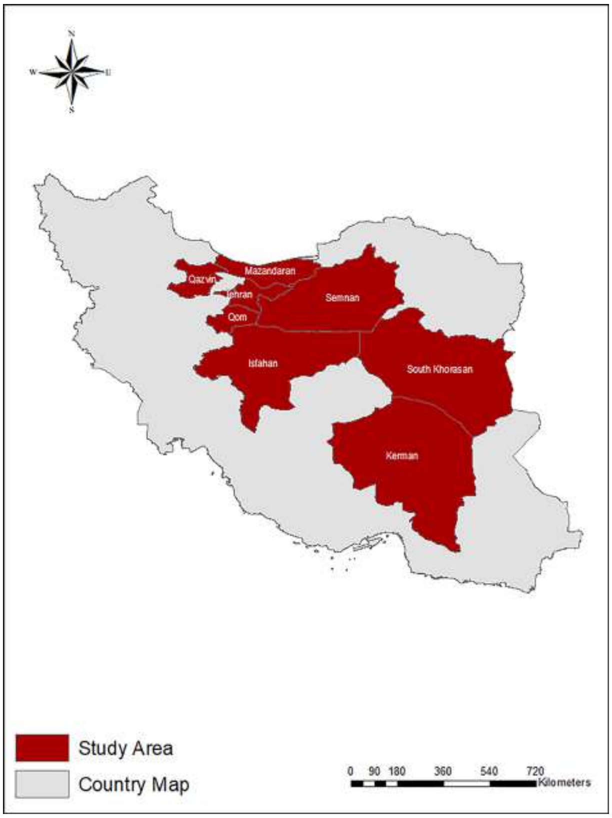

Fig. 1. The study area (eight provinces in Iran).

The data includes 8552 truck-involved crashes. 162 incomplete records have been removed due to missing data; therefore, 8390 records have been analyzed in this study. Three categories were considered to explore how the at-fault party would impact crash severity. MV crashes were divided into two separate categories: truck-involved crashes in which truck drivers were at fault (1634 crashes with 354 deaths) and truck-involved crashes in which truck drivers were not at fault (3125 crashes with 921 deaths). The third category is SV truck crashes (3631 crashes with 896 deaths). Table 2 shows the variables and their descriptive statistics involved in developing the crash severity models.

4. Methodology

4.1. Random Parameter Binary Logit model

The discrete choice models seemed more appropriate due to the discrete nature of the independent binary variable (fatal vs. non-fatal). Discrete choice models provide an opportunity to identify the causal relationship between crash severity and its features, in addition to crash severity prediction (Azimi, Rahimi, Asgari, & Jin, 2020; Ghasemzadeh, Hammit, Ahmed, & Young, 2018). In traditional models, the effect of each variable is fixed across the observation; therefore, they failed to capture the potential relationship between injury severity outcome and unobserved heterogeneity associated with the crash, such as driver behavior, roadway features, and vehicle characteristics. To overcome this shortcoming, random-parameter models were introduced, allowing the parameters to vary across observation. The response outcome was considered as a binary variable, fatal (Y = 1) and non-fatal (Y = 0). Eq. (1) shows the general form of severity function:

$$Y_{in} = \beta_i X_{in} + \varepsilon_{in} + \eta_{in} \tag{1}$$

where $\boldsymbol{\beta_i}$ is a parameter estimate for variable *i*, $\boldsymbol{X_{in}}$is an explanatory variable for variable i and observation *n*, $\boldsymbol{\eta_{in}}$is a random term for variable *i* and observation *n* with a mean of zero and a distribution that determines regarding parameters or data. Eq. (2) shows the probability function:

$$P_{in} = \int \frac{exp^{\beta_i X_{in}}}{\sum_i exp^{\beta_i X_{in}}} f(\beta|\varphi) d\beta \tag{2}$$

where $\boldsymbol{f}(\boldsymbol{\beta}|\boldsymbol{\varphi})$ is the density function of $\boldsymbol{\beta}$, and the vector of density parameters is $\boldsymbol{\varphi}$. As long as $\boldsymbol{\beta}$ is fixed, Eq. (2) is a standard binary logit model. In this study, every single estimated parameter was tested to vary across observations to account for unobserved heterogeneity. The variables with statistically significant means and standard deviations were considered to be random across all observations. The Akaike Information Criterion (AIC), percentage of correct prediction and area under the curve (AUC) were considered to compare the outcomes.

4.2. Support Vector Machine

Data mining techniques such as SVM have recently been employed in safety research, mostly due to their advantages compared to classical modeling approaches (Chen, Wang, & Van Zuylen, 2009; Dong, Huang, & Zheng, 2015; Khoda Bakhshi & Ahmed, 2021b; Mokhtarimousavi, Anderson, Azizinamini, & Hadi, 2019; Mousavi, Osman, Lord, Dixon, & Dadashova, 2021). SVM has many advantages; among those is producing a non-linear classifier with maximum generality (Li et al., 2012).

This method represents the occurrences as a set of points in N-dimensional space, then generates a (N-1) dimensional hyperplane to separate those points into groups. Considering a training data set, $\{\boldsymbol{x_n}, \boldsymbol{y_n}\} \forall \boldsymbol{n} = 1, 2, \ldots, \boldsymbol{N}$ where $\boldsymbol{x_n}$ is the vector of attributes $(1 \times \mathrm{d})$ for n^{th} crash and $\boldsymbol{y_n}$is its corresponding class label of *n*th crash (fatal vs. non-fatal), a binary variable coded by 1 or -1. If it is fatal crash, set $\boldsymbol{y_n} = -1$; otherwise, $\boldsymbol{y_n} = 1$. The final goal is to investigate the hyperplane illustrated in Eq. (3) and maximize the margin between the linear decision boundaries at the same time. Hyperplane $y(x) = 0$ is interpreted as a decision boundary in the feature space, while the parameters of a normal vector (w) and bias (b) are determined through the learning procedure on training sets.

$$\boldsymbol{y}(\boldsymbol{x}) = \boldsymbol{w^T x} + \boldsymbol{b} \tag{3}$$

To classify the data correctly with the best generalization capability, one needs to construct a separable hyperplane with the largest margin such that $\Phi(\boldsymbol{x_n}).\ w + b \geq 1$ for the positive points and $\Phi(\boldsymbol{x_n}).\ w + b \leq -1$ for the negative points where $\boldsymbol{\varepsilon_n}$ is an allowable error in estimation. The optimal hyperplane is required to satisfy the following constrained minimization as Eq. (4).

The optimal separating hyperplane between classes of data can be found employing the objective function represented in Eq. (4) and solved as a quadratic optimization problem. The first term in Eq. (4) is the original objective function and the second term captures the inequality constraints.

$$\begin{array}{l} \boldsymbol{minQ}(\boldsymbol{w}, \boldsymbol{b}, \xi) = \frac{1}{2}\|\boldsymbol{w}\|^2 + \boldsymbol{C}\sum_{\boldsymbol{i}=1}^{\boldsymbol{n}} \boldsymbol{\xi_i} \\ \boldsymbol{Subject\ to},\ \forall_i \boldsymbol{y_i}(\boldsymbol{w^T}\Phi(\boldsymbol{x_i}) + \boldsymbol{b}) \geq 1 - \xi_i \boldsymbol{\xi_j} \geq 0 \end{array} \tag{4}$$

where Φ is a feature vector, and *C* represents a trade-off between the training error term. ξ is a slack variable measures, the misclassification errors. The slack variable measures the distances between the hyperplane and samples on the wrong side of the margin.

Finally, the result of the SVM is the support vectors with the corresponding vector of weights (alpha) as well as the parameter bias specifying the distance to the hyperplane origin. To deal with a linearly non-separable problem, SVM converts the original space

Table 2
Variables descriptions.

Variable	Description	Type	Levels	Truck-driver at-fault (n = 1635)		Car-driver at-fault (n = 3124)		Single-vehicle truck crash (n = 3632)	
Response Variable				Frequency	Percentage	Frequency	Percentage	Frequency	Percentage
Crash severity	Crash Injury Severity	Binary	0 = non-fatal (ref)	1279	78.2	2203	70.5	2736	75.4
			1 = fatal	356	21.8	921	29.5	896	24.6
Explanatory Variables									
Crash type	Rollover	Binary	0 = no (ref)	1565	95.7	3046	99.7	2237	61.6
			1 = yes	70	4.3	78	0.03	1395	38.4
Fixed objects	Hitting fixed objects	Binary	0 = no (ref)	1633	98.7	3041	97.3	3448	94.9
			1 = yes	22	1.3	83	2.7	184	5.1
Vehicle(s) involved type	The type of vehicle(s) which is (are) in truck-involved crashes	Binary	pickup (yes = 1)	221	13.5	495	15.8	-	-
			sedan (yes = 1)	1481	90.5	2817	90.2	-	-
			motorcycle (yes = 1)	46	2.8	90		-	-
			SUV (yes = 1)	14	0.8	13	0.4	-	-
			Bus (yes = 1)	280	17.1	427	13.7	-	-
Contributing factor	A police-reported contributing factor of crashes	Categorical	1 = speeding (ref)	107	6.5	247	7.9	501	13.8
			2 = deviation to the left	376	22.9	1009	32.3	428	11.8
			3 = unsafe lane-changing	126	7.7	136	4.4	120	3.3
			4 = fatigue	55	3.3	95	3	480	13.2
			5 = distracted driving	418	25.5	869	27.8	1390	38.3
			6 = failure to yield the right-of-way	410	25.1	222	7.1	403	11.1
			7 = tailgating	72	4.4	143	4.6	95	2.6
			8 = motor vehicle defect	40	2.4	15	0.5	103	2.8
			9 = inability to control the vehicle	31	1.9	20	0.6	112	3.1
Age	The truck driver's age	Categorical	1 = 18–24 (ref)	66	4.1	129	4.2	235	6.5
			2 = 24–55	1191	72.8	2107	35.4	2820	77.6
			3 = 55–74	318	19.4	793	57.3	416	11.5
			4 = > 74	60	3.6	95	3.1	161	4.4
Visibility	The visibility condition based on the time of crash incidence	Categorical	1 = dusk (ref)	145	8.8	292	9.3	199	5.5
			2 = dawn	45	2.7	95	3	281	7.7
			3 = daylight	828	50.6	1618	51.7	1854	51.1
			4 = night	617	37.7	1119	35.8	1298	35.7
Road	Type of road	Categorical	1 = secondary road (ref)	195	11.9	389	12.4	529	14.6
			2 = primarily road	1386	84.7	2600	83.2	2899	79.8
			3 = rural road	52	3.1	135	4.4	204	5.6
Weather	Type of weather condition	Categorical	1 = clear (ref)	1353	82.7	2607	83.4	3151	86.8
			2 = cloudy	122	7.4	236	7.5	233	6.4
			3 = rainy	90	5.5	175	5.6	161	4.4
			4 = foggy	15	0.9	26	0.9	25	0.7
			5 = blizzard	13	0.8	25	0.8	16	0.4
			6 = dusty	17	1.2	12	0.4	18	0.5
			7 = snowy	25	1.5	43	1.4	28	0.8

(input space) to the higher dimensional space (feature space) in order to define a separable hyperplane. The function that transforms data from input space to feature space is called the kernel function. The kernel function is applied to the data in the input space and is defined as Eq. (5).

$$\mathbf{K}(\boldsymbol{x_i}, \boldsymbol{x_j}) \equiv \Phi(\boldsymbol{x_i})^{\boldsymbol{T}}\Phi(\boldsymbol{x_j}) \tag{5}$$

Different kernel functions have been employed in the SVM area. In this study, one of the most widely recommended kernels, the Gaussian radial basis function (RBF), has been applied. Eq. (6) shows the formulation of the RBF kernel with width.

$$\mathbf{K}(\boldsymbol{x_i}, \boldsymbol{x_j}) = \mathbf{exp}\left(-\frac{\|\boldsymbol{x_i} - \boldsymbol{x_j}\|^2}{2\boldsymbol{\sigma}^2}\right) \tag{6}$$

4.3. Cross-validation

The out-of-sample approach that has been widely employed to assess modeling performance may lead to overfitting since only one set is utilized for training (Lee, Derrible, & Pereira, 2018; Habibian, M., & Hosseinzadeh, A. (2018)). To alleviate this issue, the cross-validation method was employed in this study. Cross-validation is a resampling procedure used to evaluate SVM and RPBL performance. In this study, 10-fold stratified cross-validation was used for all three categories, which means that the data was randomly split into ten groups. The ratio of fatal crashes was kept constant across all groups. Each time one fold was treated as a test set, the method was fitted on the remaining data, which was trained nine times. The average accuracy was reported as the percent correct.

5. Results

5.1. Multi-vehicle truck-involved crashes (truck driver is at fault)

The results are presented in Table 3, which shows RPBL produced comparable results to SVM. In this category, the heterogeneity was not diagnosed; therefore, the random parameter logit model was reduced to the traditional binary logit model. The two implemented models produced similar results in four explanatory variables: motor vehicle defect, drowsiness and fatigue, deviation to the left and failure to yield the right-of-way. Hitting fixed objects, SUV, tailgating and night were found significant only in the SVM model. Daylight and unsafe lane-changing are only statistically significant in the logit model.

Truck drivers' unsafe lane-changing (in SVM) and failure to yield the right-of-way (in both models) were shown a negative sign, indicating these contributing factors were less likely to lead to a fatal crash. Fatigue, deviation to the left and motor vehicle defect (in both models), as well as tailgating (in SVM), of truck drivers increases the risk of fatal crashes.

5.2. Multi-vehicle truck-involved crashes (the truck driver is not at fault)

The results of modeling the truck-involved crashes in which the truck drivers were not at fault, showed in Table 4. Among the eight significant variables in RPBL and the seven in SVM, five of the variables are the same in both models. Motorcycle, unsafe lane-changing and distracted driving are significant only in RPBL. Speeding and the crashes occurring on a primary road are significant only in SVM. In both models, factors like deviation to the left, fatigue and tangling have been identified as important factors in fatal crashes. The crash occurring at night showed a significant mean and standard deviation in the RPBL, indicating the presence of heterogeneity.

5.3. Single-vehicle truck crashes

The results of RPBL and SVM for SV crashes are represented in Table 5. Among the total seven significant variables found in both models, SVM and RPBL produced similar results in four variables. For instance, deviation to the left by truck drivers increases the possibility of fatal crashes in both models. However, if the contributing factor of a crash is the failure to yield the right-of-way or unsafe lane-changing, the chance of having a fatal crash decreases.

As represented in Table 5, factors like the occurrence of a crash due to the inability of the truck driver to control the vehicle and truck rollover are only identified in the SVM model as factors affecting fatal truck crashes. The crashes occurred at night showed high variation across observations with a significant mean and standard deviation in the model, suggesting the presence of heterogeneity. According to the marginal effects results, deviation to the left shows higher importance.

Table 3
The results of MV truck-involved crash injury severity (truck driver is at fault).

Variable	SVM	RPBL	
	Hyperplane coefficient	Coefficient	Marginal effects
Fixed objects	Positive	_	_
SUV	Negative	_	_
Motor vehicle defect	Positive	0.76 *	0.168
Fatigue	Positive	1.12***	0.272
Unsafe lane-changing	_	− 1.01***	−0.071
Deviation to the left	Positive	0.91***	0.211
Failure to yield the right-of-way	Negative	−0.36**	−0.043
Tailgating	Positive	_	_
Night	Positive	_	_
Daylight	–	−0.24**	−0.037
Cons	–	−1.33***	_
LL at the null	_	−863.60	_
LL at the model	_	−809.99	_
McFadden's R^2	_	0.061	_
AIC	1581.13	1643.98	_
Percent Correct	81.87	78.39	_
AUC	0.76	0.71	_

***, ** and * represent 99%, 95%, and 90% level of significance, respectively.

Table 4
The results of MV truck-involved crash injury severity (the non-truck driver is at fault).

Variable	SVM	RPBL	
	Hyperplane coefficient	Coefficient	Marginal effects
Motorcycle	_	0.43***	0.067
Sedan	Negative	−2.15**	−0.409
Fatigue	Positive	0.97***	0.222
Unsafe lane-changing	_	−0.75***	−0.095
Speeding	Positive	–	–
Deviation to the left	Positive	1.07***	0.245
Distracted driving	–	−0.20**	−0.033
Tailgating	Negative	−0.71***	−0.090
Primary road	Positive	–	–
Night (standard deviation of parameter distribution)	Negative	−0.16* (0.23*)	–
Cons	–	0.98**	–
LL at the null	–	−1892.38	–
LL at the model	–	−1770.24	–
McFadden's R^2	–	0.069	–
AIC	3417.35	3540.72	–
Percent Correct	74.26	71.83	–
AUC	0.71	0.67	–

***, ** and * represent 99%, 95%, and 90% level of significance, respectively.

Table 5
The Results of SV Truck crashes.

Variable	SVM	RPBL	
	Hyperplane coefficient	Coefficient	Marginal effects
Rollover	Positive	–	–
Unsafe lane-changing	Negative	−0.68**	−0.062
Deviation to the left	Positive	0.59***	0.122
Failure to yield the right-of-way	Negative	−0.28**	−0.030
Inability to control the vehicle	Positive	–	–
Night (standard deviation of parameter distribution)	Positive	0.18** (0.26*)	_
Dawn	–	−0.29*	−0.035
Cons	–	−1.53***	–
LL at the null	–	−2087.37	–
LL at the model	–	−1999.40	–
McFadden's R^2	–	0.044	–
AIC	3868.18	3991.40	–
Percent Correct	78.46	76.63	–
AUC	0.74	0.67	–

***, ** and * represent 99%, 95%, and 90% level of significance, respectively.

6. Discussion

The results of this study showed a variety of contributing factors affecting injury severity of truck-involved crashes using both SVM and RPBL, which do not necessarily possess similar significant factors. Comparing factors the two models have in common, there

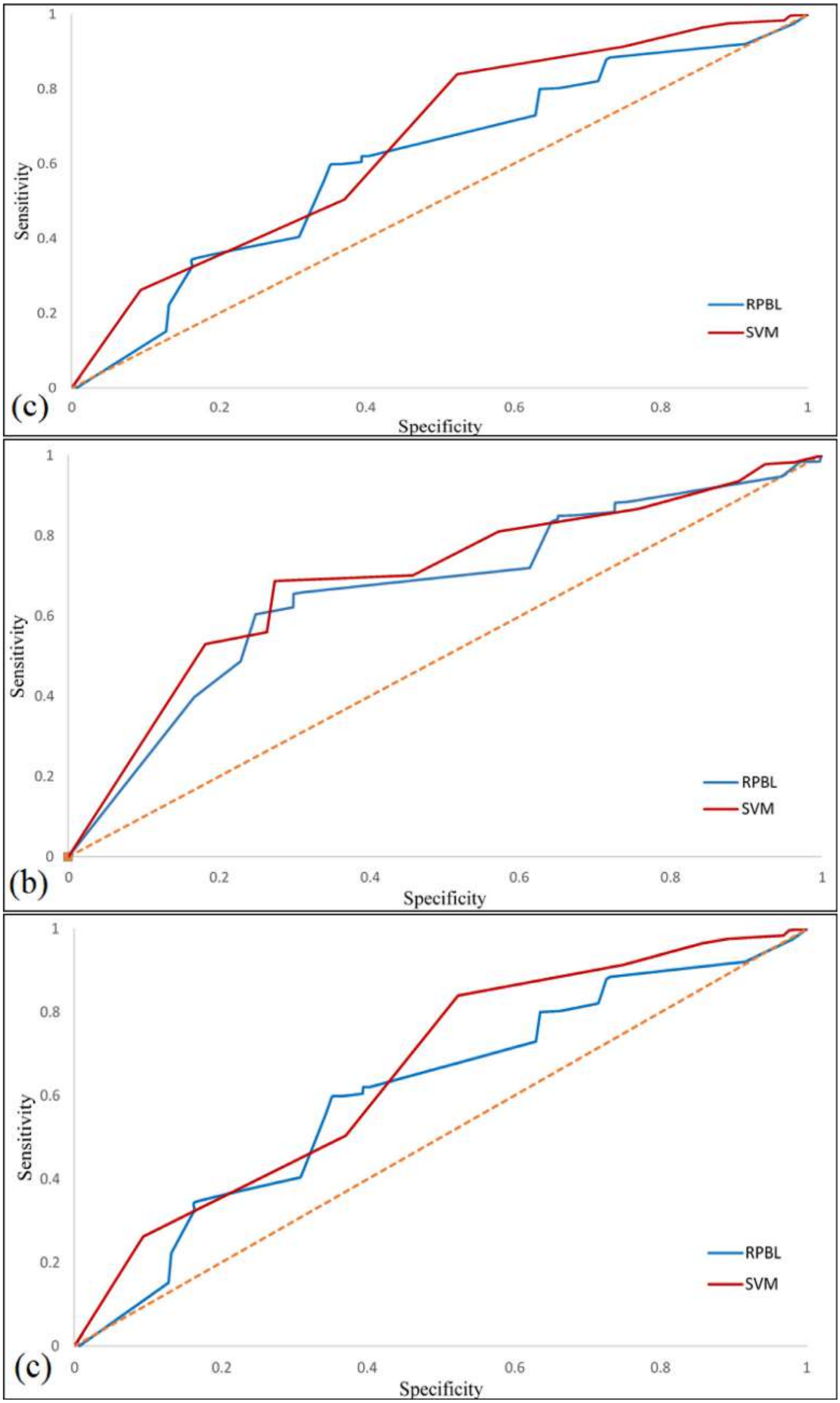

Fig. 2. (a) ROC curve truck driver is at fault (AUC RPBL = 0.71, AUC SVM = 0.76) (b) ROC curve truck driver is not at fault (AUC RPBL = 0.67, AUC SVM = 0.71) (c) ROC curve single vehicle truck crash (AUC RPBL = 0.67, AUC SVM = 0.74).

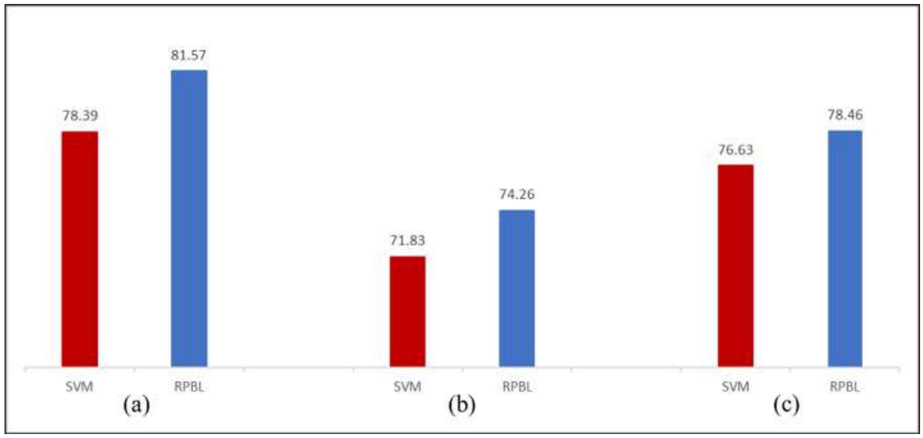

Fig. 3. Comparing the prediction power of SVM and RPBL (a) MV truck-involved crashes, a truck driver is at fault, (b) MV truck-involved crashes, a truck driver is not at fault, (c) SV truck-involved crashes.

were 40% in category one, 50% in category two, and 57.1% in category three.

Only one factor, deviation to the left, was found significant in all three categories of both model types. Based on the analysis of marginal effects in RPBL, deviation to the left was more likely to result in a fatal crash in all three categories. Deviation to the left increased the probability of a fatal crash by 0.211 in MV crashes when the truck is at fault, 0.245 in MV crashes when the truck is not at fault and 0.122 in SV crashes. In Iran, there are many inter-province, two-way highways. Due to the high importance of deviation to the left, it seems that installing more raised pavement markers (i.e., rumble strips and reflectors) and warning signs could make drivers more cautious. Also, increasing the widths of the roads, if possible, would be another helpful action. However, in the long-term, replacing existing roads with freeways could be the best policy to deal with the issue.

According to the results, tailgating increased the likelihood of fatal crashes in the first category of SVM and decreased the probability of fatal crashes in the second category of both SVM and RPBL. It indicates that, when truck drivers were at fault, tailgating was more deadly than the other categories. This finding would be because of the differences between trucks and non-trucks and the behavioral characteristics of drivers. These findings would be an example of the importance of the current categorization based on the at-fault party. Failure to yield right-of-way, as another contributing factor, was found to reduce the probability of a fatal crash in the first and third categories of both models compared to speeding, the base level of contributing factors.

The results also showed fatigue to be a contributing factor in enhancing MV fatal crashes, but not in SV crashes. Drivers with fatigue resulted in a 0.272 increase in the probability of a fatal crash when truck drivers were at fault. Fatigue was still important in truck-involved crashes when non-truck drivers were at fault, with an increase of 0.245 in probability of fatality. Installing more warning signs and having frequent or constant surveillance in different road segments would be beneficial, especially for truck drivers, as it would discourage them from driving long hours. On a larger scale, enhancing the awareness of drivers by media education could teach individuals about the consequences of driving with fatigue.

Heterogeneity was captured in the second and third categories of crashes that occurred at night. Although, the mean is positive in these crashes, the presence of heterogeneity suggests the magnitude of the attribute may not reveal the actual impact. In fact, the standard deviation may also turn the sign of the impact and show a contradictory impact across different crashes. The results suggest some personal traits (e.g., drivers' level of conservativeness) could have brought variation across observations.

According to the findings, some factors highlight the differences between the two models. Crashes that recorded unsafe lane-changing as the contributing factor were less severe and resulted in fewer fatalities. Unsafe lane-changing was found significant in all three RPBL models, but only in the SV truck crashes of SVM. Some variables identified as significant factors in the RPBL models were not found significant in the SVM model, and vice versa. For instance, rollover was significant in the third category (SV truck crashes category) of SVM, but not in the RPBL.

There are intrinsic differences between RPBL and SVM. First, SVM tries to maximize the margin between the closest support vectors, while RPBL maximizes the likelihood probability. Second, RPBL produces probabilistic values, while SVM produces binary values, and its performance greatly depends on the learning procedure. Third, SVM only considers the points near the margin (support vectors), while RPBL takes into account all the data points. Therefore, RPBL is more sensitive to outliers than SVM. Considering these differences, the SVM model has a more accurate prediction than RPBL in all three modeling categories, as shown in Fig. 2. Moreover, Receiver Operating Characteristic (ROC) curves of all models are present in Fig. 3. ROC helps in illustrating the diagnostic ability of a binary classifier system as its discrimination threshold is varied. Higher Area Under the Curve (AUC) in Fig. 3 confirms the superiority of SVM models in all three categories.

7. Conclusion

This research studies injury severity in truck-involved crashes in eight provinces of Iran. Two models (SVM and RPBL) have been developed and compared based on three different categories (MV truck-involved crashes – truck-drivers at fault, MV truck-involved crashes – non-truck drivers at fault and SV truck crashes). Results reveal the differences between the models and highlight the necessity of at-fault party classification. According to the findings, deviation to the left was found significant in all six models. Some factors were found significant only in MV categories (e.g., tailgating as the crash-contributing factor), and others were only found significant in one of the models. The results showed the importance of the complementary approaches to incorporate both parametric RPBL and non-parametric SVM approaches to identify the main contributing factors affecting the severity of truck-involved collisions.

Some limitations are important to point out in this study. The data used in this study contains several shortcomings. First, most crash types are not available in the dataset. Second, injury severity levels are not commonly listed according to five-level KABCO scale; instead, crashes were labeled as fatal or non-fatal. Details about road characteristics (e.g., surface type, surface condition, number of lanes, and median type) and traffic conditions are not available in this study dataset. Still, they would help to reach a more accurate result. Furthermore, more models can be utilized in analyses to reach higher prediction power.

8. Practical Applications

According to RPBL results, fatigue, deviation to the left, and motor vehicle defect show highest importance. Truck-involved crashes when truck-drivers were at fault were twice as likely to be fatal when the contributing factor was fatigue. Unrealistic schedules and expectations of trucking companies can place excessive stress on truck drivers, potentially leading them to neglect their fatigue and drive even more. Enacting and enforcing comprehensive regulation regarding truck drivers' working schedules and direct and constant surveillance by authorities would significantly decrease this type of crash. Moreover, deviation to the left was associated with a 0.245 increase in the probability of fatality in crashes when non-truck drivers were at fault. Truck drivers' deviation to the left could also be due to unnecessary maneuvers that could be prevented by constant monitoring of truck drivers in different road segments.

The results of this study help identify contributing factors in fatal truck-involved crashes in a developing country. Policymakers can use the implications of this research to reduce the severity of truck-involved crashes in suburban areas, therefore, reducing the causalities to move forward to safer roads in Iran.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgement

We thank Lauren Cline for her useful review and discussion.

Source of funding

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

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Aryan Hosseinzadeh is a PhD student of Transportation Planning at University of Louisville, Kenucky. He has a few years of research and work experiences in transportation research institutes and traffic engineering consultant firms. His research interests are transportation safety and health related outcome assessment.

Amin Moeinaddini is a PhD student of Transportation Planinning at Amirkabir University of Technology, Tehran, Iran. His research interests are transportation safety and transportation demand modeling. He is now working on his dissertation about developing integrated choice and latent variable models.

Ali Ghasemzadeh is a research associate in the Department of Civil and Architectural Engineering at the University of Wyoming (UW). He received his Ph.D. degree in Transportation Engineering from the University of Wyoming (UW). He has been actively involved in a number of research projects focusing on transportation safety and operations. Ali's PhD dissertation was mainly focused on driver behavior and performance in adverse weather conditions from safety and operations perspectives using the SHRP2 Naturalistic Driving Data and Roadway Information Database.

Journal of Safety Research 77 (2021) 105–113

Contents lists available at ScienceDirect

Journal of Safety Research

journal homepage: www.elsevier.com/locate/jsr

Investigating the uniqueness of crash injury severity in freeway tunnels: A comparative study in Guizhou, China

Zichu Zhou [a], Fanyu Meng [b,e,*], Cancan Song [a], N.N. Sze [c], Zhongyin Guo [a], Nan Ouyang [d]

[a] Key Laboratory of Road and Traffic Engineering of the Ministry of Education, Tongji University, Shanghai, China
[b] Academy for Advanced Interdisciplinary Studies, Southern University of Science and Technology, Shenzhen, China
[c] Department of Civil and Environmental Engineering, The Hong Kong Polytechnic University, Hong Kong, China
[d] Guizhou Transportation Planning Survey & Design Co., Ltd, Guiyang, China
[e] Department of Statistics and Data Science, Soutern University of Science and Technology, Shenzhen, China

ARTICLE INFO

Article history:
Received 24 August 2020
Received in revised form 24 October 2020
Accepted 11 February 2021
Available online 26 March 2021

Keywords:
Crash injury severity
Freeway tunnel
Multilevel model
Unobserved heterogeneity
Road safety

ABSTRACT

Introduction: With the rapid development of transportation infrastructures in precipitous areas, the mileage of freeway tunnels in China has been mounting during the past decade. Provided the semi-constrained space and the monotonous driving environment of freeway tunnels, safety concerns still remain. This study aims to investigate the uniqueness of the relationships between crash severity in freeway tunnels and various contributory factors. *Method:* The information of 10,081 crashes in the entire freeway network of Guizhou Province, China in 2018 is adopted, from which a subset of 591 crashes in tunnels is extracted. To address spatial variations across various road segments, a two-level binary logistic approach is applied to model crash severity in freeway tunnels. A similar model is also established for crash severity on general freeways as a benchmark. *Results:* The uniqueness of crash severity in tunnels mainly includes three aspects: (a) the road-segment-level effects are quantifiable with the environmental factors for crash severity in tunnels, but only exist in the random effects for general freeways; (b) tunnel has a significantly higher propensity to cause severe injury in a crash than other locations of a freeway; and (c) different influential factors and levels of contributions are found to crash severity in tunnels compared with on general freeways. Factors including speed limit, tunnel length, truck involvement, rear-end crash, rainy and foggy weather and sequential crash have positive contributions to crash severity in freeway tunnels. *Practical applications:* Policy implications for traffic control and management are advised to improve traffic safety level in freeway tunnels.

1. Introduction

With the growing need of transport connectivity of modern transportation network, transport developments in precipitous areas (such as mountains, waters, and valleys) have become utterly necessary and popular. Owing to the advancement in road designing and construction capabilities, infrastructures such as tunnels and bridges have been widely used to fulfill the requirements of massive highway network development, in which road tunnels play a crucial part. In China, the total number of highway tunnels has reached 17,738, with the total mileage passing 17,000 km (Ministry of Transport, 2019). The increasing number and total mileage has brought difficulties in tunnel maintenance and tunnel traffic organization to a higher level.

Safety concerns of highway tunnels have always been of concern to researchers and practitioners. Unlike driving on an open road, driving in a highway tunnel has more hidden hazards by nature. First, visual adaptation to different lighting conditions inside and outside a tunnel has proven to be hazardous. The entrance and the exit, where the adaptations exist, have been proven to hinder the driver from proper visual processing and thus induces higher crash risks (Mehri et al., 2019). In addition, driving within a tunnel may generate anxiety since the environment is rather constrained, dark, and monotonous (Caliendo & De Guglielmo, 2012; Ma, Shao, & Zhang, 2009). While driving in a tunnel, a driver needs to keep in mind speed limit, lane changing, the distance to the tunnel wall, and so forth. Nerves originating from this unique driving environment makes distracting drivers from identifying risks from the traffic possible, and may cause fatigued driving behaviors (Meng, Wong, Yan, Li, & Yang, 2019). Moreover, combinations between the unique driving environment and other factors

* Corresponding author at: 1088 Xueyuan Ave, Shenzhen 518055, China.
E-mail address: mengfy@sustech.edu.cn (F. Meng).

https://doi.org/10.1016/j.jsr.2021.02.008
0022-4375/

(e.g., road alignment, traffic and weather), may also give way to a severe road accident in a tunnel. For example, due to terrain restrains, freeways in mountainous and plateaued areas are commonly designed with more curves, higher slopes, and longer downhills compared to freeways on the plains (Huang, Peng, Wang, Luo, & Li, 2018). Intercity highways and freeways with active cargo transportation can lead to higher percentage of heavy trucks, which may then result in visual problems to the rear car (Das, Le, Pratt, & Morgan, 2020; Jo, Kim, Oh, Kim, & Lee, 2019). Extreme weather such as rain, snow, and fog can also give rise to more severe and fatal injuries based on multiple previous studies (Ma et al., 2019; Meng et al., 2017a,b; Sun, Wang, Chen, & Lu, 2018). The existing hazards of the abovementioned characteristics can only aggravate the risk level of road tunnels.

In addition to the hazardous and complicated driving environment, the consequences of an accident occurring in a tunnel tend to be more destructive and catastrophic than an accident on an open road, as the narrower and more constrained space in a tunnel hampers the post-accident proposal and evacuation, which may cause a slowdown or a breakdown of the transport system and may also give rise to subsequent crashes (Amundsen & Ranes, 2000; Huang et al., 2018; Yeung and Wong, 2013). If a fire is caused in the tunnel, the narrow and enclosed space may also slow down the dissipation process of heat and smoke (Ma et al., 2009). Complications in post-accident management emphasizes the importance of understanding factors imposing severe tunnel traffic accidents and implementing effective precautions for them.

Given the existence of potential hazards in a road tunnel, studies regarding driving behaviors in tunnels have been carried out, mostly using a driving simulator, and the effects of different tunnel wall patterns, lighting conditions, and information reminders have proved to be significant in affecting driving behaviors in tunnels (He, Chen, Wang, & Shi, 2010; Hirata, Mahara, & Yai, 2006; Shimojo, Takagi, & Onuma, 1995; Törnros, 2000). Regarding road tunnel safety, much effort has been made in predicting crash frequencies, where significant factors associated with high crash risks have been identified with possible unobserved heterogeneities and spatial/temporal effects addressed (Caliendo & De Guglielmo, 2012; Caliendo, De Guglielmo, & Guida, 2013; Caliendo, De Guglielmo, & Russo, 2019; Hou, Tarko, & Meng, 2018; Meng & Qu, 2012; Yeung & Wong, 2013). However, few studies have established models on the crash severity in road tunnels, especially in freeway tunnels. Ma, Chien, Dong, Hu, and Xu (2016) adopted a generalized ordered logit modeling approach to investigate contributive factors associating with crash severity of 134 crashes in four specific freeway tunnels occurring over a two-year period. Factors including time of day, location of crash, tunnel length, and weather were proven to contribute to freeway tunnel crash severity. Huang et al. (2018) employed a classification and regression tree model to identify risk factors associating with injury severity of crashes on a 61-kilometer-long freeway segment with continuous 12 one-way two-tube tunnels, and concluded that factors such as unsafe driving behaviors, crash time, grade, and vehicle types significantly affected the crash severity.

Although several studies have shed light on possible influential factors for freeway tunnel crash injury severity, there are still obvious limitations in two dimensions. First, the exiting studies failed to analyze freeway tunnel crash severities with a comparative perspective. A thorough comparison between crash severities for freeways in general, and specifically for freeway tunnels should be conducted to unmask the uniqueness of freeway tunnel crashes. Second, unobserved heterogeneities, as commonly addressed while modeling crash frequency and severity (Aldred, García-Herrero, Anaya, Herrera, & Mariscal, 2019; Anastasopoulos & Mannering, 2009; Chen, Song, & Ma, 2019; Mannering & Bhat, 2014; Mannering, Shankar, & Bhat, 2016; Xu, Wali, Li, & Yang, 2019), haven't been tested in previous studies on crash severity in freeway tunnels. Most crash datasets are hierarchical with some hyperparameters (i.e., traffic-site-level factors) having spatially different effects on crash severity, therefore facility qualities and enforcement levels may vary across traffic sites (Dupont, Papadimitriou, Martensen, & Yannis, 2013; Huang & Abdel-Aty, 2010). It is also nearly impossible for empirical datasets to incorporate all contributive spatial factors associating with crash severity. Hence, spatial heterogeneities (cross-group variations) may still exist and cause biased results if not properly addressed (Besharati, Tavakoli Kashani, & Washington, 2020; Meng et al., 2017a,b; Venkataraman, Ulfarsson, Shankar, Oh, & Park, 2011).

The current study aims to investigate the relationships between influential factors and crash severity in freeway tunnels of Guizhou province, China. As a typical mountainous province, Guizhou has raised its number of freeway tunnels to 1,433, and the kilometrage has reached 1,493, nearly double for both since 2016 (Guizhou Traffic Information and Emergency Control Center, 2018). A two-level binary logistic regression model was established to quantify the relationships between crash severities in freeway tunnels and contributory factors based on police-recorded crashes in 2018, where hierarchical spatial effects are addressed. The same approach is also applied to general freeways in Guizhou province, as a benchmark for its tunnel counterparts. Significant factors influencing tunnel crash severity are identified, and policy implications are made to improve further safety management in freeway tunnels.

2. Data

A crash database provided by Guizhou Traffic Information and Emergency Control Center (affiliated to Department of Transportation of Guizhou Province) is applied. The data were originally recorded and managed by onsite traffic police teams who proposed all incidents taking place in the freeway network. The database recorded crash information of freeways in Guizhou Province covering all crashes occurring on the total of 6,390 km of national, provincial and local freeways in the province in 2018. The percentage of tunnel lengths in the freeway network was 23.1% (1,493 km). To facilitate freeway management, the whole network is further divided into 75 road segments, and the average length 85.2 km. A total of 10,081 crashes on the freeways were recorded in 2018 and 591 of them happened in a tunnel, covering 45 road segments and 343 tunnels. Crash-level characteristics including crash type, number of vehicles involved, vehicle involvement, fatality, and injury are recorded for each crash. Among all crashes in 2018, 8,903 are crashes with property damages only (PDO) and 115 are fatal crashes (with no less than one death within 7 days), and the rest caused as least one injury per crash (without fatality). In this study, the crashes were classified into two severity categories: non-severe crashes (PDO crashes) and severe crashes (fatal crashes and crashes with injuries).

To facilitate a multilevel modeling scheme, predictors are classified as crash characteristics (level 1 variables) and environmental factors (level 2 variables), as shown in Table 1. Crash-level attributes include crash types, involvement of various types of vehicles, number of involved vehicles, and sequential crash. The type of vehicles involved in each crash was logged based on the vehicle type categorization scheme designed to differentiate levels of toll fees for various vehicle types. All vehicles are divided to two main categories: passenger vehicle and cargo vehicle. Passenger vehicles are further classified into small passenger vehicles, mini-buses, and buses, according to their different sizes and numbers of seats. Cargo vehicles are categorized based on the size and weight into mini-truck, truck, and trailer truck. In this study, crashes with

Table 1
Descriptive statistics of dependent and independent variables.

Variable name	Category/explanation	General freeway model (GFM)		Tunnel model (TM)	
		Mean/Percentage	SD	Mean/Percentage	SD
Dependent variable:					
Crash severity	Severe	11.7%		27.9%	
	Non-severe (base)	88.3%		72.1%	
Crash characteristics:					
Truck involvement	Truck involved	26.9%		29.3%	
	No Truck involved (base)	73.1%		71.7%	
Trailer truck involvement	Trailer truck involved	7.1%		6.6%	
	No trailer truck involved (base)	92.9%		93.4%	
Bus involvement	Bus involved	1.1%		1.5%	
	No bus involved (base)	98.9%		98.5%	
Crash type	Rear-end	36.7%		57.4%	
	Flip-over	6.1%		5.2%	
	Side-swipe	4.8%		1.7%	
	Hitting fixtures (base)	52.4%		35.7%	
Number of vehicles	Single-vehicle	58.2%		48.6%	
	Multi-vehicle (base)	41.8%		51.4%	
Sequential crash	Crash belonging to a crash sequence	5.9%		19.6%	
	Crash belonging to no crash sequence (base)	94.1%		80.4%	
Environmental factors:					
Speed limit	In: km/h	115.8	11.34	89.1	16.8
Time period	Dawn (3:00–7:00)	5.8%		3.2%	
	Morning (7:00–11:00)	17.0%		15.9%	
	Noon (11:00–15:00, base)	24.9%		36.2%	
	Afternoon (15:00–19:00)	25.5%		27.9%	
	Evening (19:00–23:00)	18.0%		10.0%	
	Night (23:00–3:00)	8.8%		6.8%	
Location	Tunnel	5.8%		–	–
	Ramp	4.4%		–	–
	Bridge	0.5%		–	–
	Open road (base)	94.2%		–	–
Number of lanes	Two-lane (base)	87.6%		100%	
	Three-lane	12.4%		0%	
Weather	Rainy	19.4%		15.6%	
	Cloudy	62.2%		62.6%	
	Foggy	0.5%		1.0%	
	frozen	1.4%		0.7%	
	Sunny (base)	16.5%		20.1%	
Tunnel length	Super-long tunnel	–	–	49.1%	
	Long tunnel	–	–	24.4%	
	Short and medium tunnel (base)	–	–	26.6%	

trailer trucks, buses, and trucks involved are the mainly studied vehicle involvement types. As these types of vehicles are heavy and large in sizes, it is relatively easier to lose control at a high speed, and more difficult for the drivers to properly control the vehicle to evade from an emergency situation.

Environmental information of each crash, such as date, time, location, and weather, is also extracted from the database. Based on previous research on road safety, six representative time periods within a day are defined in this study: dawn (3 a.m. to 7 a.m.), morning (7 a.m. to 11 a.m.), noon (11 a.m. to 3 p.m.), afternoon (3 p.m. to 7 p.m.), evening (7 p.m. to 11 p.m.), and night (11 p.m. to 3 a.m. of the next day) (Pei, Wong, & Sze, 2012). Adverse weather was proven to be more likely to cause severe injuries in tunnels (Ma et al., 2016), and thus in this study, typical adverse weather conditions including rainy, cloudy, foggy, and frozen were defined.

Road design information such as speed limit (80/100/120 km/h according to regulations of Chinese freeways) and number of lanes (two/three lanes for uni-direction freeways) at each crash point are also classified as upper-level attributes, as they are usually identical for the entire road segment. If a crash took place in a tunnel, the length of the tunnel is also collected. According to the designing codes of highway tunnels in China, highway tunnels are categorized into four types based on its length: super-long tunnel (longer than 3000 m), long tunnel (1000–3000 m), middle-long tunnel (500–1000 m), and short tunnel (shorter than 500 m), and different designing standards apply to different categories (Ministry of Transport, 2004). In 2018, crashes occurred in 328 tunnels in Guizhou freeways, and the average length of these tunnels is 1,428 m. Among these tunnels, 33 were super-long tunnels, and the maximum length of them were 4,755 m (Zhaoxing Tunnel). Previous studies have found that both crash risk and injury severity in tunnels tend to increase with tunnel length. Besides, only 11 crashes occurred in short tunnels among all 591 tunnel crashes in our database. Hence, short and medium tunnels were further combined as “others” and used as the baseline category, and the focus is gathered on the effects of relatively longer tunnels (i.e., the riskier ones proven by previous studies).

The descriptive statistics of the variables incorporated in the models are displayed in Table 1. For the continuous variable (speed limit), the minimum and maximum values, and mean values and standard deviations (SDs) are provided; categorical variables were transformed to dummy variables, and the percentage of each category among all observations were provided.

3. Method

3.1. Two-level binary logistic model

To quantify the relationships between explanatory variables and various severity levels, a logistic function has been widely used in previous studies (Çelik & Oktay, 2014; Huang, Li, & Zeng, 2016; Shaheed, Gkritza, Carriquiry, & Hallmark, 2016; Wu et al., 2014). To avoid biased estimations cause by within-road-segment correlation, the spatial heterogeneity varying across road segments is address by a two-level modeling scheme. On the crash level (level 1), the outcome variable representing the severity levels of each crash has two categories: severe and non-severe. Hence, denote Y_{ij} as the severity of crash i on road segment j. $Y_{ij} = 1$ means that the crash i is severe, and $Y_{ij} = 0$ means that the crash i is non-severe. A binary logistic function is able to link the probability of $Y_{ij} = 1$ (denoted as π_{ij}) with the crash-level independent variables as follows (McFadden, 1973):

$$\mathrm{logit}(\pi_{ij}) = \log\left(\frac{\pi_{ij}}{1-\pi_{ij}}\right) = \beta_{0j} + \sum_{k=1}^{K} \beta_{1jk} X_{ijk} + \varepsilon_{ij} \tag{1}$$

where X_{ijk} is the value of the kth level 1 independent variable for crash i on road segment j, $\beta_{0j}$is the crash-level intercept, β_{1jk} is the estimated coefficient for X_{ijk}, and ε_{ij} is the random error term following a logistic distribution.

To account for the cross-crash variations, the road-segment-level (level 2) model is specified as:

$$\beta_{0j} = \gamma_{00} + \sum_{l=1}^{L} \gamma_{0l} Z_{jl} + \mu_{0j} \tag{2}$$

$$\beta_{1jk} = \gamma_{1k} + \mu_{1jk} \tag{3}$$

where γ_{00} and γ_{1k} are estimated intercepts on the road segment level; Z_{jl} is lth level 2 independent variable representing environmental factors for road segment j, and γ_{0l} is the estimated coefficient for Z_{jl}; μ_{0j} and μ_{1jk} are the random effects varying across road segments for the crash-level intercept and crash-level covariate k with means zero and variances $\sigma_o{}^2$ and $\sigma_k{}^2$, respectively (Snijders & Bosker, 1999). Note that the random effects, μ_{0j} and μ_{1jk}, are random across road segments and constant for all crashes on the same road segment, which enables unobservable spatial effects varying between road segments (Kim, Kim, Ulfarsson, & Porrello, 2007).

A simulated maximum likelihood estimation method with 200 Halton draws is applied to estimate the coefficients (McFadden, 1973; Train, 2009). A Z test was applied to each estimated coefficient to acquire the statistical significance level.

3.2. Elasticity analysis

An elasticity analysis is extensively considered necessary for understanding the effect of each independent variable on the dependent variable (Kim, Ulfarsson, Kim, & Shankar, 2013; Wu et al., 2014; Li et al., 2019). The elasticity for a continuous independent variable k on the probability of a severe crash is calculated from t partial derivative of each observations (Washington, Karlaftis, Mannering, & Anastasopoulos, 2020):

$$E_{ijk} = \frac{\partial \pi_{ij}}{\partial X_{ijk}} \frac{X_{ijk}}{\pi_{ij}}, \tag{4}$$

where the E_{ijk} is the elasticity outcome for continuous variable k of crash observation i in road segment j. As the probability for a crash to be severe is not differentiable with dummy independent variables, a pseudo-elasticity is defined for indicators as follows (Kim et al., 2007):

$$E_{ijk}{}^{(p)} = \frac{\partial \pi_{ij}(X_{ijk}=1) - \partial \pi_{ij}(X_{ijk}=0)}{\partial \pi_{ij}(X_{ijk}=0)} \tag{5}$$

where $E_{ijk}{}^{(p)}$ is the pseudo elasticity of dummy variable k of crash observation i in road segment j. The final elasticity of a variable is calculated as the sample mean of the elasticity outcomes for all observations.

4. Results

Based on the two-level binary logistic modeling scheme, two crash severity models were established: the model for general freeways (GFM) and the model for freeway tunnels (TM). The GFM contained the crashes occurring on the whole freeway network of Guizhou province in the observation period, with all road segments and infrastructures (i.e., open-road, bridge, tunnel and ramp) included. The TM included only the crashes occurring in the tunnels of the same freeway network. As crash injury severity on general freeways have been investigated thoroughly from various aspects, the GFM in this study serves as a benchmark, and the comparison between the TM and the GFM provide insights of the mechanism and the uniqueness of crash severity in freeway tunnels.

Before performing the regression, Pearson correlation between each pair of the independent variables was calculated, and all the Pearson correlation value were smaller than 0.6, meaning that there is no significant correlation between independent variables in this study. As illustrated in “Data,” the full dataset displayed in Table 1 was adopted to estimate the GFM, and its subset of tunnel crashes was used to estimate the coefficients in the TM. Certain differences existed in the choices of independent variables in the two models. First, as the GFM covered crashes taking place in the whole freeway network, the location effect (i.e., tunnel, bridge, ramp and others) was assumed to contribute to general freeway crash severity (see Table 1). Second, tunnel length was adopted in the TM to quantify the effects of super-long, long and short tunnels to crash severity in tunnels. Third, as all observations in tunnels in this case took place in two-lane tunnels, “number of lanes” had to be excluded from the TM. Besides, the unique variable, “tunnel length,” were interacted with the involvement of various types of vehicles and “crash type,” respectively, and incorporated in the TM. As drivers’ adaptation abilities to hazardous driving environment may vary, the effect of tunnel length (especially in long and super-long tunnels) on driving safety has been ambiguous in previous studies (Caliendo et al., 2013). Hence, interactions between tunnel length and crash-level attributes is assumed to unveil this complicated nature. The interaction terms with insignificant coefficient at the 95% confidence level or above were excluded from the final model, and only the ones with significant coefficients were kept.

At first, all variables on both levels are incorporated according to the two-level settings stated in "Methods." For environmental effects (level 2 variables), if the fixed coefficients of all its subcategories are insignificant, the variable is assumed to have no significant effect on the dependent variable and thus excluded from the modeling. For the crash characteristics (level 1 variables), insignificant random effects are assumed to have weak associations with the dependent variable and removed from the modeling. For categorical variables on both levels, the estimates for the dummy variables of all categories are kept if at least one category is significant at the 95% confidence level, to keep the consistency for variable definition and facilitate comparison between models. Final estimation and elasticity results were listed in Tables 2 and 3, for the GFM and TM, respectively.

In the GFM (see Table 2), 8 fixed effects were significant at the 0.05 level or above including the intercept, γ_{00}. Among all crash-level variables with a significant fixed coefficient, 1 variable (sequential crash) had a significant random slope. The random intercept varying across road segments was also significant at the 0.05 level. In the TM model (see Table 3), nine fixed effects were significant at the 0.05 level or above. Among the tested interactions terms, the interaction between "rear-end" and "super-long" tunnel was significant, and thus kept in the final model. The S.D. of road-segment-level random intercept and the S.D. of "rear-end" were also significant at the 0.05 level.

5. Discussion

This section aims to discuss the unique associations between tunnel crash severity and various crash and environmental characteristics. To facilitate the discussions on the uniqueness of tunnel crash severity, the significant influential factors associating with crash severity in freeway tunnels in the TM are discussed in a comparative manner, with the GFM as a benchmark.

5.1. General differences between GFM and TM

Based on the multilevel model structure, moderating effects of various road segments were proven solid in both the GFM and the TM. In the GFM, four crash-level variables were statistically significant at the 0.05 level, namely truck involvement, trailer truck involvement, rear-end crash, and sequential crash, among which the higher-level random effect for sequential crash was significant (coefficient = 1.045). Besides, the crash-level intercept can be expressed as a function of various locations (i.e., tunnel, ramp and bridge) of the crashes and a negative constant (coefficient = −3.292). The significant random effects in the intercept and "rear-end" crash explains the cross-road-segment variances.

In the TM, similar random effects were found significant in the intercept and "read-end," addressing the heterogeneity across various road segments. Three crash-level factors had a significant estimated coefficient after the road-segment random effects being addressed. Unlike the results in the GFM, multiple level 2 variables were significant at the 0.05 level in the TM, including tunnel length, rainy and foggy weather, and afternoon. This result indicates that compared to general freeways, the higher-level spatial effects of tunnel crash severity are rather unique, as they are quantifiable with higher-level covariates but can only be addressed by random terms for general freeway severity.

Moreover, the coefficients of "tunnel" (coefficient = 1.034), "ramp" (coefficient = 1.033) and "bridge" (coefficient = 1.740) were significantly positive at the 0.05 level or above in the GM. Compared to open road sections, infrastructures like tunnels, ramps, and bridges place potential hazards of a collision. When an emer-

Table 2
Estimation results for the crash severity model for general freeways (GFM).

Variable	Coefficient	Standard error	P>|Z|	Elasticity
Fixed effects:				
Intercept	−3.292***	0.168	0.000	–
Location:				
- Tunnel	1.034***	0.243	0.000	4.6%
- Ramp	1.033***	0.273	0.000	3.8%
- Bridge	1.740**	0.760	0.022	0.6%
- Open road (base)				
Truck involvement:				
- Truck involved	1.137***	0.183	0.000	24.0%
- No truck involved (base)	–	–	–	–
Trailer truck involvement:				
- Trailer truck involved	1.136***	0.263	0.000	5.4%
- No trailer truck involved (base)	–	–	–	–
Crash type:				
- Rear-end	0.045	0.186	0.808	1.5%
- Flip-over	0.688**	0.257	0.007	3.3%
- Side swipe	−0.399	0.489	0.415	1.7%
- Hitting fixture (base)	–	–	–	–
Crash-chain:				
- Sequential crash	0.959**	0.243	0.000	5.7%
- Non-sequential crash (base)	–	–	–	–
Random effects:				
Intercept (S.D.)	0.439***	0.121	0.000	–
Sequential crash (S.D.)	1.045**	0.432	0.016	–
Number of observations	10,081			
Log-likelihood at convergence	−1387.439			
McFadden Pseudo	0.801			
χ^2	11200.355			
AIC	2798.9			

** Estimated coefficient significant at the 95% confidence level.
*** Estimated coefficient significant at the 99% confidence level.

Table 3
Estimation results for the crash severity model for tunnels (TM).

Variable	Coefficient	Standard error	P>|Z|	Elasticity
Fixed effects:				
Intercept	−4.356***	0.899	0.000	–
Speed limit	0.016**	0.008	0.044	102.4%
Tunnel length:				
- Long tunnel	1.101***	0.373	0.003	37.4%
- Super-long tunnel	0.601	0.538	0.264	9.9%
- Short and medium tunnel (base)	–	–	–	–
Weather:				
- Rainy	1.425***	0.444	0.001	11.8%
- Cloudy	0.388	0.364	0.286	17.1%
- Foggy	4.085***	1.164	0.000	1.1%
- Frozen	0.684	1.377	0.620	0.3%
- Sunny (base)	–	–	–	–
Time period:				
- Dawn	0.923	0.629	0.143	1.6%
- Morning	−0.724*	0.375	0.053	−8.3%
- Afternoon	−0.713**	0.339	0.036	−15.0%
- Evening	−0.719	0.479	0.134	−5.2%
- Night	−0.864	0.545	0.113	−4.3%
- Noon (base)	–	–	–	–
Truck involvement:				
- Truck involved	1.315***	0.286	0.000	21.8%
- No truck involved (base)	–	–	–	–
Crash type:				
- Rear-end	1.118***	0.424	0.008	37.2%
- Flip-over	0.587	0.533	0.271	1.9%
- Side swipe	1.349	0.922	0.144	1.1%
- Hitting fixture (base)	–	–	–	–
Crash-chain:				
- Sequential crash	0.878**	0.389	0.024	9.7%
- Non-sequential crash (base)	–	–	–	–
Interaction term:				
Rear-end × super-long tunnel	1.777***	0.608	0.004	–
Random effects:				
Intercept (S.D.)	0.837***	0.183	0.000	–
Rear-end (S.D.)	0.550**	0.244	0.024	–
Number of observations	591			
Log-likelihood at convergence	−240.607			
McFadden Pseudo	0.413			
χ^2	338.087			
AIC	523.2			

* Estimated coefficient significant at the 90% confidence level.
** Estimated coefficient significant at the 95% confidence level.
*** Estimated coefficient significant at the 99% confidence level.

gency situation takes place, it is also more difficult for a driver to promptly react and take further actions to avoid crashes while driving inside a tunnel, on a ramp or on a bridge. The significantly positive result of "tunnel" once again proves the uniqueness of crash severity patterns in tunnels compared with general freeways and serves as a foundation of the subsequent analyses and discussions of key factors affecting severity levels of crashes in freeway tunnels.

Based on the significance levels and the estimated coefficients of the other variable in both models, the uniqueness is also in the differences in most of the factors included in the two models. Detailed discussions on these factors are stated in the following subsections.

5.2. Tunnel length

Two variables representing different tunnel lengths where crashes happened were included in the TM (see Table 3). "Long tunnel" had a positive fixed coefficient that is significant at the 99% confidence level (coefficient = 1.101). According to the elasticity analysis, a long tunnel has 37.4% higher probability to cause a severe crash than a shorter tunnel. Compare to the reference level (short and medium tunnel), a crash in a tunnel longer than 1000 m and shorter than 3000 m is more likely to cause severe or fatal injuries than the one in a shorter tunnel. Caliendo et al. (2013) concluded that driving in long tunnels were more likely to be engaged into a collision. Ma et al. (2016) proved that crashes in long tunnels have higher likelihood to be severe or fatal. Driving in tunnels longer than 1000 m may cause fatigued driving behaviors provided that the constraint environment and dim light might induce nerves for the drivers. Hence, a slow reaction under fatigued driving condition may cause more severe injuries in a crash.

5.3. Crash type

Rear-end crash was the only type of collision that held a significant coefficient while modeling crash severity in freeway tunnels, and the coefficient was positively significant (coefficient = 1.118, elasticity = 37.25%) at the 0.05 level. The result indicates that rear-end crashes in a freeway tunnel have a 37.2% higher likelihood to cause fatality or severe injury than hitting fixtures of a tunnel. Indeed, rear-end accounts for 57.4% of all crashes occurring in tunnels in our database, ranking the highest among all crash types, and this number is much higher than the percentage of rear-end crashes in total freeway crashes. Because lane changing is prohibited in Chinese tunnels, the chance for a crash from the following car or to the front car is much higher than other crash directions. Drivers driving in a tunnel may also be distracted by controlling lateral positions (e.g., controlling the lane position or keeping a distance from the tunnel wall, keeping a proper headway may be neglected to some degrees, especially for some novice drivers). Hence, the chance for an uncontrollable rear-end collision leading to severe injuries or fatalities is relatively higher.

In a tunnel longer than 3000 m, the probability for a rear-end collision to cause severe injury or fatality is higher. According to a modeling result for the interaction term between rear-end crash and super-long tunnel, the coefficient (1.777) was positively significant at the 99% confidence level. Rear-end crash is mainly caused by poor control of headways and slow reactions, both of which are fatigued driving behaviors (Yeung & Wong, 2014). As the effect of a super-long tunnel is rather blurry, this significant effect proves that although drivers may be familiar with the tunnel environment after continuous driving in the same tunnel from longer than 3000 m, there might still be a deficit in headway control and front hazard perceptions.

The estimated coefficient for "flip-over" was statistically insignificant for crash severity in freeway tunnels, but it was significant for crash severity on freeways in general (coefficient = 0.688, elasticity = 3.3%). For crashes on freeways, flip-over crashes have the highest likelihood to result in severe injuries or fatalities among all crash types. A possible explanation for these results is that flip-over crashes are relatively less dangerous in tunnels because the motion of flipped vehicle is protected by the tunnel structure, unlike in open area.

5.4. Sequential crash

Sequential crash is a novel definition of crash-level effect on crash severity in this study. The coefficients of this factor were significant at the 0.05 level or above and positively correlated with severity of crashes both on general freeways and in freeway tunnels. In the dataset, the percentage of sequential crashes in tunnels is nearly four times of that on the whole freeway network. Because the drivers are not allowed to change lanes in Chinese freeway tunnels, emergency braking is commonly the first reaction of the driver and the only legal method to avoid a crash in the front, which produces new hazards and spreads them to the vehicles behind in the whole lane according to the traffic wave theory (Daganzo, 1992; Richards, 1956). As the hazard of a crash spread mainly in the same lane backwards, rear-end collision chain or multi-vehicle rear-end collisions are more likely to happen in freeway tunnels, and hence results in more severe crashes.

On general freeways, a significant random effect (coefficient = 1.045) is found for "sequential crash" varying across different road segments. The differences in geometric design, infrastructure quality, and other environmental attributes in various road segments are possible to lead to this significant variation, as these factors are likely to affect drivers' attention and reaction speed to the motion change of the front vehicles, and thus lead to different levels of crash severity.

5.5. Vehicle involvement

Among all studied types of vehicles, truck involvement was the only one with a significant coefficient in the TM, indicating that compared to a tunnel crash with no truck, one or more involved truck tends to have a 21.8% higher possibility to cause severe injuries or fatalities (coefficient = 1.315). The same factor also places a relatively higher propensity on causing a severe injury or a fatality on general freeways (coefficient = 1.137, elasticity = 24.0%). These results are intuitive as the massive size of a truck can block drivers from surrounding vehicles and from identifying the hazards in the traffic, and the weight of a truck (especially when filled with cargos) would incur longer braking distance and more severe injuries (Chang & Chien, 2013; Tay, Choi, Kattan, & Khan, 2011).

Trailer trucks had a statistically significant coefficient while modeling crash severity on general freeways (coefficient = 1.136, elasticity = 5.4%), but were insignificant for crash severity in tunnels. As trailer trucks are extremely long in size, the lane changing process is cumbersome and slow, with a considerably large influential area. Since this action is prohibited in Chinese freeway tunnels, the hazardous influences are naturally eliminated.

5.6. Weather and time

In freeway tunnels, rainy and foggy days place significantly higher likelihoods on crash severity, but cloudy and frozen days has no significant difference with sunny days. Although adverse weather in general has been proven to cause more severe injuries in freeway tunnels (Ma et al., 2016), different adverse weather conditions contribute differently to tunnel crash severity. For tunnel crashes, fog (coefficient = 4.085, elasticity = 1.1%) has a slightly higher possibility to incur severe injuries than sunny weather, as it is able to spread into the tunnel hole and result in worse visibility inside the tunnel (note that low visibility is already an issue resulted from poor illumination and visual adaptation problems (Mehri et al., 2019) and may impair car-following performance (Gao et al., 2020); rain (coefficient = 1.425, elasticity = 11.8%) is able to wet the types of vehicles or go downgrade into the tunnel, and thus lower the friction and result in severe injuries inside tunnels (Ma et al., 2009). It is worth noting that frozen weather is considered an extreme weather in southern China, when temperature drastically drops below 0 degree Celsius and a thin layer of ice may randomly distribute in the top layer of the pavement. This adverse weather is not significantly associated with tunnel crash severity, possibly because prohibition of lane changing in tunnels considerably reduce potential risks of misbehaviors of the vehicles because of the slippery pavement in frozen weather.

In the TM, the only significant time-of-day effect was "afternoon" (coefficient = −0.713), holding a 15.0% lower probability to cause severe injuries or fatalities in a tunnel crash than a crash occurring at noon. This possibly results from the differences in driving fatigue levels of the drivers at noon and in the afternoon. Most drivers take a short break at lunch time, and thus could refresh from fatigued driving in the afternoon.

5.7. Speed limit

The coefficient estimation for speed limit was positively significant while modeling crash severity in tunnels at the 0.05 level (coefficient = 0.016, elasticity = 102.4%), but it had no significant contribution to severity of crashes on a general freeway. One possible reason for the different levels of effect of speed limit on crash severity in the two studied contexts is that the monotonous driving environment in tunnels tend to cause more fatigued driving behaviors, thus lead to more frequent and aggressive speeding violations. As speeding has been found to be positively correlated with injury severity on freeways (Abegaz, Berhane, Worku, Assrat, & Assefa, 2014; Huang et al., 2018), speed limit is more effective in controlling speed limit in tunnels than general freeways, and consequently has relatively more significant effect on the crash severity in freeway tunnels.

6. Conclusion

This study investigated the unique relationships between crash severity in freeway tunnels and various influential factors. The information of crashes of 10,081 crashes on Guizhou freeway network in 2018 was incorporated, in which 591 crashes took place in tunnels. A two-level binary logistic modeling approach was adopted to identify significant influential factors with tunnel crash safety while addressing the road-segment-level spatial effects across observations. The similar approach was adopted for crash severity on freeway in general as a benchmark. The uniqueness of crash severity patterns in freeway tunnels mainly located in: (1) the quantifiable environmental effects, (2) the significantly higher general levels of crash severity and (3) the different levels of the effects of influential factors on crash severity compared to general freeways. Factors including speed limit, tunnel length, truck involvement, rear-end crash, rainy and foggy weather, and sequential crash were found to be positively associated with crash severity in freeway tunnels. Rear-end crash was also proven to have interactive effects with super-long tunnel on tunnel crash severity.

Policy suggestions can be implied to improve driving safety in freeway tunnels based on the results in this study. For example, dynamic warning signs should be placed in and outside a tunnel (especially a long tunnel) in adverse weathers such as rainy days and foggy days. Similar measures can be implemented in long and super-long tunnels reminding the drivers to keep a decent headway with the front car in order to avoid rear-end crashes or sequential crashes in a tunnel. In addition, a stricter punishment scheme for speeding in tunnels is suggested, as the results indicated that speed limit was more effective in tunnels than general freeways.

The crash-level information in the dataset was the most disaggregated data that one could possibly acquire for modeling injury severity in this study, and thus the injury severity model was on a crash-level. Further studies could establish multi-level models (i.e., combining crash level, vehicle level, and occupant level) for severity of injuries in tunnels based on more detailed injury information. Also, only 2018 crash information was acquired and analyzed in this study. Multi-year data are suggested to be incorporated when available to enlarge the sample size while considering space–time interaction effects for injury severity in freeway tunnels.

Author biography

Zichu Zhou: Conceptualization, Data curation, Visualization, Review and Editing. **Fanyu Meng:** Conceptualization, Formal analysis, Methodology, Software and Validation, Original draft Preparation, Review and Editing. **Cancan Song:** Data duration, Software, Validation, Funding acquisition. **N.N. Sze:** Original draft Preparation, Review and Editing. **Zhongyin Guo:** Supervision, Funding acquisition. **Nan Ouyang:** Funding acquisition.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

This work was supported by the National Natural Science Foundation of China, Grant No. 7177113; National Key R&D Program of China, Grant Nos. 2018YFC0807000 and 2019YFC0810705; Department of Transportation, Shandong, China under Grant 2019B32; Department of Transportation, Guizhou, China under Grant 2020-141-022. We would also like to acknowledge the Guizhou Transport Information and Emergency Control Center for providing the crash database.

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Journal of Safety Research 77 (2021) 161–169

Contents lists available at ScienceDirect

Journal of Safety Research

journal homepage: www.elsevier.com/locate/jsr

Investigation of injury severities in single-vehicle crashes in North Carolina using mixed logit models

Carlos Roque [a,*], Mohammad Jalayer [b], Ahmed Sajid Hasan [b]

[a] Laboratório Nacional de Engenharia Civil, Departamento de Transportes, Núcleo de Planeamento, Tráfego e Segurança Av. do Brasil 101, Lisboa 1700-066, Portugal
[b] Department of Civil and Environmental Engineering, Rowan University, Glassboro, NJ 08028, United States

A R T I C L E I N F O

Article history:
Received 9 June 2020
Received in revised form 2 November 2020
Accepted 23 February 2021
Available online 17 March 2021

Keywords:
Roadway departure
Run-off-road
Mixed logit model
Crash severity model

A B S T R A C T

Introduction: Roadway departure (RwD) crashes, comprising run-off-road (ROR) and cross-median/centerline head-on collisions, are one of the most lethal crash types. According to the FHWA, between 2015 and 2017, an average of 52 percent of motor vehicle traffic fatalities occurred each year due to roadway departure crashes. An avoidance maneuver, inattention or fatigue, or traveling too fast with respect to weather or geometric road conditions are among the most common reasons a driver leaves the travel lane. Roadway and roadside geometric design features such as clear zones play a significant role in whether human error results in a crash.in a crash. *Method*: In this we used mixed-logit models to investigate the contributing factors on injury severity of single-vehicle ROR crashes. To that end, we obtained five years' (2010–2014) of crash data related to roadway departures (i.e., overturn and fixed-object crashes) from the Federal Highway Administration's Highway Safety Information System Database. *Results*: The results indicate that factors such as driver conditions (e.g., age), environmental conditions (e.g., weather conditions), roadway geometric design features (e.g., shoulder width), and vehicle conditions significantly contributed to the severity of ROR crashes. *Conclusions*: Our results provide valuable information for traffic design and management agencies to improve roadside design policies and implementing appropriately forgiving roadsides for errant vehicles. *Practical applications*: Our results show that increasing shoulder width and keeping fences at the road can reduce ROR crash severity significantly. Also, increasing road friction by innovative materials and raising awareness campaigns for careful driving at daylight can decrease the ROR crash severity.

1. Introduction

According to the Federal Highway Administration (FHWA), a roadway departure (RwD) happens when a vehicle departs from the traveled way by either crossing an edge line or a centerline (Federal Highway Administration (FHWA), 2019). Therefore, RwD crashes include both run-off-road (ROR) and cross-median or centerline head-on collisions, resulting in crashes with more severe outcomes. As reported by the FHWA Roadway Departure Safety Program, RwD crashes account for more than 50% of motor-vehicle fatalities in the United States. To be specific, more than 70% of all RwD crashes are due to overturns (30%), followed by opposite direction (23%), and trees/shrubs (19%) crashes. These sobering statistics necessitate providing greater insight into the crash contributing factors and mitigation strategies.

Contributing factors to ROR crashes can be grouped into three major categories include: (1) infrastructure/environmental factors (e.g., weather, roadway condition); (2) driver factors (e.g., driver condition, speeding or inattention); and (3) vehicle factor (e.g., brake system, crash avoidance and lane departure systems; Neuman et al., 2003). Roadway and roadside geometric design features (e.g., lane and shoulder widths, sideslope, fixed-object density, and offset from fixed objects) play a significant role in whether human error will result in a crash.

A considerable number of studies have identified various contributing factors to ROR crashes based on a variety of data collection and data analysis methods. By taking advantage of mixed model analysis of variance (ANOVA), Freeman et al. (2015) evaluated the role of training programs in reducing ROR crashes through a set of simulated ROR scenarios (i.e., high speed highway, horizontal curve, and residential area). These scenarios were designed to examine, by means of drivers' attitudes, the effect of a training video on driver behaviors by comparing the treatment group with the control one. The treatment group watched a custom ROR train-

* Corresponding author.
E-mail address: croque@lnec.pt (C. Roque).

https://doi.org/10.1016/j.jsr.2021.02.013
0022-4375/

ing video while the control group just watched a placebo video. The results indicated that the frequency of spinouts among the treatment group dropped by 54%, with no significant improvement in the control group. Kusano and Gabler (2013) evaluated characteristics of opposite-direction RwD crashes in the United States using National Automotive Sampling Systems (NASS) data from 2006 to 2010. The results revealed that approximately 90% of cross-over-to-left crashes on rural roads occurred through the curves. Lord et al. (2011) investigated the contributing factors to RwD crashes, from 2003 to 2008, on two-lane two-way rural roads in Texas by employing regression analysis. The studied contributing factors were divided into three different categories including: (1) highway design characteristics (i.e., lane width; shoulder width and type; roadside design; pavement edge drop-off; horizontal curvature and grades; driveways; pavement surface; and traffic volume); (2) human factors (i.e., alcohol and drugs; speeding; and age and gender); and (3) other factors (i.e., time of day; and vehicle type). It was found that most of RwD crashes occurred during weekends, attributing people with driving under influence (DUI) on weekends. Unlike the driveway density, which had little impact on RwD crashes, lighting conditions had a great influence on probability of a RwD occurring.

A study by Roy and Dissanayke (2011) showed that fatigue/asleep/DUI, speeding, a loss of friction between tire and road, wet roadway surface condition, ruts, holes, and bumps increased the likelihood of ROR crashes. In another study conducted by the National Highway Traffic Safety Administration (NHTSA), driver inattention, driver fatigue, roadway surface conditions, driver alcohol presence, drivers' level of familiarity with the roadway, and drivers' gender are among the most significant ROR contributing factors (Liu & Ye, 2011). In order to evaluate the effectiveness of installed sealed shoulder and audible edge line in reducing ROR crashes in Western Australia, Meuoeners et al. (2011) gathered four-years (2000–2004) worth of crash data for 13 treatment sites. Authors concluded that this countermeasure, as a very highly effective tool, decreased crash rate for all severity and causality crashes by 58%, and 80%, respectively. Liu and Subramanian (2009) investigated the different contributing factors associated with single-vehicle ROR crashes. Based on the analysis results, horizontal alignments (i.e., curve), area type (i.e., rural and urban), speed limit, roadway geometric characteristics (i.e., number of lanes), and lighting conditions significantly affect frequency and severity of ROR crashes. In another study, McLaughlin et al. (2009) gathered the required dataset from 100-car naturalistic driving study to identify ROR contributing factors. In the study, a ROR event occurs when the subject vehicle passed or touched a roadway boundary (e.g., edge line marking and pavement edge). The study results revealed that a single factor was contributed in 75% of the ROR events, followed by 22% with two factors. Based on the analysis results, the most common ROR contributing factors include: distraction, short following distance, low friction, narrower lane, and roadside geometric configurations. Additionally, 36% of ROR events involved distractions due to the non-driving tasks and 30% of the ROR events happened on the curves. Roque et al. (2015) collected ROR crash data on freeway road sections in Portugal and developed multinomial and mixed logit regression models in order to identify contributing factors to unforgiving roadsides. The empirical findings of their study indicated that critical slopes and horizontal curves significantly contributed to fatal ROR crashes. Several previous studies (Cai et al., 2015; Jalayer et al., 2016) have reported that bridge-related crashes result in more fatalities due to their being mostly the fixed-object crash type, and a recent study, using North Carolina crash data, revealed problems in the current roadside design, especially with regard to clear zones criteria (Roque & Jalayer, 2018).

Gong and Fan (2017) used a mixed logit model to investigate the factors affecting single-vehicle ROR crashes in North Carolina considering various age groups. The authors demonstrated that the restraint device and horizontal curves contributed to fatal and serious injury of all age groups. However, reckless driving, speeding, distraction, inexperience, drug or alcohol involvement, presence of passengers, and driving an SUV or a van had more effect on young and middle-aged drivers.

In order to account for unobserved heterogeneity of ROR crashes in North Carolina, Yu et al. (2020) used a random parameter ordered probit model. The authors demonstrated that factors such as curved roadways, alcohol involved, and male drivers increase the risk of fatal and incapacitating injuries in the ROR crashes.

Al-Bdairi and Hernandez (2020) employed a latent class ordered probit model to investigate the effect of unobserved heterogeneity for area type (i.e., urban vs. rural) on the injury severity outcomes of ROR crashes involving large trucks. The results showed that factors like crashes on horizontal curves, not wearing a seatbelt, and driver fatigue increases the probability of higher injury levels, regardless of the land use setting.

In another study, Al-Bdairi and Hernandez (2017) employed an ordered random parameter probit model to predict the likelihood of injury severities of ROR crashes in Oregon. Factors such as the month of crash, raised median type, loss of control of a vehicle, and the total number of vehicles involved in the crashes contributed significantly to the severity of ROR crashes.

Jalayer et al. (2019) utilized the multiple correspondence analysis (MCA) method to identify the factors contributing to ROR crashes by combining usRAP data and historical crash records of the state of Illinois. The major contributing factors that increased the crash severity due to ROR crashes were roadside severity, horizontal curvature, fixed object crashes, and reduced shoulder width. Albuquerque and Awadalla (2020) aimed to quantify the odds of fatal injuries due to single-vehicle run-off-road (SVROR) crashes using multivariate logistic regression models. Based on the results, W-beam guardrail crashes showed the lowest odds of motorist death compared to other fixed object (tree, pole, and concrete barrier) crashes.

To evaluate the effect of various confounding factors on injury severity of ROR crashes, two mixed-logit models were developed. Of particular interest to this study are overturn and fixed-object crashes. Our study findings provide valuable insights into the underlying relationship between risk factors, crash injury, and the distance traveled by an errant vehicle in a ROR event. These findings will also help to promote the implementation of more efficient roadside safety countermeasures to mitigate ROR crash severity.

2. Methodology

This section describes the methodological approach and techniques applied to analyze injury severity data in this research. A variety of methodological techniques was applied in studying the crash severity data. Recent research has focused on random parameter approaches to account for possible unobserved heterogeneity (Milton et al., 2008; Eluru et al., 2008; Anastasopoulos & Mannering, 2011; Kim et al., 2013; Venkataraman et al., 2013; Roque et al., 2015; Saleem & Al-Bdairi, 2020).

Savolainen et al. (2011) and Mannering and Bhat (2014) extensively reviewed these methodological alternatives. For this study, mixed logit modeling on the injury severity of the occupants of an errant vehicle in a run-off-road crash is undertaken. The mixed logit model was introduced into transportation research in 1980 (Boyd & Mellman, 1980; Cardell & Dunbar, 1980). Mixed logit models have been applied since then to overcome inefficiencies of the multinomial logit (MNL) models by allowing for heterogeneous effects and correlation in unobserved factors. A mixed logit model is derived from MNL by allowing *j* to be random across *i* individuals in the severity function (Train, 2009):

$$T_{ij} = \beta_{ij} X_{ij} + \varepsilon_{ij} \tag{1}$$

with $\beta_i \sim f(\beta|\theta)$

Where T_{ij} is the specific injury severity level *j* for observation *i*, β_j is a vector of coefficients to be estimated for outcome *j*, X_{ij} is a vector of exogenous (or explanatory) variables, θ are the parameters of the distribution of β_{ij} over the population, such as the mean and variance of β_{ij}, and ε_{ij} is the error term that is independent and identically distributed (*iid* extreme value property), and does not depend on underlying parameters or data characteristics. The mixed logit is a generalization of the multinomial structure that allows the parameter vector β_j to vary across each most severely injured occupant. The injury outcome-specific constants and each element of β_{ij} may be either fixed or randomly distributed over all parameters with fixed means, allowing for heterogeneity in effects (Roque et al., 2015). A mixing distribution is introduced to the model formulation, resulting in injury severity probabilities as follows (Train, 2009):

$$P_{ij} = \int_x \frac{e^{\beta_i X_{ij}}}{\sum_x \beta_i X_{ix}} f(\beta|\varphi) d\beta \tag{2}$$

where $f(\beta|\varphi)$ is a density function of β and φ is a vector of parameters that describe the density function, with all other terms as previously defined (Milton et al., 2008). The injury severity outcome probability is then simply a mixture of logits (Train, 2009). The distribution is flexible in that β can also be fixed, and when all parameters are fixed, the model reduces to the standard MNL formulation. In those instances where β is allowed to vary, the model is in the open form, and the probability of an observation having a particular outcome can be calculated through integration (Savolainen et al., 2011).

In this study, the parameters vary across the population according to a normal distribution (less well-fitting distributions considered but discarded, such as the log-normal and uniform). Estimation can be done by solving the integral with Monte Carlo simulation. Efficiency has been increased using simulation with Halton draws, a popular and efficient estimation technique for random parameters models (Train, 2009). The freeware BIOGEME software (Bierlaire, 2003) was used for model estimation, taking advantage of its versatility in specifying the models formulated for this analysis.

2.1. Elasticities

The estimated model coefficients are not sufficient for exploring how changes in the explanatory variables affect the outcome probabilities. The reason for this is that the marginal effect of a variable depends on all the coefficients in the model, so the actual net effect cannot readily be determined from just the value or sign of any single coefficient (Khorashadi et al., 2005). To assess the vector of estimated coefficients (β_j), elasticities are calculated, which measure the magnitude of the impact of specific variables on the injury outcome probabilities. The elasticity of parameter estimates for continuous regressors is computed for each most severely injured occupant *i* as (Washington et al., 2011):

$$E_{x_{ik}}^{P_{ij}} = [1 - P_{ij}] \beta_j X_{kj} \tag{3}$$

where P_{ij} is the probability of outcome *j* and X_{kj} is the value of variable *k* for specific injury severity level *j*. Elasticities are not applicable to dummy variables, however. In these cases, the pseudo-elasticity, $E_{x_{ik}}^{P_{ij}}$, of the *k*th variable from the vector X_i, denoted X_{ik}, with respect to the probability, P_{ij}, of a person (*i*) experiencing outcome *j* can be computed by the following equation (Ulfarsson & Mannering, 2004):

$$E_{x_{ik}}^{P_{ij}} = \left[e^{\beta_{jk}} \frac{\sum_{j'=1}^{J} e^{\beta'_j X_i}}{\sum_{j'=1}^{J} e^{\Delta\left(\beta'_j X_i\right)}} - 1 \right] \times 100 \tag{4}$$

where *J* is the number of possible outcomes, $\Delta(\beta'_j X_i)$ is the value of the function determining the outcome, T_{ij}, after X_{ik} has been changed from zero to one, whereas $\beta'_j X_i$ is the value when $X_{ik} = 0$, X_i is a vector of *k* explanatory variables shared by all outcomes, β_j is a vector of estimated coefficients on the *k* variables for outcome *j*, and β_{jk} is the coefficient on X_{ik} in outcome *j*.

Elasticities were calculated as an average of the elasticities over the sample since it is not reasonable to use the average value of dummy variables. The elasticity value for a variable X_{ik} can be roughly interpreted as the percent effect that a 1% change in X_{ik} has on the injury severity outcome probability P_{ij}. The pseudo-elasticity of a dummy variable with respect to a ROR injury-severity category represents the percent change in the probability of that injury severity category when the variable is changed from zero to one. Thus, a pseudo-elasticity of 30% for a variable in the fatal category means that when the values of the variable in the subset of observations where $X_{ik} = 0$ are changed from 0 to 1, the probability of a fatal outcome for these observations increases, on average, by 30% (Savolainen & Mannering, 2007).

2.2. Goodness-of-fit statistics

Likelihood ratio (LR) tests were used to compare the models and select the preferred one. The LR test statistic is computed as:

$$X^2 = -2[LL_U - LL_R] \tag{5}$$

where LL_U and LL_R are the log-likelihood of the unrestricted and the restricted models, respectively. The computed value of the LR test is compared with the χ^2 value for the corresponding degrees of freedom (*dof*). This test is an efficient way of testing for the significance of individual variables by comparing the improvement in likelihoods as individual variables are added (Washington et al., 2011). Furthermore, the McFadden adjusted-ρ^2 statistic was chosen from many other ρ^2 proposals to measure the explanatory power of the models fitted based on our sample data, according to Eq. (6) (Hensher et al., 2005):

$$adjusted - \rho^2 = 1 - \frac{LL^* - p}{LL^0} \tag{6}$$

where LL^0 and LL^* are the log-likelihood of the base (i.e., all β parameters are 0) and the estimated models, respectively; and *p* is the number of parameters used in the estimated model – thus, accounting for model parsimony and avoiding over-fitting.

3. Data

In this study, we used North Carolina crash data, which we obtained from the FHWA's Highway Safety Information System (HSIS). The HSIS database contains four sub-files, including accident, vehicle, occupant, and roadway. When the sub-files are linked together, variables such as case number, vehicle number, county, route number, and milepost can be of interest. For a complete description of the linking process, readers are encouraged to refer to the HSIS North Carolina Guidebook. Given the focus of this study, we considered for further analysis only single-vehicle ROR crashes that occurred due to collisions with fixed objects and overturning.

We note that the HSIS database encompasses a five-level injury severity scale, including fatality (K), incapacitating injury (A-injury), non-incapacitating injury (B-injury), possible injury (C-injury), and no injury (PDO). As per the DMV-349 Instructional Manual of North Carolina (2018), Fatal crashes (K) imply the death of one or more persons due to motor-vehicle crashes within 12 months of the crash incident. Incapacitating or A-category injury prevents the injured person from performing normal activities for at least one day, and it includes massive loss of blood, suspected skull or chest injury, a broken bone, or significant burning in the body. Non-incapacitating injury (B-injury) is the visible injuries like a lump on the head, minor cuts on the skin surface with minimal bleeding, abrasions, and bruises. Possible injuries (C-injury) are not evident on the crash spot, rather claimed by a person as slight pains or wounds, limping, momentary loss of consciousness, etc (NCDOT, 2018).

Based on this categorization in North Carolina, we identified 293 (1.5%) fatal crashes, 323 (1.7%) incapacitating-injury, 2,832 (14.6%) non-incapacitating-injury, 4,377 (22.6%) possible-injury, and 11,513 (59.5%) no-injury crashes in the crash dataset. The final dataset consists of 19,338 crashes, that occurred between 2010 and 2014 in North Carolina, including 1,996 (10.3%) overturn crashes and 17,342 (89.7%) fixed-object crashes. The dataset contains information regarding several attributes related to the study crashes, as listed in Tables 1–3, depending on whether the variables are related to overturns or fixed-object crashes models.

The posted speed limit was considered but was not significant for both models and all injury severity levels included in the analysis. One possible reason could be that a lower speed limit is associated with more challenging roadway geometry, which might increase the severity of ROR crashes. In addition, increases in posted speed limits increase mean vehicle speeds that are associated with increases in injury crashes.

4. Results and discussion

This section describes the results of the analysis for two separate mixed logit models for overturns and fixed-object crashes to explore the differences between these two groups. To improve the numerical stability, the number of Halton draws to evaluate the log-likelihood function was 1000.

4.1. Significant variables

In this analysis, a host of variables were selected from five broad categories: seasonal variables (including clear weather, daylight, and wet), roadway variables (including shoulder width, rural road, two-way road, and underpass), crash variables (including roadside obstacles like fence, tree, and sign non-breakaway), vehicle-related information (including distance traveled, point of contact, and airbag deployment), and driver characteristics (including driver physical condition, occupant ejection, and driver gender).

Table 1
Descriptive statistics of ROR crash severity (Most severely injured occupant).

Outcome variable	Injury	Possible injury	No injury	Total
Fixed-object crashes				
Number of occurrences	2755	3814	10,773	17,342
Percentage	15.9%	22.0%	62.1%	100.0%
Overturns				
Number of occurrences	693	563	740	1996
Percentage	34.7%	28.2%	37.1%	100.0%

Altogether, 30 parameters were calibrated across two models, through which we could identify the potential effects of different factors related to the categories listed above. It is important to point out that almost all parameters were statistically significant, with *p-values* below 5% (i.e., confidence levels above 95%), with one exception where p-value went up to 15% (variable "Wet" in the overturns model). The aim of our study is to detect injury contributors through a retrospective severity analysis of ROR crash data and therefore use the models for explanatory purposes (within the range of values observed, only), where lower *p-values* are acceptable (Washington et al., 2011).

Only statistically significant explanatory variables were considered in the final specification models. A minimum confidence level of 85% was considered as criterion, which was met by 1 regressors out of 30 in the two calibrated models. In those cases where the variable effects were not significantly different, their coefficients were restricted to be equal. The severity of the most severely injured occupant was categorized into three levels: injury (including fatal, incapacitating, and non-incapacitating injuries), possible injury, and no injury.

According to Ye and Lord (2011), selecting an outcome with a large, unreported rate as a baseline level should be avoided. Also, it has been commonly assumed that the highest severity level (typically, the fatal injury severity level) has the highest reporting rate (Yamamoto et al., 2008) and should be set as a baseline severity level to minimize bias and reduce the variability of the models (Celik & Oktay, 2014; Ye & Lord, 2014; Vajari et al., 2020). Thus, *injury* was set as the baseline severity level for both mixed logit models, and the Alternative Specific Constant (ASC) was defined accordingly.

4.2. Models and interpretation

We begin by reporting the estimation results for both models, using the most severely injured occupant as the outcome variables. Table 4 shows the estimated parameters. We note that both models have different specifications. Whenever both models include the same variable, the signs of the parameters are preserved, and the respective p-values remain roughly the same. Nevertheless, the expected values of the parameters differ between the fixed-object crashes and overturns models, which are mirrored in the differences in respective elasticities (see Table 5). In both models, the explanatory variable *gender* has a random coefficient for the category *possible injury*. In both cases, the estimated standard deviations of the random coefficients are about twice the estimated coefficients, which indicates that positive effects are likely for those variables (the probability of the coefficient to shifting signs is 78% and 70% for fixed-object crashes and overturns models, respectively). Their estimated parameters were found to be normally distributed instead of having fixed values across all observations. The fixed-object crashes model resulted in greater log-likelihoods: from −19052 to −14593 and from −2192 to −1928 for the fixed-object crashes and overturns models, respectively. Accordingly, the forthcoming analysis will be based on the fixed-object crashes model calibration results and complemented with additional comments addressing the differences highlighted above.

As mentioned above, the parameter coefficient estimates may be misinterpreted, since a positive coefficient does not necessarily indicate an increase in the likelihood of that particular injury severity level. In order to assess the vector of the estimated parameter coefficients properly, parameter-specific elasticities (for continuous variables) and pseudo-elasticities (for categorical variables) are used in Table 5 to measure the impact of individual parameters on the likelihood of the three injury severity outcomes for both models. When analyzing the effects of continuous variables, the percent variation of crash outcomes is compared with

Table 2
Descriptive statistics of the continuous variables.

Type of crash	Variable	Description	Mean (Std. Dev.)	Minimum	Maximum
Fixed-object crashes	*Roadway Variables*				
	Shoulder Width (ft)	Paved shoulder width (Right)	6.496 (3.562)	0	22
	Vehicle Information				
	Distance traveled (ft)	Distance traveled after impact (ft)	63.366 (98.021)	0	1421
Overturns	*Vehicle Information*				
	Distance traveled (ft)	Distance traveled after impact (ft)	60.008 (79.062)	0	999

a 10% variation of the stimulus variable (in this case, the factors we are analyzing). In the case of categorical variables, since the variation in the stimulus factors (i.e., dummy variables) is necessarily from 0 (the baseline) to 1, then the percent variation of crashes outcomes refers to a variation of 100% in the regressors.

4.2.1. Continuous variables

The continuous variable 'distance traveled' was found statistically significant for the severity level 'injury' in both fixed object crashes and overturns with estimate values of 0.168 and 0.712, respectively. The traveled distance also increases the time elapsed after the crash occurred, which in turn can increase the possibility of getting injured. One of the continuous variable 'shoulder width' was found statistically significant at $p < 0.05$ but with a t-test value less than zero for 'injury' at fixed object crashes. The width of the shoulder can play an essential role in shaping the severity of the crash since the vehicle goes away the road during run-off-road crashes. Shoulder width also decreases the extent of injury in fixed object crashes to some extent. The results imply a wider shoulder width would reduce the possibility of injury to 8%. In several studies where shoulder data are available for use in the crash model, it was found to be a significant factor affecting traffic injury severities (Wang et al. 2009; Wang et al., 2011; Yang et al., 2011).

4.2.2. Seasonal variables

'Clear weather' is an essential factor for crash severity as driving has some issues during rainfall or snow days. The model estimate for clear weather for a severity category of 'no injury' during a fixed crash is statistically significant for $p < 0.001$, but it shows a negative value for the t-test. 'Clear weather' has been found to increase

Table 3
Descriptive statistics of the categorical variables.

Type of crash	Variable	Description	Percentage	Frequency
Fixed-object crashes	*Seasonal Variables*			
	Clear weather	1 = if the crash occurred with clear weather conditions/0 = otherwise	57.6%/ 42.4%	10,049/ 7,408
	Roadway Variables			
	Rural	1 = if the crash occurred in a rural road/0 = otherwise	90.3%/9.7%	15,763/ 1,694
	Two-way	1 = if the crash occurred in a two-way, not divided road/0 = otherwise	71.5%/ 28.5%	12,483/ 4,974
	Underpass	1 = if the crash occurred on an underpass/0 = otherwise	0.4%/99.6%	64/17,278
	Crash Variables			
	Fence	1 = if first harmful event is collision with fence/0 = otherwise	0.7%/99.3%	117/17,225
	Tree	1 = if first harmful event is collision with tree/0 = otherwise	0.8%/99.2%	148/17,309
	Sign non-breakaway	1 = if first harmful event is collision with sign non-breakaway/0 = otherwise	1.2%/98.8%	212/17,245
	Vehicle Information			
	Front of the vehicle	1 = if the point of contact of the vehicle was its central front/0 = otherwise	10.3%/ 89.7%	1,801/ 15,656
	Airbag deploy	1 = if the vehicle's airbag was deployed when the crash occurred/0 = otherwise	65.6%/ 34.4%	11,456/ 6,001
	Driver Characteristics			
	Normal condition	1 = if the physical condition of the driver when the crash occurred was apparently normal/ 0 = otherwise	77.7%/ 22.3%	13,563/ 3,894
	Ejection	1 = if occupant not ejected in the crash/0 = otherwise	97.6%/2.4%	17,041/416
	Gender	1 = if male driver/0 = if female driver	61.1%/ 38.9%	10,673/ 6,784
Overturns	*Seasonal Variables*			
	Clear weather	1 = if the crash occurred with clear weather conditions/0 = otherwise	70.2%/ 29.8%	1411/598
	Daylight	1 = if the crash occurred during daylight/0 = otherwise	63.3%/ 36.7%	1271/738
	Wet	1 = if the road surface was wet when the crash occurred/0 = otherwise	13.5%/ 86.5%	272/1737
	Vehicle Information			
	Airbag deploy	1 = if the vehicle's airbag was deployed when the crash occurred/0 = otherwise	56.9%/ 43.1%	1143/866
	Driver Characteristics			
	Normal condition	1 = if the physical condition of the driver when the crash occurred was apparently normal/ 0 = otherwise	81.6%/ 18.4%	1640/369
	Ejection	1 = if occupant not ejected in the crash/0 = otherwise	80.7%/ 19.3%	1610/386
	Gender	1 = if male driver/0 = otherwise	73.4%/ 26.6%	1474/535

Table 4
Estimated Coefficients of the Models.

Severity level	Variable Coefficient	Fixed-object crashes			Overturns		
		Coefficient estimate	t-test	p-value	Coefficient estimate	t-test	p-value
Injury (Fatal, incapacitating, non– incapacitating)	Clear weather	-	-		0.527	3.18	<0.001
	Daylight	-	-		0.288	2.24	0.03
	Wet	-	-		0.325	1.51	0.13
	Two way	0.512	9.84	<0.001	-	-	
	Fence	−3.380	−3.11	<0.001	-	-	
	Tree	−0.750	−2.31	0.02	-	-	
	Airbag deploy	−1.270	−26.83	<0.001	−0.685	−5.35	<0.001
	Distance traveled (ft)/100	0.168	8.00	<0.001	0.712	7.26	<0.001
	Ejection	−3.080	−17.61	<0.001	-	-	
	Shoulder width (ft)	−0.015	−1.97	0.05	-	-	
Possible injury	Constant	−3.030	−16.49	<0.001	−1.620	−5.81	<0.001
	Two_way	0.512	9.84	<0.001	-	-	
	Gender	−4.920	−4.77	<0.001	−5.390	−2.12	0.03
	Std. dev. of parameter (Gender)	6.460	5.37	<0.001	10.400	2.53	0.01
	Ejection	-	-		2.540	11.78	<0.001
No injury	Constant	−2.040	−9.99	<0.001	−1.920	−6.56	<0.001
	Clear weather	−0.325	−8.11	<0.001	-	-	-
	Rural	−0.252	−3.35	<0.001	-	-	-
	Normal condition	0.701	15.32	<0.001	0.610	3.94	<0.001
	Front of the vehicle	−0.227	−3.72	<0.001	-	-	-
	Underpass	5.180	3.04	<0.001	-	-	-
	Sign Non-breakaway	1.360	5.54	<0.001	-	-	-
	Ejection	-	-	-	2.540	11.78	<0.001
Number of observations		17,342			1996		
Log Likelihood at zero		−19052.134			−2192.830		
Log Likelihood at convergence		−14593.763			−1928.820		
ρ^2		0.234			0.120		

Notes: In the fixed-object crashes model, the *Two_way* indicator was restricted to be equal across injury and possible injury severity levels. In the overturn model, the *Ejection* indicator was restricted to be equal across injury and possible injury severity levels.

the chance of no injury by 137%, while for overturn, the possibility of injury increases by 43%. Perhaps, the clear vision of the driver gives him/her more time to react to the situation of a fixed object crash. However, the overturning movement of cars deteriorates the control over the situation even in the clear weather. The variable 'daylight' is statistically significant at overturns for the severity type' injury' with an estimate of 0.527 at a p-value of 0.03. The presence and absence of daylight influence the clarity of vision for the driver. Also, some people might have issues in driving during the nighttime conditions. We found that 'daylight' increase the injury due to overturn by 21%. Although Kim et al. (2013); Wu et al. (2014), Xie et al. (2009) found the daylight decreases the possibility of fatal crashes. Another study has shown mixed results where the probability was less in nighttime conditions (Ahmadi et al., 2020). One possible cause is the driver remaining more alert during the nighttime conditions or might be feeling overconfident in the daytime, which could make them more susceptible to injury in daylight. 'Wet' road condition increases overturn injury by 23%. Due to low friction of the surface, the vehicle could lose control while moving at a faster rate in wet roads. Moreover, in the slippery road surface, it could take more time to decelerate for the vehicle to a safe speed, which in turn could expose it for injury or fatal crashes. These results are consistent with previous studies that showed severe injuries are more likely to happen on the wet

Table 5
(Pseudo-)Elasticities.

Variable	Fixed-object crashes			Overturns		
	Injury	Possible injury	No injury	Injury	Possible injury	No injury
Clear weather				0.43		
Daylight				0.21		
Wet				0.23		
Fence	−0.94					
Tree	−0.42					
Two way	0.44	0.54				
Airbag deploy	−0.55			−0.35		
Distance traveled (ft)/100	0.09			0.00		
Ejection	−0.66				10.44	4.25
Shoulder width (ft)	−0.08					
Gender		−0.96			−0.99	
Clear weather			1.37			
Rural			−0.37			
Normal condition			−0.27			0.37
Front of the vehicle			−0.27			
Underpass			0.86			
Sign Non-breakaway			−0.41			

Note: This table reports the elasticities corresponding to the estimation results in Table 4. Elasticities are averaged over all observations. *Distance traveled after impact* and *Shoulder width* are continuous variables, and their elasticities are computed per Eq. (3). For binary regressors we report the pseudo-elasticities using Eq. (4).

and slippery roads (Liu & Subramanian, 2009; Roy & Dissanayake, 2011). Improving the drainage facility of the road surface and the resistance of the road surface can mitigate the overturn crashes.

4.2.3. Roadway variables

'Two-way' roads are statistically significant for crash severities' injury' and 'possible injury' for fixed object crashes with a coefficient value of 0.512. It is quite evident that 'two-way' roads are more prone to injury than the one-way roads since swerving to avoid head-on collision on the road is sometimes necessary, resulting in fixed-objects and overturn crashes. The elasticity estimates reveal that the injury possibility increases to 44% while the possible injury increases to 54% for fixed object crashes at two-way injuries. A fixed object crashes in the 'rural' roadway decreases the probability of no injury by 37%. Compared to urban roads, people use more speed in rural roadways. Due to high-speed collisions, it becomes hard for the driver to control the situation after the impact of the crash. Kusano and Gabler (2013) have demonstrated that the injury severity for RwD in the two-way rural roadway is more than urban. Crashes occurred in 'underpass' due to fixed object has little chance to get driver injured since the shield is at both of the sides of the road. The elasticity result shows that the chance of getting uninjured increases by 86% if the location of the crash is at an underpass.

4.2.4. Crash variables

The first object to hit after the fixed crash is vital for crash severity. As our model estimates, the 'fence' is a significant variable at $p < 0.001$ for the severity of the injury. However, the value of t-test is found negative in our model for the impact of this variable on crash severity. It is not surprising that hitting a 'fence' for the first time after the crash decreases the possibility of fixed object injuries to 94%. The presence of a fence in a catastrophic event absorbs the shock and mitigates the chance to get injured. However, the overturning movement has less likelihood to decrease the injury due to the complex situation over there. Another variable found statistically significant for 'no injury' at fixed object crashes was 'sign non-breakaway' with a coefficient value of 1.36. If the fixed object crash is with 'sign non-breakaway,' the chance of remaining uninjured decreases to 41%. Since the breakaways are thin fixed objects, collision with those has a chance to wreck the car and thus harming the driver. It should be stressed that, according to the forgiving roadside concept, appropriate breakaway devices may protect occupants from roadside hazards, when these cannot be removed or relocated. Breakaway supports for signs and lighting are designed and constructed to break or yield when hit by a vehicle, reducing crash severity (Jalayer & Zhou, 2016). However, this inherent advantage of using breakaway devices is not captured by the model because severity level "injury" includes all types of injuries (fatal, disabling, and non-incapacitating).

4.2.5. Vehicle information

'Airbag' deploys are usually designed to produce a response to the possible severity of the crash in the space of 1/20 seconds. For both the cases of crashes, we found that the deployment of airbag decreases the injury possibility. Deployment of airbag reduces possible injury in the fixed crash and overturns to 55% and 35%, respectively. Winston et al. (2006) also showed that airbag deployment is efficient for decreasing the severity of crash injuries. It is found that the variable' front of the vehicle' is statistically significant at $p < 0.001$ with a negative value of t-test for the fixed end crash with 'no injury.' The location of the first point of contact during the crash plays a role in shaping the severity of the crash. Getting hit by any vehicle at the 'front of the vehicle' impedes the driver's possibility to remain uninjured by 27%.

4.2.6. Driver characteristics

A random parameter 'gender' is found to be statistically significant over the overturn crashes for severity level of 'possible injury' in both fixed objects and overturn crashes. The estimated variation in standard deviation is found to be 6.4 and 10.4 for fixed object crashes and overturn crashes, respectively. The model estimate of gender is also significant for $p < 0.001$ and $p < 0.03$ for 'possible injury' of fixed object crashes and overturns, respectively. However, in both cases, the estimated value of t-tests are negative. As the male and female drivers have differences in skills and decision making during complex situations, gender is relatable with an impact on the crash severity. The elasticity analysis shows the 'male' drivers have less likelihood to get injured than female drivers. Male driver's presence decreases the chance of fixed object crashes and overturns crashes by 96% and 99%, respectively. Previous researchers also confirmed that male drivers have better driving performance and provide additional safety levels in the areas of complex circumstances than females. (Li et al., 2019; Staff et al., 2014; Yasmin et al., 2014). For overturn crashes, the variable ejection is found statistically significant for severities of both 'possible injury' and 'no injury' with a coefficient of 2.54. However, for 'injury' in fixed end crashes, the model predicts a negative value of t-test for ejection, although it is still significant at $p < 0.001$. Ejection of the passenger from the vehicle decreases the chance to get injured by fixed object crashes by 66%, while it increases the likelihood of no injury and possible injury by 4.25 times and 10.44 times in overturn crashes. Overturn crashes are likely to be facing the vehicle in the opposite direction. Ejecting passengers out of the vehicle would make them more prone to possible injury. However, it is also possible that the location where the ejection occurred threw the passenger out of the danger zone.

The 'Normal condition' of the driver is statistically significant for both fixed object crashes and overturns for 'no injury' with coefficient estimates of 0.71 and 0.61, respectively. Logically, the physiological and mental health of the driver plays a significant role in handling the complicated situation and making the right decision at the right time. Since the fixed object crashes are usually more rapid, the drivers have a little to do. Hence, the fixed object crash with the normal condition also decreases the possibility of no injury by 27%. However, overturn crashes often give the driver a chance to control the situation. The result of elasticity shows that no injury can increase up to 37% with a driver in normal physical condition.

5. Conclusion

This study investigated the HSIS crash data in North Carolina for five years (2010–2004) to find the contributing factors of ROR crashes utilizing a mixed logit model. The analyzed variables included seasonal variables (e.g., weather), roadway variables (e.g., functional classification of road), crash variables (e.g., hitting fence or tree), vehicle variables (e.g., hitting at the front of vehicle and airbag deploy), and driver characteristics (e.g., gender and health condition of the driver).

Several variables were found statistically significant for various injury severities. Clear weather, two way, and distance traveled had a significant impact on the injury and fatality due to ROR crashes. Gender of driver and ejection were found significant for possible injury, whereas the normal condition of the driver, sign non-breakaway, and ejection was significant for no injury. These results indicate a complex interaction of various classes of variables behind ROR crashes. Random parameters calibrated for both models allow for a probabilistic interpretation of the attribute *gender* for both models. In both cases, we conclude that the probability of the corresponding coefficients shifting signs (i.e., from positive to negative or vice-versa, respectively) is high (≥70%). This suggests that there are different propensities of severity levels for the crashes analyzed herein and that they may change the type of effect (i.e., from positive to negative, or vice-versa) when varying the attribute *gender*.

The elasticity analysis found a decrease of the probability of crash severity for hitting a fence, trees, deployment of the airbag, presence of the male driver, and increasing shoulder width. However, clear weather, daylight, and wet surface increase the severity of ROR crashes. Some of the features have a dual nature for different crashes. For instance, normal conditions of driver decreases injury for overturns, but increases it for fixed object crashes. The outcomes from both the calibrated models indicate that we should prioritize some issues over others while taking countermeasures that improve roadside design by reducing the severity of ROR crashes.

6. Practical applications

In terms of roadside treatments, our results show that increasing shoulder width and keeping fences on the road can reduce ROR crash severity significantly. Fences are often installed along roads with high traffic volumes and where game animals are frequently crossing. Some studies have evaluated the effects of game fences on road stretches, concluding that they reduce the number of game crashes (Elvik et al., 2009). Our study adds new findings on the effect that fences have on ROR crash severity, showing that they significantly decrease the risk of injury in fixed-object crashes.

Also, keeping well-functioning airbags inside the car, increasing road friction by innovative materials, raising awareness campaigns for careful driving at daylight can decrease the ROR crash severity.

There are some interesting topics to focus on and explore as future work developments, namely the joint analysis of ROR crash frequency and severity, through machine learning methods. Also, the methods used in this paper may be implemented to other ROR crash datasets (e.g., in European countries) to investigate whether the conclusions of this paper are data-specific or generalizable.

Acknowledgements

Carlos Roque gratefully acknowledges the scholarship SFRH/BPD/118499/2016 by the Portuguese Science and Technology Foundation Agency (FCT-Fundação para a Ciência e a Tecnologia, IP). The authors would also like to acknowledge Anusha Patel Nujjetty, Manager at the Highway Safety Information System (HSIS) Laboratory, for providing the crash data used in this study.

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Carlos Roque Carlos Roque is an assistant researcher at the National Laboratory for Civil Engineering (LNEC). He holds an M.Sc. and Ph.D. degrees in Transportation Systems from Instituto Superior Técnico. His research interests are in the application of machine learning, statistical and econometric methods to highway safety, traffic engineering, and transportation economics.

Mohammad Jalayer is an assistant professor in the department of civil and environmental engineering at Rowan University. His area of expertise includes traffic safety, intelligent transportation systems, and big data analytics. He received his Ph. D. from Auburn University in 2016.

Sajid Hasan is currently a graduate student in the department of civil and environmental engineering at Rowan University. His area of interest is traffic engineering, machine learning, and application of GIS in transportation.

Journal of Safety Research 77 (2021) 99–104

Contents lists available at ScienceDirect

Journal of Safety Research

journal homepage: www.elsevier.com/locate/jsr

Land-traffic crash leading to passenger vehicle submersion, drowning and other fatal injuries: A 44-year study based on records from the Finnish Crash Data Institute

Julius Tikka [a,b,*], Philippe Lunetta [b,c,1]

[a] Forensic Medicine Unit, The National Institute for Health and Welfare, Helsinki, Finland
[b] Department of Biomedicine, Forensic Medicine, University of Turku, Turku, Finland
[c] Department of Forensic Medicine, University of Oulu, Oulu, Finland

ARTICLE INFO

Article history:
Received 15 June 2020
Received in revised form 15 June 2020
Accepted 23 November 2020
Available online 5 March 2021

Keywords:
Road safety
Traffic accident
Prevention
Water
Immersion

ABSTRACT

Background: Land motor traffic crash (LMTC) -related drownings are an overlooked and preventable cause of injury death. The aim of this study was to analyze the profile of water-related LMTCs involving passenger cars and leading to drowning and fatal injuries in Finland, 1972 through 2015. *Materials and methods:* The database of the Finnish Crash Data Institute (FCDI) that gathers detailed information on fatal traffic accidents provided records on all LMTCs leading to drowning during the study period and, from 2002 to 2015, on all water-related LMTCs, regardless of the cause of death. For each crash, we considered variables on circumstances, vehicle, and fatality profiles. *Results:* During the study period, the FCDI investigated 225 water-related LMTCs resulting in 285 fatalities. The majority of crashes involved passenger cars (124), and the cause of death was mostly drowning (167). Only 61 (36.5%) fatalities suffered some–generally mild–injuries. The crashes frequently occurred during fall or summer (63.7%), in a river or ditch (60.5%), and resulted in complete vehicle's submersion (53.7 %). Half of the crashes occurred in adverse weather conditions and in over 40% of the cases, the driver had exceeded the speed limit. Among drivers, 77 (68.8%) tested positive for alcohol (mean BAC 1.8%). *Conclusion:* Multidisciplinary investigations of LMTCs have a much higher potential than do exclusive police and medico-legal investigations. The risk factors of water-related LMTCs are similar to those of other traffic crashes. However, generally the fatal event in water-related LMTC is not the crash itself, but drowning. The paucity of severe physical injuries suggests that victims' functional capacity is usually preserved during vehicle submersion. *Practical Applications:* In water-related LMTCs, expansion of safety measures is warranted from general traffic-injury prevention to prevention of drowning, including development of safety features for submerged vehicles and simple self-rescue protocols to escape from a sinking vehicle.

1. Introduction

Data on land-traffic crash leading to vehicle submersion is scarce, with general and in-depth studies being limited to only a few countries (Austin, 2011; Stjernbrandt, Öström, Eriksson, & Björnstig, 2008; Wintemute, Kraus, Teret, & Wright, 1990). According to these studies, vehicle submersion accounts for up to 11% of overall drowning deaths and 4.7% of all traffic fatalities (McDonald & Giesbrecht, 2013a, 2013b). In recent years, development of safety instructions and vehicle safety features specific for this type of crashes has gained attention (Giesbrecht and McDonald (2010 and 2011); McDonald & Giesbrecht, 2013a, 2013b; Gagnon, McDonald, Pretorius, & Giesbrecht, 2012; Giesbrecht, 2016; Giesbrecht et al., 2017; McDonald, Moser, & Giesbrecht, 2019). In Finland, motor-vehicle submersion accounts for approximately 5% of all fatal unintentional drownings and nearly 4% of all fatal land-traffic accidents (Lunetta & Haikonen, 2020).

In this study, based on data provided by the Finnish Crash Data Institute (FCDI), we evaluated the circumstantial and individual profile of land motor traffic crashes (LMTC) leading to vehicle submersion, involving drowning and other fatal injuries, in Finland, 1972 to 2015, Finnish Crash Data Institute (2020).

* Corresponding author at: The National Institute for Health and Welfare, Turku Forensic Medicine Unit, Mustionkatu 10, 20750 Turku, Finland.

E-mail addresses: Julius.tikka@utu.fi (J. Tikka), philippe.lunetta@utu.fi (P. Lunetta).

[1] Address: Department of Biomedicine, Forensic medicine, Kiinamyllynkatu 10, 20520 Turku, Finland.

https://doi.org/10.1016/j.jsr.2021.02.007
0022-4375/

2. Material and methods

2.1. Source of data

The Finnish Crash Data Institute (FCDI), a unit of the Finnish Motor Insurers' center, coordinates a national investigative system that assesses land traffic crashes leading to death or to severe trauma. The system includes 20 regional investigation teams, which have representatives from differing fields of expertise: police, traffic, and vehicle engineering, behavioral science and medicine, often forensic pathologists. The teams aim to assess the underlying cause of each crash and recommend ways to improve traffic safety, but their conclusions cannot be factors in any insurance, civil, or penal litigation.

In each accident, the investigation teams collect hundreds of variables, which are stored in a database maintained by the FCDI. Moreover, the FCDI archives the entire file of each investigation, which includes a detailed standard form filled in by each expert, documents of the police investigation and medico legal examination, photos, and possible drawings of the crash site, and a summary report. The database allows extraction of specific case groups by any individual variable. The FCDI makes available on request this data and original files for organizations and for individual researchers involved in road safety and traffic injury prevention. In addition to these tabulated data, we also performed a manual review of the original files.

2.2. Data selection

All LMTCs resulting in fatal drowning from 1972 to 2015 were extracted from the FCDI database and individual files using WHO ICD injury codes (I-code) for drowning that were in use during the study period (ICD 8th and 9th: 994.1; ICD 10th: T75.1). Moreover, for the period 2002–2015, extraction of LMTCs resulting in vehicle submersion was possible—regardless of cause of death—utilizing the variable "*incomplete or complete vehicle submersion.*"

A total of 225 LMTCs were found involving 285 fatalities. These cases included 137 passenger motor-vehicle crashes (resulting in 182 fatalities), 32 crashes in vehicles other than passenger cars (resulting in 36 fatalities), and 56 snowmobile crashes (resulting in 67 fatalities). By a general definition, provided by Statistics Finland (SF), a passenger car is "a road motor vehicle, other than a moped or a motor cycle, intended for the carriage of passengers and designed to seat no more than nine persons (including the driver)" Statistics Finland, 2020. The 137 passenger motor-vehicle crashes included 124 crashes where drowning was the cause of death ($n = 167$) and 13 crashes were the cause of death was other than drowning ($n = 15$). This survey focuses on the 124 crashes where drowning was the cause of death. The 32 crashes involving non-passenger motor vehicles were examined separately. Snowmobile crashes related to vehicle submersion (56 accidents leading to 67 fatalities) were excluded from this report, as they have been the focus of separate, detailed surveys (Gustafsson & Eriksson, 2013; Öström & Eriksson, 2002). Crashes involving submersion of industrial vehicles are usually occupational events investigated by the Workers' The Finnish Workerś Compensation Center (2020), which publishes detailed reports on selected cases.

2.3. Data analysis

Throughout the study period (1972–2015), the following variables were considered in regard to each crash: number of vehicles involved, number of fatalities, level of submersion (complete or partial), position in water (upright, upside down, and on the side), type of watercourse, presence of guardrails, calendar month, weather conditions, and, from 2002 onwards, the target of the vehicle's first impact. As to the fatalities profile, we considered age, sex, manner and cause of death, location in vehicle, use of safety equipment, injuries sustained, and detectable alcohol and drugs.

Since 1984, the FCDI has tabulated injuries by means of the Abbreviated Injury Scale system (AIS), which classifies the location, type, and severity of the injury (Loftis, Price, & Gillich, 2018). Injury severity is classified on a scale from 1 to 6, where 3 or more is considered severe or life-threatening. From 1972 through to 1983, we retrospectively coded the injuries by reviewing the original autopsy reports.

Fatalities' blood alcohol concentration (BAC) was determined from samples collected at medico-legal autopsy. In surviving drivers, alcohol concentration was determined either by breath alcohol or by blood test. In this study, BAC and breath alcohol results were merged for practical reasons. The BAC unit used is per mille, ‰ (=1mg/g = ≈10 mg/100 mL). In addition to alcohol, we scrutinized medicinal drugs and drugs of abuse with the potential of impairing driving skills.

3. Results

Overall, 225 water-related LMTCs involving all types of motor vehicles and leading to 285 fatalities were extractable from the FCDI database. These comprised 124 passenger car crashes, which led to 167 drowning deaths, and 13 passenger car crashes in which 15 fatalities died from causes other than drowning: 11 from injury, 1 each from intoxication or mechanical asphyxia, 1 from suffocation by mud, and 1 from a medical condition. As to the manner of death, the majority of the drowning fatalities were accidents (139, 83.2%). The remaining cases included 9 suicides, 1 homicide, and 9 cases for which the intent remained undetermined after full investigations; in 9 cases, the manner of death was not recorded.

In addition, 32 crashes, accounting for 36 fatalities (30 drivers, 6 passengers), involved motor vehicles other than passenger cars: 12 tractors, 10 trucks, 4 all-terrain vehicles, 2 motorcycles, and 1 case each involving a mobility scooter, a light quadricycle, an excavator, and a riding lawn mower. The manner of death was in all these cases unintentional. Twelve drivers tested positive for alcohol and two for a psychotropic drug. In one single crash, four serviceman passengers drowned when an army truck on a bridge, trying to evade a collision with an oncoming vehicle, fell into a river. The driver died of mechanical asphyxia.

The availability of data differed between variables, but generally, it was high. Data were complete for season of the event, type of watercourse, age and sex of fatalities, number of vehicles involved, injuries, each at 100%, and near complete for weather conditions (98.4%), vehicle submersion (97.6%), position of the fatalities in the vehicle (97.6%), road design for crashes that occurred on a public road (96.9%), blood alcohol content for fatalities (94.6%) and breath or blood alcohol content for all drivers (90.3%). The percentage of available information was lower for guardrails, position of the submerged vehicle, and vehicles speed: 83.8%, 70.8%, and 58%, respectively.

Tables 1 and 2 summarize the crash, vehicle, and fatality characteristics of land-traffic crash resulting in passenger vehicle submersion leading to drowning (1972–2015), and those of similar crashes leading to other injury deaths (2002–2015). Furthermore, the following sections display additional information for the former cases of drowning deaths.

3.1. Crash and vehicle characteristics

Guardrails were present in 36 (34.6%) crashes. In 16 crashes, the vehicles went over the rail, in 7 penetrated the rail, and in 13

Table 1
Crash and vehicle characteristics of land-traffic crashes resulting in passenger vehicle[1] submersion and drowning (1972–2015: 124 crashes) and other causes of death (2002–2015: 13 crashes).

Crash and vehicle characteristics	Drowning n (%)[3]	Death other than drowning[2] n (%)[3]
Total number of crashes	124 (100)	13 (100)
Season		
Fall	44 (35.5)	4 (30.8)
Summer	35 (28.2)	2 (15.4)
Winter	23 (18.5)	2 (15.4)
Spring	22 (17.8)	5 (38.5)
Data unavailable	0	0
Weather type		
Dry (summer)	54 (44.3)	8 (66.7)
Snow or ice	38 (31.1)	0
Wet	23 (18.9)	1 (8.3)
Dry (winter)	7 (5.7)	3 (25.0)
Data unavailable	2	1
Watercourse		
River or ditch	75 (60.5)	10 (76.9)
Lake or pond	28 (22.6)	2 (15.4)
Sea	21 (16.9)	1 (7.7)
Data unavailable	0	0
Guardrails		
In place	36 (34.6)	2 (25.0)
No guardrails (public road)	40 (38.5)	6 (75.0)
No guardrails (off road)	28 (26.9)	0
Data unavailable	20	5
Road profile of crash site (public road)		
Curve	57 (61.3)	7 (58.3)
Straight road	36 (38.7)	5 (41.7)
Data unavailable	3	0
Speed limit		
Exceeded	42 (43.4)	3 (25.0)
Data unavailable	52	1
Level of submersion of vehicle		
Complete	65 (53.7)	2 (15.4)
Partial	52 (43.0)	11 (84.6)
Vehicle did not submerge (victim ejected into water)	4 (3.3)	0
Data unavailable	3	0
Position of vehicle in water		
Upside down	54 (63.5)	5 (62.5)
Upright	20 (23.5)	1 (12.5)
On side	11 (13.0)	2 (25.0)
Data unavailable	35	5

[1] Passenger vehicle is "a road motor vehicle, other than a moped or a motor cycle, intended for the carriage of passengers and designed to seat no more than nine persons (including the driver)"(Statistics Finland).
[2] Other causes of death included injuries, intoxication, mechanical asphyxia, and natural death.
[3] Percentage of cases for which information was available.

Table 2
Characteristics of fatalities in passenger vehicle land-traffic crashes resulting in vehicle submersion and death by either drowning (1972–2015: 124 crashes) or other causes (2002–2015: 13 crashes).

Fatalities' characteristics	Drowning n (%) [2]	Death other than drowning [1] n (%) [2]
Total number of fatalities	167 (100)	15 (100)
Manner of death		
Accident	139 (88.0)	13 (86.7)
Suicide	9 (5.7)	1 (6.7)
Homicide	1 (0.6)	0
Undetermined	9 (5.7)	0
Natural death	0	1 (6.7)
Data unavailable	9	0
Location of victim		
Driveŕs seat	95 (58.3)	11 (73.3)
Front passenger seat	40 (24.5)	2 (13.3)
Rear passenger seat	28 (17.2)	2 (13.3)
Data unavailable	4	0
Seatbelt		
In use	49 (29.5)	8 (53.3)
Not in use or unknown[3]	117 (70.5)	7 (46.7)
Safety seat	1	0
Injuries		
Any injury	61 (36.5)	
Head region	45 (26.9)	11 (73.3)
Bone fracture	13 (7.8)	
Internal organs	7 (4.2)	
Crush injury/multiple severe injuries	0	11 (73.3)
Data unavailable	0	0
Alcohol positive[4]		
Overall fatalities	103 (65.2)	5 (33.3)
Driver fatalities	60 (53.6)	4 (36.4)
Passenger fatalities	43 (69.4)	2 (50)
Data unavailable, overall fatalities	9	0
Other drugs positive		
Driver fatalities	17	1

[1] Other causes of death included injuries, intoxication, mechanical asphyxia, and natural death.
[2] Percentage of cases for which information was available.
[3] Including cases where the individual had possibly unbuckled the seatbelt before death.
[4] The study material disclosed also 17 crashes where the vehicle's driver survived but tested positive for alcohol.

missed the rail or hit the head of the rail and were redirected towards the water.

In 42 (43.3%) cases, the speed limit had been exceeded. Average excess speed was 35 km/h (range 5–120 km/h).

In only four crashes were two or more vehicles involved. As the first target of the crash, other than water itself or a guardrail, these were reported from 2002 onwards: a tree or a sign or light pole in each of two cases, and in one case each, the target was a junction embankment or an elk.

3.2. Fatalities' characteristics and autopsy findings

Fatalities' overall mean age was 34.7 years (range 1–92; SD: 19). Mean age for drivers was 39.4 (range 16–92; SD: 18.5) and for passengers 28.4 years (range 1–76; SD: 18).

Overall, in fatal crashes, 95 drivers died and 29 survived. In 29 (24.4%) crashes, more than one fatality was involved, the average number of fatalities being, in these cases, 2.5. There were no crashes in which one of the fatalities drowned and the other(s) died of other cause(s).

Information about survival time after the crash was available only from 2002 to 2015, in a total of 52 cases. Most fatalities died at the crash site (45, 86.5%). Two died 1 to 3 h after the crash, four after 4 to 7 h, and one died 2 months later at hospital. Eight fatalities received resuscitation at the crash site: one died at the scene, the remaining died during transport to hospital or at hospital.

The investigation team concluded that in 26 cases, the use of a seatbelt could have improved the probability of survival. On the other hand, in one fatality, the seatbelt and airbag might have contributed to death by hampering the attempts to escape.

In the cause-of-death certificate, injuries—6 of which were intracranial—represented a contributing factor in 20 cases, and a medical condition, mostly a cardiac disease, in 15. Moreover, hypothermia and thoracic compression were contributing factors, each in one case.

Among the 61 fatalities who suffered injuries, 45 (73.8%) had severe injuries in the head region. Only nine, however, were intracranial (subdural and subarachcnoidal hemorrhages, brain contusions, brain edema; AIS code ≥ 3). Mild external head injuries (AIS code 1-2) included bruising, abrasion, or laceration of the scalp or face. Bone fractures (AIS ≥ 3) occurred in 13 fatalities, and included fractures of the femur, humerus, or ribs. Only seven fatalities sustained severe injuries (AIS 4 or 5) to the internal organs (lungs, heart, aorta, or liver).

Among all drivers, including fatalities and survivors, mean breath alcohol content (BAC) was 1.8‰ (range 0.3–4.2‰). For fatalities of all ages, drivers or passengers, BAC was also 1.8‰ (range 0.2–4.2‰), as well as for passengers alone (range 0.3–4‰). Additionally, 17 deceased drivers tested positive for one or more psychotropic drugs (benzodiazepines, tramadol, citalopram, amitriptyline, carbamazepine, amphetamine, cannabis). Ten of these drivers were under the influence of both alcohol and psychotropic drugs. Six of the passengers tested positive for psychotropic drugs (benzodiazepines, citalopram, amphetamine, cannabis), and three of them were also under the influence of alcohol.

4. Discussion

Data collected by SF, with cross-examination of ICD-10 I- and E codes for drowning, allow extraction of data on all LMTCs leading to drowning (Lunetta, Penttilä, & Sajantila, 2002). During the period 1971–2013, 547 fatal drownings occurred as a result of LMTCs, (i.e., annually 2.5 fatalities/ 1,000,000 inhabitants; Lunetta & Haikonen, 2020). In Finland, LMTC-related drowning represents 3.8% of all land-traffic accidents and 5.1% of all unintentional drowning (Lunetta & Haikonen, 2020). In other high-income countries, vehicle submersion accounts for up to 4.7% (New Zealand) of all traffic fatalities and up to 11.6% (New Zealand) of all unintentional drowning deaths (McDonald & Giesbrecht, 2013a, 2013b). In Sweden, a Nordic country like Finland, the share of LMTC-related drownings of all traffic deaths was 1.5% (Stjernbrandt et al., 2008), whereas in the United States it was 1% (Austin, 2011), even though the latter number of drowning fatalities could be underestimated. The differences between these countries might be a result from differences in geography and in extent of road networks adjacent to watercourse or from the studies' differing inclusion criteria for cases.

The rational for WHO ICD classification under "traffic accidents" of land-traffic related drowning is the collection of data for road safety work and crash prevention. However, this approach hinders assessment of the actual burden of drowning (Lunetta, Penttilä, & Sajantila, 2002; Smith & Langley, 1998).

SF data does not allow in-depth survey of LMTCs and provide no information on LMTCs that result in vehicle submersion and death for causes other than drowning. The FCDI, established in 1967 as the Traffic Safety Committee of Insurance Companies (VALT), maintains a database, which provides more comprehensive data. These data was the basis of the present study.

Although the FCDI aims, by statute, to investigate all fatal LMTCs in Finland, coverage is not 100%, however. During the period 1996–2013, the FCDI covered approximately 84.3% of passenger vehicle and 56.7% of snowmobile-submersion related drownings reported in a recent study based on SF data (Lunetta & Haikonen, 2020). Missing cases may be due, at least in part, to absent or delayed communications between the local police and the FCDI, resulting in a lack of adequate investigations.

A thorough analysis of the sequence of events in LMTCs leading to vehicle submersion and drowning may allow the disentangling of factors that may be targeted for primary, secondary, and tertiary preventive actions.

Our survey discloses risk factors crucial for primary prevention; these are similar to those in all other LMTCs: hazardous road conditions (adverse weather, inadequate design, poor management), drivers' human errors, speeding, use of alcohol, and use of other drugs. Indeed, 61 of the crashes happened in adverse weather conditions, and in 17 of these, the driver was speeding. Enforcing the speed limit during the dark winter season has contributed to reduction in fatal traffic accidents (VTT Technical Research center). Furthermore, adapting speed limits to weather conditions is already the practice on motorways in several EU countries (European Commission mobility and transport), including Finland, and expansion of this measure on other public roads could be beneficial.

In our study, only one-third of the crash sites were equipped with guardrails, and of these, some were ineffective in preventing the vehicle entering the body of water. Similar reports have appeared in other studies (Wintemute et al., 1990). Developing the network of effective guardrails near water systems might reduce crash-related drowning.

Driving under the influence of alcohol or psychotropic drugs is a well-known risk factor for fatal and nonfatal LMTCs (Penning, Veldstra, Daamen, Olivier, & Verster, 2010; Brady & Li, 2014). In our study, alcohol was the most important single risk factor for LMTC-related drowning. Our percentage of alcohol-positive LMTC-related drowning (65.2%) is much higher than that reported in Finland for overall land-traffic crashes (about 20%), but is similar to that reported for accidental drowning (about 55%; Pajunen et al., 2017; Lunetta & Haikonen, 2020). This percentage is much higher than that reported in Sweden (Stjernbrandt et al., 2008), but somewhat lower than in a U.S. survey (Wintemute et al., 1990). Moreover, the percentage in our study is higher than in the data provided by SF (Lunetta & Haikonen, 2020). This could be, at least in part, due to inconsistencies in determining alcohol as a contributing factor in the cause-of-death certificate, primarily in the earlier years of our study period.

Alcohol and psychotropic drugs play a role in the chain of events leading to the crash itself, but may also hamper drivers' and passengers' attempts to escape from the submerged vehicle. In our study, the high percentage of alcohol-positive fatalities among passengers corroborates this hypothesis. As for psychotropic drugs, only 17 of the drivers and 6 of the passengers tested positive. The effects of alcohol and other drugs in hampering the occupants' escape from submerged vehicles could be emphasized in preventive campaigns.

A medical condition, most often cardiac, was considered a contributing factor in only 15 cases. It may, however, be almost impossible to assess whether a disease has initiated the course of events leading to a crash, has precipitated the fatal outcome after submersion, or has had no effect at all.

Similarly to other surveys (Hammett, Watts, Hooper, Pearse, & Naito, 2007; Stjernbrandt et al., 2008; Wintemute et al., 1990), our study showed that only a minority of fatalities (14.4%) sustained severe injuries. This suggests that, if sober and not limited by age or by any medical condition, a victim's capability to escape a submerged vehicle is in most cases preserved, although even minor head traumas may also affect a victim's state of consciousness.

The present study also emphasizes the potential role of secondary prevention. Contrary to other land-traffic crashes, the fatal event is not the crash itself, but drowning following vehicle submersion. Once the vehicle is submerged, preventive countermeasures shift significantly from traffic safety issues to drowning prevention.

In addition to rescue service planning, general swimming- and lifesaving education and resuscitation training, secondary prevention includes development of vehicle safety features and safety instruction on how to escape promptly from a submerged vehicle.

This will be based on knowledge of the chronological sequence of vehicle submersion (Giesbrecht, 2016).

The "vehicle in water" emergency dispatch protocol includes instructions on how to escape from a sinking vehicle by unfastening seatbelts and exiting through a window while the vehicle is still floating. When performed rapidly, within approximately one minute, the self-rescue and escape SWOC protocol (Seatbelts off, Windows open or broken, Out immediately, Children first) can contribute efficiently to prevent the fatal outcome of these vehicle accidents (Giesbrecht, 2016; McDonald et al., 2019). Since many victims may not know, or forget, that they must open a window to escape, an automatic window opening system that operates upon contact with water could improve the chances of survival (Giesbrecht et al., 2017).

An issue under debate regarding a submerged vehicle is whether a seatbelt (or an airbag) may hamper the victim's attempt to promptly escape. In our study, this occurred likely in only one case. Moreover, the present study disclosed that only one-third of the fatalities were found wearing a seat-belt, a figure lower than the 52% reported in the United States (Austin, 2011). In some crashes, however, the investigation team did not report whether fatalities were found wearing their seatbelt or not; it is also likely that some fatalities had unfastened their seatbelts after the crash but were unable to exit the vehicle. Here, most of the submerged vehicles were in an upside down position. If the passenger compartment is not filled completely with water, for example in cases of partial vehicle submersion, the victim's body weight can prevent opening the seatbelt buckle. Mechanisms that make unbuckling the belt easier in this situation could be useful. Our paucity of data on the response of rescue and emergency services after the crash lessens the possibility of any adequate evaluation of such measures. Although most fatalities died at the scene before any intervention, tertiary prevention measures such as first intervention and medical care after rescue should be developed with a focus not only on injuries but also on drowning.

Water-related LMTCs resulting in deaths other than drowning were infrequent and almost exclusively characterized by partial submersion of the vehicle. In these fatalities, aspiration of liquid may be difficult to assess at autopsy even it may play a contributing role in the chain of events leading to death.

5. Conclusion and practical applications

The nationwide investigation system operated by the FCDI provides detailed data on LMTCs leading to vehicle submersion, drowning, or other injury deaths, more so than do regular police and medico-legal investigations. Regardless of this, what is warranted is more systematic data collection and the introduction of further variables such as water depth and temperature at the site of vehicle submersion. In Finland, water-related LMTCs are an overlooked but preventable cause of death. Instead of the crash itself, in the majority of the cases, the fatal event is drowning. Therefore, LMTCs resulting in vehicle submersion call for specific preventive counter-measures that encompass not only those of typical LMTCs but also partially overlap those developed for general drowning. Counter-measures could include public education on how to escape from a sinking vehicle and automatic window opening systems that provide an exit when a vehicle is submersed in water.

Funding sources

This work was supported with a grant by the Finnish Crash Data Institute. Any opinions, findings, and conclusions expressed in this article are those of the authors and do not necessarily reflect the views of the Finnish Crash Data Institute.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Julius Tikka, works as a forensic pathologist in the National Institute for Health and Welfare in Finland. He is currently a medical expert member in a traffic accident investigation team coordinated by the Finnish Crash Data Institute. Tikka received

his Licentiate of Medicine (MD) degree from University of Turku in 2013 and Specialist degree in forensic medicine in 2019.

Philippe Lunetta is professor of Forensic Medicine at the University of Turku and at the University of Oulu, in Finland. He has worked as a senior researcher at the Injury Prevention Unit of the Finnish National Institute for Health and Welfare, 2006–2008. His main research interests focus on epidemiological and medico-legal aspects of drowning. He has contributed on this topic 38 peer-reviewed articles and textbook chapters and over 20 invited lectures or other presentations in scientific conferences.

Journal of Safety Research 77 (2021) 30–39

Contents lists available at ScienceDirect

Journal of Safety Research

journal homepage: www.elsevier.com/locate/jsr

Mobile phone use while driving: Development and validation of knowledge, attitude, and practice survey instruments

Oluwaseun John Adeyemi *

University of North Carolina at Charlotte, United States
University of Edinburgh, United Kingdom

ARTICLE INFO

Article history:
Received 15 March 2020
Received in revised form 24 October 2020
Accepted 28 January 2021
Available online 21 February 2021

Keywords:
Distracted driving
Road crashes
Mobile phone
Knowledge, attitude, and practice
Nigeria

ABSTRACT

Introduction: Instruments that assess the knowledge, attitude, and practice (KAP) of mobile phone use serve as a primary assessment tool on which mobile phone distracted driving interventions can be designed. The objective of this study is to develop and validate KAP-modeled survey instruments that measure the knowledge of mobile phone hazards while driving (KMPHD), the attitude of drivers towards mobile phone use while driving (AMPUD), and the practice of mobile phone use while driving (PMPUD). *Method:* This study was a cross-sectional analytical survey conducted in Ibadan, Nigeria. Three instruments were designed to measure KMPHD, AMPUD, and PMPUD. Content validity, item analysis, exploratory factor analysis were conducted, and items were excluded based on the collective results of the analysis. The domains of the constructs and the reliability of the instruments are reported. A confirmatory factor analysis was used to assess the regression weights of each item and the model fit. *Results:* From an original list of 13, 12, and 10 items in the KMPHD, AMPUD, and PMPUD instruments, a final list of 7, 5, and 7 items were generated in each survey instrument, respectively. Two domains of the knowledge of hazards and practice of mobile phone use were obtained, and attitude to phone use while driving was a single domain. The reliabilities (Cronbach alpha) of the KMPHD (0.881), AMPUD (0.954), and PMPUD (0.920) were sufficiently high. Also, all items in the three instruments had moderate-to-high regression coefficients, and the model fits of the instruments were good. *Conclusions*: This study provides KAP-modeled survey instruments that can be used to assess a population-based knowledge, attitude, and practice of mobile phone use while driving. *Practical Applications:* This survey instrument can be used in assessing baseline knowledge, attitude, and practice of phone use while driving and determine the focus and effectiveness of mobile phone-induced distracted driving interventions.

1. Introduction

Mobile phone use while driving is a dangerous distracted driving behavior and a cause of poor driving performance (Choudhary & Velaga, 2017; Yannis, Laiou, Papantoniou, & Gkartzonikas, 2016). Across the world, driving distraction is a growing challenge (World Health Organization, 2011), with reports suggesting more than half of drivers in some countries (Sullman & Baas, 2004) interact with their mobile phones while driving. Drivers most commonly type or read text messages, initiate or receive phone calls, or interact with installed phone applications for navigation, entertainment, communication, or relaxation while driving (Caird, Johnston, Willness, & Asbridge, 2014; Simmons, Hicks, & Caird, 2016). While teenagers and adults are more frequent users of mobile phones (Atchley, Hadlock, & Lane, 2012), all age groups engage in mobile phone use while driving (Pew Research Center, 2019). In Nigeria, Africa's most populous country (Central Intelligence Agency, 2019), about 40% of drivers text or chat on their phones while driving (Olumami, Ojo, & Mireku, 2014). Road crashes account for about 25 deaths per 100,000 in Nigeria, with rates as high as 75 per 100,000 reported elsewhere in the continent (World Life Expectancy, 2017).

Mobile phone use while driving can have unfavorable consequences. Phone texting has been associated with reduced driving responsiveness, reduced vehicle control, near-collisions, unintentional lane deviation, and crash-related injuries and deaths (Caird et al., 2014; Klauer et al., 2014; Olson et al., 2016; Rumschlag et al., 2015). Also, receiving and initiating phone calls while driving has been associated with road crashes (Kumar & Ghosh, 2014) as the cognitive and visual aspects of distraction persist irrespective

* Address: Department of Public Health Sciences, University of North Carolina at Charlotte, United States.

E-mail address: oadeyemi@uncc.edu

https://doi.org/10.1016/j.jsr.2021.01.004
0022-4375/

of whether the phone device used while driving is hands-free or handheld (Tornros & Bolling, 2005). Both handheld and hands-free phones are associated with road crashes (Oviedo-Trespalacios, Haque, King, & Washington, 2017; Oviedo-Trespalacios & Scott-Parker, 2017).

The objective of this study is to develop and validate a Knowledge, Attitude, and Practice-modeled (KAP) survey instrument that measures the knowledge of mobile phone hazards while driving, the attitude of drivers toward mobile phone use while driving, and the practice of mobile phone use while driving. The rationale of this study is based on the high and increasing fatal motor-vehicle crash rates in Nigeria and the need for validated and reliable measures of assessing interventions aimed at reducing phone-related distracted driving (International Transport Forum, 2018; World Health Organization, 2015, 2018; World Life Expectancy, 2017). Designing and validating instruments that will assess the knowledge, attitude, and practice of mobile phone use will serve as an assessment tool for interventions aimed at reducing phone use while driving.

2. Review of literature

The KAP model is a tool that obtains baseline information on what is known about a public health problem, identify areas of intervention, and assess the impact of an intervention (Gumicio et al., 2011). Across crash injury prevention literature, the KAP model has been used to evaluate helmet use and road sharing among motorcyclists (Bachani et al., 2013; Bao et al., 2017; Wood, Lacherez, Marszalek, & King, 2009), drunk-driving behavior (Bachani et al., 2013), over-speeding (Kalla et al., 2010), seatbelt use (Amaya & Pinto, 2016), and phone-related distracted driving behaviors (Amaya & Pinto, 2016; Arosanyin, Olowosulu, & Oyeyemi, 2013; Nevin et al., 2017). Conceptually, knowledge and attitude should influence practice, and any deviation in such a pattern would present areas of research and intervention. However, recent and available crash injury prevention literature has a paucity of validated KAP-modeled instruments that specifically target knowledge of risks, attitudes toward, and practice of phone use while driving.

Knowledge refers to the awareness of and a measure of understanding of a phenomenon of interest (Kaliyaperumal, 2004). Few crash injury prevention studies assessed knowledge of the risks of phone use while driving (Adeola, Omorogbe, & Johnson, 2016; Kulkarni et al., 2013). Contrastingly, perception of phone use, an indirect proxy of knowledge assessment (Lavrakas, 2008), is a commonly researched domain (Hallett, Lambert, & Regan, 2011; Nguyen-Phuoc, Oviedo-Trespalacios, Su, De Gruyter, & Nguyen, 2020; Oviedo-Trespalacios, King, Haque, & Washington, 2017). Of the few studies that assess the knowledge of the risks of phone use while driving, the focus was aimed at texting while driving (Adeola et al., 2016). The limited research that assesses knowledge in this area presents a gap in the literature.

Attitude refers to an unconscious mental predisposition to a behavior or an action (Altmann, 2008). In road accident prevention research, earlier studies have examined attitude toward driving violations (Vardaki & Yannis, 2013; Zhao, Xu, Ma, & Gao, 2018), use of in-vehicle technological devices (Chen & Donmez, 2016), and legislation banning cellphone use while driving (Hallett et al., 2011; Sanbonmatsu, Strayer, Behrends, Ward, & Watson, 2016). Additionally, there is a robust literature on the attitude toward texting while driving (Atchley, Atwood, & Boulton, 2011; Bazargan-Hejazi et al., 2017; Gauld, Lewis, & White, 2014; Kim, Ghimire, Pant, & Yamashita, 2019; Preece, Watson, Kaye, & Fleiter, 2018) as well as other general cellphone use while driving (Baig et al., 2018; Cardamone, Eboli, Forciniti, & Mazzulla, 2016; Hill et al., 2015; Oviedo-Trespalacios, Briant, Kaye, & King, 2020; Oviedo-Trespalacios et al., 2017). With advances in mobile devices and the increasing use of social media, currently available instruments do not capture other distracting activities such as video chatting, internet surfing, and gaming.

Practice refers to the way knowledge and attitude is exhibited (Kaliyaperumal, 2004). The practice of phone use while driving is the self-reported or observed driving and phone use interaction. Previous studies have assessed mobile phone use using discrete measures such as frequency of use (Atchley et al., 2011; Chen & Donmez, 2016; Nguyen-Phuoc et al., 2020; Oviedo-Trespalacios et al., 2017; Zhao et al., 2018) or time spent performing specific phone activities while driving (Hallett et al., 2011). A few studies have approached practice as a conceptual domain using a string of questions (Atchley et al., 2011; Nguyen-Phuoc et al., 2020; Vardaki & Yannis, 2013). Most measures of practice have focused on primary phone functions (initiating and reading texts, and initiating and receiving calls; Atchley et al., 2011; Baig et al., 2018; Gauld et al., 2014; Hallett et al., 2011; Hill et al., 2015; Hill, Sullman, & Stephens, 2019). Recent practice-focused instruments less commonly captured smartphone-related activities such as video chatting practice, internet use, and social media engagement.

Technological advancement in smartphone functionality has created the need for a review of available measures of knowledge, attitude, and practice. With distracted driving being a worldwide challenge, the need for validated and reliable survey instruments becomes imperative. Designing a reliable and validated KAP-modeled instrument to evaluate knowledge, attitude, and practice of mobile phone use while driving will inform our current understanding of this risky behavior and serve as an assessment tool for interventions aimed at reducing distracted driving.

3. Materials and methods

3.1. Scale development

Knowledge of Mobile Phone Hazard while Driving (KMPHD) scale measures the level of knowledge of drivers on the risks associated with mobile phone use while driving. Using the domains of common mobile-phone related distracted driving activities (Caird et al., 2014; Macy, Carter, Bingham, Cunningham, & Freed, 2014; Simmons et al., 2016), 13 items were drafted to measure the knowledge of the hazards of mobile phone use while driving. The KMPHD uses a five-point Likert scale (1-strongly disagree to 5-strongly agree) to measure items.

Attitude toward Mobile Phone Use While Driving (AMPUD) scale measures the attitude of drivers towards using mobile phones while driving. In measuring attitude, the items apply the KAP model (Gumicio et al., 2011) to driving behavior. Ten items were drafted to measure the attitude towards mobile phone use while driving. Participants respond using a five-point Likert scale (1 – strongly disagree to 5 – strongly agree).

Practice of Mobile Phone Use While Driving (PMPUD) scale measures the use of mobile phones by drivers while driving. The items in the scale use the KAP model. The domains of phone use were drawn from the results of prior meta-analyses (Caird et al., 2014; Simmons et al., 2016). Twelve items were created to assess practice on a five-point Likert scale (1 – not at all to 5 – every time).

3.2. Study population

This analytical cross-sectional study was conducted among commercial and non-commercial motor-vehicle drivers in Ibadan, Nigeria. Ibadan is the third-largest city in Nigeria, with a population of over 3 million residents (Central Intelligence Agency, 2019).

Instrument experts assessed the validity of the items in the three survey instruments. Thereafter, the researcher conducted a pilot study. These study participants were identified through a convenience sampling method. The inclusion criteria for the pilot study was that participants must be English-speaking Nigerians, aged 18 years and older, with a valid driving license. Individuals without a valid driving license were excluded from the study. Ethical approval was obtained from the Oyo State Institution Review Board before the start of the study.

3.3. Analytical plan

3.3.1. Content analysis

A Content Validity Index (Polit & Beck, 2006) was used to measure the KMPHD, AMPUD, and PMPUD scales. The selected instrument experts assessed the elements of the scales based on a four-point ordinal scale (1-irrelevant; 2-unable to assess relevance without revision; 3-relevant but needs minor alteration; 4- extremely relevant) that measures the relevance of the items. Responses of 3 and 4 were recoded as 1, representing relevance while responses of 1 and 2 were recoded as 0, representing irrelevance. A computed mean score of each item was used to judge item relevance.

Across each expert's response, the number of relevant agreements for each item was calculated. An item's content validity index (I-CVI) is the proportion of relevant agreement of the item, and it was calculated as the number of relevant responses divided by the number of experts (Polit & Beck, 2006). The Cohen's kappa (McHugh, 2012) statistics were calculated using the formula: $\kappa = \frac{p_0 - .5}{1 - .5}$, where p_0 was the observed relevant proportion. Items with minimal agreement ($k > 0.2$) were retained. Additionally, the mean item content validity index (Mean I-CVI) was calculated as the average of the individual item CVI in the scale. The scale content validity index (S-CVI) was the mean of the expert proportion, measured as the average of the relevant proportion scores of each expert and the number of experts.

3.3.2. Item analysis

Item analysis was performed for each of the survey instruments. Item difficulty (represented by mean scores) and item variability (represented by standard deviation) were reported. A mid-range mean and standard deviation scores were considered ideal (McGahee & Ball, 2009). The item consistency was determined by the result of the scale's alpha value if the item is deleted. The item discrimination represents the final total item corrected value. The scale's reliability was determined using the Cronbach alpha value after retaining items whose removal will not improve the collective consistency of the scale.

3.3.3. Exploratory factor analysis

Exploratory factor analyses were performed for the items in each survey instrument. For each instrument, the analytical steps were repeated, with factors extracted using the maximum likelihood methods. First, the number of domains was determined using three sets of criteria: The Eigenvalue, the scree plot, and the cumulative percentage of factors. The least number of potential domains was determined by the number of extracted factors with Eigenvalues greater than 1. The maximum number of domains was determined by the point of sharpest bend on the scree plot. The number of factors extracted also represented those whose cumulative proportion exceeded 50%. Upon selecting the range of extractable factors, the simplest model, determined by the absence of cross loading after suppressing coefficients less than 0.3, was selected. During the iterative analysis steps, all rotation decisions started with no rotation and changed to Varimax and Direct Oblimin, in that order, until a simple structure was obtained. The regression coefficients of the items in each survey instrument were reported.

3.3.4. Confirmatory factor analysis

Confirmatory factor analyses were performed for the KMPHD, AMPUD, and the PMPUD scales. Statistical model adjustments were performed on the error assumptions for the models as specified in the modification indices. The Normed Fit Index (NFI), Tucker-Lewis Index (TLI), and Confirmatory Fit Index (CFI) and the Root Mean Square Error Approximation (RMSEA) were reported for each survey instrument. For this study, NFI, TLI, and CFI values greater than 0.9 were classified as adequate, while values of 0.95 or higher represented a good fit (Byrne, 2010; Hu & Bentler, 1999). Also, RMSEA values of 0.08–0.05 represented adequate fit, while values lesser than 0.05 represented a good fit (Byrne, 2010; Hu & Bentler, 1999). Structural models were generated, and the regression coefficients and correlation values were reported. The modification of the error of the items was guided by the modification indices.

3.4. Data analysis

Data from the instrument experts and the study population were collected using Qualtrics, version XM (Qualtrics, 2019). Data were extracted and analyzed using the Statistical Package for Social Sciences (SPSS), version 25 (IBM Corp., 2018). Structural modeling and model testing was performed using SPSS AMOS, version 25 (Arbuckle, 2016).

4. Results

Six instrument experts conducted a content validity assessment of the items. A total of 125 respondents were recruited for the pilot study. Respondents were predominantly teenagers and young adults aged 18 to 30 years (62%), males (62%), married as at the time of the interview (54%), and had at least a bachelor's degree (79%). About 49% of the respondents reported 2 to 5 years of driving experience (Table 1).

Table 1
Sociodemographic characteristics of Nigerian motor vehicle drivers, ages 18 years and older ($N = 125$).

Variable ($N = 125$)	Frequency (%)
Age categories	
18–30 years	77 (61.6)
31–40 years	33 (26.4)
41–50 years	15 (12.0)
Gender	
Male	78 (62.4)
Female	47 (37.6)
Marital Status	
Never Married	56 (44.8)
Currently married	67 (53.6)
Divorced/Separated	2 (1.6)
Educational Attainment	
Secondary School	26 (20.8)
Bachelor's degree	80 (64.0)
Graduate Degree	19 (15.2)
Years of Driving Experience	
Less than 2 years	11 (8.8)
2–5 years	61 (48.8)
6–10 years	33 (26.4)
More than 10 years	20 (16.0)

4.1. Content validity

4.1.1. Knowledge of mobile phone hazards while driving (KMPHD)

The original draft of the KMPHD survey had 13 items. Two negatively worded items were reverse-coded. The mean expert proportion was 0.92, and the mean item content validity was 0.91. The scale content validity index was 0.92. One item had a 50% agreement with a Kappa value of 0. This item was removed from the survey. Following content validity, 12 of the 13 items were kept (Table 2).

4.1.2. Attitude towards mobile phone use while driving (AMPUD)

The original AMPUD survey had 10 items. Six negatively worded items were reverse-coded. The mean expert agreement was 0.83. The mean item content validity index was 0.83, and the scale content validity index 0.83. The Kappa value of the items ranged between 0.66 and 1.0. Following content validity, all ten items were kept (Table 2).

4.1.3. Practice of mobile phone use while driving (PMPUD)

The original PMPUD had 12 items. The mean of the relevant proportion was 0.99. The mean item content validity index was 0.99. The scale content validity was 0.99. The Kappa value of the items ranged from 0.66 to 1.00. Following content validity, all items in the scale were kept (Table 2).

4.2. Item analysis

4.2.1. Knowledge of mobile phone hazards while driving (KMPHD)

An item analysis was performed on the 12 items on the KMPHD scale. The mean item difficulty ranged from 2.14 and 3.54. The item variability ranged from 0.74 to 1.33. Five of the 12 items had an item discrimination value of less than 0.30. Removing these five items improved the reliability of the scale. Following their removal, the item consistency of the remaining seven items ranged from 0.84 to 0.88. The final internal consistency (Cronbach alpha) value was 0.881 (Table 3).

4.2.2. Attitude towards mobile phone use while driving (AMPUD)

An item analysis was performed on the ten items in the AMPUD survey. The mean item difficulty ranged from 2.00 to 3.50. The item variability ranged from 0.60 to 1.34. Sequential removal of 5 of the 10 items improved the internal reliability of the scale. The remaining five items had item consistency values ranging from 0.93 to

Table 2
Content validation of the items in the Knowledge of Mobile Phone Hazards while Driving (KMPHD), the Attitude towards Mobile Phone Use While Driving (AMPUD), and the Practice of Mobile Phone Use While Driving (PMPUD) scales.

Item	Expert 1	Expert 2	Expert 3	Expert 4	Expert 5	Expert 6	Number in Agreement	Item CVI	Kappa	Decision
Knowledge of Mobile Phone Hazards while Driving (KMPHD)										
K1	1	1	1	1	1	1	6	1.00	1.00	Retain
K2	1	1	1	1	1	1	6	1.00	1.00	Retain
K3	1	1	0	1	1	1	5	0.83	0.67	Retain
K4	1	1	1	1	1	1	6	1.00	1.00	Retain
K5	1	1	0	1	1	1	5	0.83	0.67	Retain
K6	1	1	1	1	1	1	6	1.00	1.00	Retain
K7	0	1	1	1	1	1	5	0.83	0.67	Retain
K8	1	1	1	1	1	1	6	1.00	1.00	Retain
K9*	1	1	1	0	1	1	5	0.83	0.67	Retain
K10	1	1	1	1	1	1	6	1.00	1.00	Retain
K11	1	1	1	1	1	1	6	1.00	1.00	Retain
K12	1	1	1	1	1	1	6	1.00	1.00	Retain
K13*	0	1	0	0	1	1	3	0.50	0.00	Consider Removing
Proportion Relevant	0.85	1.00	0.77	0.85	1.00	1.00	Mean I-CVI = 0.91 S-CVI = 0.92			
Attitude towards Mobile Phone Use While Driving (AMPUD)										
A1*	0	1	0	1	1	1	4	0.67	0.34	Retain
A2	0	1	1	0	1	1	4	0.67	0.34	Retain
A3*	1	1	1	0	1	1	5	0.83	0.66	Retain
A4*	1	1	1	1	1	1	6	1.00	1.00	Retain
A5*	1	1	1	0	1	1	5	0.83	0.66	Retain
A6*	1	1	1	0	1	1	5	0.83	0.66	Retain
A7*	1	1	1	0	1	1	5	0.83	0.66	Retain
A8*	1	1	1	0	1	1	5	0.83	0.66	Retain
A9	1	1	1	1	1	1	6	1.00	1.00	Retain
A10	1	1	0	1	1	1	5	0.83	0.66	Retain
Proportion Relevant	0.80	1.00	0.80	0.40	1.0	1.0	Mean I-CVI = 0.83 S-CVI = 0.83			
Practice of Mobile Phone Use While Driving (PMPUD)										
P1	1	1	1	1	1	1	6	1.00	1.00	Retain
P2	1	1	1	1	1	1	6	1.00	1.00	Retain
P3	1	1	1	1	1	1	6	1.00	1.00	Retain
P4	1	1	1	1	1	1	6	1.00	1.00	Retain
P5	1	1	1	1	1	1	6	1.00	1.00	Retain
P6	1	1	1	1	1	1	6	1.00	1.00	Retain
P7	1	1	1	1	1	1	6	1.00	1.00	Retain
P8	1	1	1	1	1	1	6	1.00	1.00	Retain
P9	1	1	1	1	1	1	6	1.00	1.00	Retain
P10	1	1	1	1	1	1	6	1.00	1.00	Retain
P11	1	1	1	0	1	1	5	0.83	0.66	Retain
P12	1	1	1	1	1	1	6	1.00	1.00	Retain
Proportion Relevant	1.00	1.00	1.00	0.92	1.00	1.00	Mean I-CVI = 0.99 S-CVI = 0.99			

* Negative coded. CVI. Content Validity Index; I-CVI: Item Content Validity Index; S-CVI. Scale Content validity Index.

Table 3
Item Analysis of the items in the Knowledge of Mobile Phone Hazards while Driving (KMPHD), the Attitude towards Mobile Phone Use While Driving (AMPUD), and the Practice of Mobile Phone Use While Driving (PMPUD) scales.

ID	Item (*N* = 125)	Item Difficulty Mean	Item Variability Std Dev	Item Discrimination Initial total item corrected	Decision	Item Consistency Alpha if deleted	Item Discrimination Final total item corrected
Knowledge of Mobile Phone Hazards while Driving (KMPHD)							
K1	All usage of hand-held phones while driving is wrong	3.54	1.07	0.730	Retain	0.872	0.601
K4	Scrolling a mobile phone for any reason while driving is wrong	2.65	0.94	0.503	Retain	0.872	0.599
K5	Using the hand-held phone for navigation while driving is wrong	2.87	0.74	0.598	Retain	0.882	0.508
K7	Using the hand-free phone to receive urgent calls while driving is wrong	3.57	1.02	0.679	Retain	0.869	0.630
K8	Checking Facebook, Instagram, Twitter, WhatsApp or Snapchat is wrong while driving	3.14	1.29	0.706	Retain	0.839	0.838
K10	Using the hand-held phone in a slowly moving traffic is wrong	3.27	1.17	0.640	Retain	0.847	0.789
K12	Typing a text while driving is wrong	3.05	1.33	0.655	Retain	0.857	0.730
K2	It is permissible to use a hands-free phone while driving	2.94	0.78	−0.240	Consider Removing		
K3	Touching a hands-free phone while driving is wrong	2.92	0.81	0.199	Consider Removing		
K6	Using the hand-held phone to receive urgent calls while driving is wrong	3.02	1.00	0.202	Consider Removing		
K9*	It is acceptable to check Facebook, Instagram, WhatsApp or Snapchat as long as driving is done slowly	3.05	1.03	−0.135	Consider Removing		
K11	Reading a text while driving is wrong	2.14	0.83	0.301	Consider Removing		
KMPHD. Scale Cronbach Alpha. 0.881; Scale Mean (Std Dev): 22.10 (5.85)							
Attitude towards Mobile Phone Use While Driving (AMPUD)							
A2	My handheld mobile phone can distract me while driving	3.10	1.33	0.502	Retain	0.959	0.783
A7*	Playing games on the phone while driving is sometimes helpful in driving	2.98	1.33	0.824	Retain	0.932	0.941
A8*	Taking photographs while driving is sometimes helpful in driving	3.04	1.33	0.848	Retain	0.936	0.917
A9	Phones should be kept away whenever driving starts	3.19	1.26	0.704	Retain	0.960	0.772
A10	Packing safely before using the handheld phone is always required whenever one is driving	2.95	1.34	0.803	Retain	0.929	0.958
A1*	I need my handheld mobile phone is needed when driving	2.17	0.67	0.080	Consider Removing		
A3*	Texting on a handheld mobile phone while driving can be done if I can handle both tasks	3.50	1.07	0.277	Consider Removing		
A4*	Skilled drivers can use the handheld mobile phone while driving easily	2.44	0.97	−0.241	Consider Removing		
A5*	Reading text or chat messages on a handheld mobile phone can be done without affecting my driving	2.06	0.64	0.347	Consider Removing		
A6*	Scrolling through the phone while driving is sometimes helpful in driving	2.00	0.60	0.457	Consider Removing		
AMPUD. Scale Cronbach Alpha. 0.954; Scale Mean (Std Dev). 15.26 (6.06)							
Practice of Mobile Phone Use While Driving (PMPUD)							
P1	I make calls with my mobile phones while driving	2.19	0.40	0.683	Retain	0.899	0.714
P2	I receive calls with my mobile phones while driving	1.57	0.75	0.601	Retain	0.907	0.660
P4	I read text messages on my mobile phones while driving	2.23	0.46	0.676	Retain	0.896	0.721
P6	I play music on my mobile phones while driving	2.03	0.55	0.589	Retain	0.905	0.608
P8	I play games on my mobile phones while driving	2.19	0.61	0.899	Retain	0.886	0.814
P10	I browse the internet my mobile phones while driving	2.20	0.60	0.914	Retain	0.883	0.846
P11	I get driving directions on my mobile phones while driving	2.22	0.44	0.760	Retain	0.894	0.760
P12	I scroll my phone for any other reason while driving	2.10	0.59	0.719	Retain	0.900	0.667
P3	I send text messages on my mobile phones while driving	2.39	0.49	0.485	Consider Removing		
P5	I check my WhatsApp, Facebook, Instagram, Snapchat, Twitter or other social media tools on my mobile phones while driving	2.37	0.48	0.473	Consider Removing		
P7	I use the camera on my mobile phone to take pictures while driving	2.76	0.64	0.313	Consider Removing		
P9	I watch short videos on my mobile phones while driving	2.75	0.62	0.364	Consider Removing		
PMPUD. Scale Cronbach Alpha. 0.920; Scale Mean (Std Dev). 16.74 (3.49)							

* Items that were reverse-coded. Std Dev: Standard Deviation.

0.96. The final internal consistency (Cronbach alpha) of the scale was 0.954 (Table 3).

4.2.3. Practice of mobile phone use while driving (PMPUD)

An item analysis was performed on the 12 items in the PMPUD scale. The mean item difficulty ranged from 1.57 to 2.76. The item variability ranged from 0.40 to 0.75. Guided by the results of the Cronbach alpha value of the scale, if an item is deleted, the sequential removal of four of the 12 items improved the internal consistency of the items in the scale. The remaining eight items had item consistency values ranging from 0.88 to 0.91. The final scale had an internal consistency (Cronbach alpha) of 0.920 (Table 3).

4.3. Exploratory factor analysis

4.3.1. Knowledge of mobile phone hazards while driving (KMPHD)

An exploratory factor analysis was performed to assess the domains of the KMPHD scale using the maximum likelihood method (Table 4). A Direct Oblimin rotation generated the most parsimonious and simplest structure. Two domains were identified with three items loaded on the first domain and the four items loaded on the second domain. The items in the first domain represented questions that assessed knowledge of the hazards that accompany phone activities (Knowledge of Distracting Phone Activities: KDPA). The second domain represented questions that assessed the differences in handheld and hands-free phone use while driving (Knowledge of Handheld/Hands-Free Phone Use: KHPU).

4.3.2. Attitude towards mobile phone use while driving (AMPUD)

An exploratory factor analysis was performed to assess the domains of the AMPUD scale using the maximum likelihood method (Table 4). A parsimonious and simple result was generated without rotation. There was only one domain generated from the five items. All the five items loaded strongly with factor loadings ranging from 0.79 to 0.98.

4.3.3. Practice of mobile phone use while driving (PMPUD)

An exploratory factor analysis was performed to assess the domains of the PMPUD scale using the maximum likelihood method (Table 4). A Direct Oblimin rotation generated the most parsimonious and simplest structure. Two domains were identified. One of the eight items loaded weakly on both domains, and it was subsequently removed. Of the remaining seven items, three items loaded on the first domain and four items loaded on the second domain. The items in the first domain represented questions that assessed primary phone tasks such as calling and texting (Practice of Primary Phone Tasks: PPPT), while the second domain represented questions that assessed the practice of secondary phone tasks such as playing games and browsing through the internet (Practice of Secondary Phone Tasks: PSPT).

4.4. Confirmatory factor analysis

4.4.1. Knowledge of mobile phone hazards while driving (KMPHD)

A confirmatory factor analysis was performed on the KMPHD scale to confirm the model structure and its predictive ability. The structural model of the two domains of the KMPHD scale is shown in Fig. 1. The NFI, TLI, and CFI were 0.992, 1.007, and 1.000, respectively (Table 5). The RMSEA was 0.00 (90% confidence interval: 0.000–0.094). The standardized regression estimates of all the items ranged from 0.49 to 0.93. The two domains of the KMPHD scale had a moderate correlation ($r = 0.62$).Table 6.

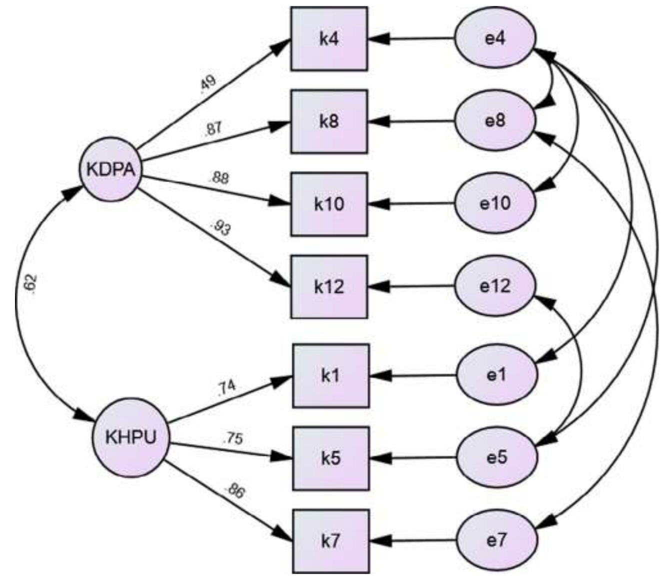

Fig. 1. Structural equation model showing the result of the confirmatory factor analysis of the factors in the Knowledge of Mobile Phone Hazards while Driving (KMPHD) scale. KDPA: Knowledge of Distracting Phone Activities; KHPU: Knowledge of Hand-held/Hand-free Phone Use; k represents factor items, e represents the error of the item variance.

4.4.2. Attitude towards mobile phone use while driving (AMPUD)

A confirmatory factor analysis was performed on the AMPUD scale to confirm the model structure and its predictive ability. The structural model of the AMPUD scale is shown in Fig. 2. The NFI, TLI, and CFI were 0.997, 0.995, and 0.998, respectively (Table 5). The RMSEA was 0.057 (90% confidence interval: 0.000–0.146). The standardized regression estimates of all the items ranged from 0.79 to 0.98.

4.4.3. Practice of mobile phone use while driving (PMPUD)

A confirmatory factor analysis was performed on the PMPUD scale to confirm the model structure and its predictive ability. The structural model of the two domains of the PMPUD scale is shown in Fig. 3. The NFI, TLI, and CFI were 0.984, 0.979, and 0.993, respectively (Table 5). The RMSEA was 0.080 (90% confidence interval: 0.000–0.150). The standardized regression estimates of all the items ranged from 0.53 to 1.02, and they were

Table 4
Exploratory Factor Analysis of the items in the Knowledge of Mobile Phone Hazards while Driving (KMPHD), the Attitude towards Mobile Phone Use While Driving (AMPUD), and the Practice of Mobile Phone Use While Driving (PMPUD) scales.

Scale	KMPHD				AMPUD		PMPUD[*]			
Domains	KDPU		KHPU		Attitude		PPPT		PSPT	
	Factors	Loadings	Factors	Loadings	Factors	Loadings	Factors	Loadings	Factors	Loadings
Items	K12	1.013	K7	0.988	A9	0.983	P2	1.080	P8	1.031
	K10	0.880	K5	0.662	A7	0.980	P1	0.678	P10	0.963
	K8	0.797	K1	0.517	A8	0.940	P4	0.676	P12	0.703
	K4	0.540			A10	0.788			P6	0.531
					A2	0.809				
Extraction Methods	Maximum Likelihood				Maximum likelihood		Maximum likelihood			
Rotation	Direct Oblimin				None		Direct Oblimin			

KDPA. Knowledge of Distracting Phone Activities; KHPU. Knowledge of Handheld/Hands-Free Phone Use: PPT: Practice of Primary Phone Tasks; PSPT: Practice of Secondary Phone Tasks.
[*] P11 removed because of moderate cross-loading on the two domains.

Table 5
Summary of confirmatory factor analysis of the items in the Knowledge of Mobile Phone Hazards while Driving (KMPHD), the Attitude Towards Mobile Phone Use While Driving (AMPUD), and the Practice of Mobile Phone Use While Driving (PMPUD) scales.

Model Diagnostics	KMPHD				AMPUD		PMPUD			
	KDPA		KHPU		Attitude		PPT		SPT	
	Factors	Regression Estimates	Factors	Regression Estimates	Factors	Regression Estimates	Factors	Regression Estimates	Factors	Regression Estimates
	K12	0.93	K7	0.86	A2	0.81	P2	0.79	P8	0.95
	K10	0.88	K5	0.75	A7	0.98	P1	0.93	P10	1.02
	K8	0.87	K1	0.74	A8	0.94	P4	0.91	P12	0.68
	K4	0.49			A9	0.79			P6	0.53
					A10	0.98				
CMIN	5.46				9.0		12.58			
DF	7.6				5.2		7.0			
P CMIN/DF	0.78				1.40		1.80			
NFI	0.992				0.997		0.984			
TLI	1.007				0.995		0.979			
CFI	1.000				0.998		0.993			
RMSEA	0.000				0.057		0.080			
90% CI	0.000–0.094				0.000–0.146		0.000–0.150			
PCLOSE	0.769				0.379		0.210			

KDPA: Knowledge of Distracting Phone Activities; KHPU: Knowledge of Handheld/Hands-Free Phone Use: PPT: Practice of Primary Phone Tasks; PSPT: Practice of Secondary Phone Tasks; CMIN: Model Chi-Square value; DF: Degree of Freedom; P CMIN/DF: Ratio of Chi-Square and the Degree of Freedom; NFI: Normed Fit Index; TLI: Tucker-Lewis Index; CFI: Confirmatory Fit Index; RMSEA: Root Mean Square Error Approximation; 90% CI: 90% Confidence Interval; PCLOSE: p-value (significance > 0.05).

Table 6
Final items in the Knowledge of Mobile Phone Hazards while Driving (KMPHD), the Attitude Towards Mobile Phone Use While Driving (AMPUD), and the Practice of Mobile Phone Use While Driving (PMPUD) scales.

Knowledge of Mobile Phone Hazards while Driving (KMPHD) (5-point Likert Scale: Strongly Agree to Strong Disagree)	
Item 1	All usage of hand-held phones while driving is wrong
Item 4	Scrolling a mobile phone for any reason while driving is wrong
Item 5	Using the hand-held phone for navigation while driving is wrong
Item 7*	Using the hand-free phone to receive urgent calls while driving is wrong
Item 8	Checking Facebook, Instagram, Twitter, WhatsApp or Snapchat is wrong while driving
Item 10	Using the hand-held phone in a slowly moving traffic is wrong
Item 12	Typing a text while driving is wrong
Attitude towards Mobile Phone Use While Driving (AMPUD) (5-point Likert Scale: Strongly Agree to Strong Disagree)	
Item 2	My handheld mobile phone can distract me while driving
Item 7*	Playing games on the phone while driving is sometimes helpful in driving
Item 8*	Taking photographs while driving is sometimes helpful in driving
Item 9	Phones should be kept away whenever driving starts
Item 10	Packing safely before using the handheld phone is always required whenever one is driving
Practice of Mobile Phone Use While Driving (PMPUD) (5-point Likert Scale: Every time to Not at all)	
Item 1	I make calls with my mobile phones while driving
Item 2	I receive calls with my mobile phones while driving
Item 4	I read text messages on my mobile phones while driving
Item 6	I play music on my mobile phones while driving
Item 8	I play games on my mobile phones while driving
Item 10	I browse the internet my mobile phones while driving
Item 12	I scroll my phone for any other reason while driving

* Negative coded.

statistically significant. The two domains of the KMPHD scale had a moderate correlation ($r = 0.67$).

5. Discussion

This study presents three KAP-modeled validated scales for assessing knowledge of mobile phone hazards while driving, the attitude of mobile phone use while driving, and the practice of mobile phone use while driving. From a collective decision based on content validity, item analysis, exploratory - factor analysis results, 7, 5, and 7 items were generated from an original list of 13, 12, and 10 items in the KMPHD, AMPUD, and PMPUD survey instruments, respectively. Two domains of the knowledge of hazards and practice of mobile phone use were obtained, while attitude to phone use while driving was a single domain. The high CFI, NFI, and TLI values and the very low RMSEA values showed that the items in each survey instruments were good fits. Also, all the item had significantly moderate-to-high regression coefficients, showing that the items in the scales significantly influences the interpretation of the constructs.

The stepwise reduction of items in the scale from content and item analysis and the resulting high-reliability values makes these instruments a reliable tool in objective assessments of domains of knowledge, attitude, and practice of driving in the survey sample. Other instruments that were derived using the KAP model reported high-reliability values (Shamsipour et al., 2016; Xu, Wang, Zhao, Wang, & Zhao, 2019). The domains of knowledge of hazards and practice extracted showcased issues earlier researchers were inter-

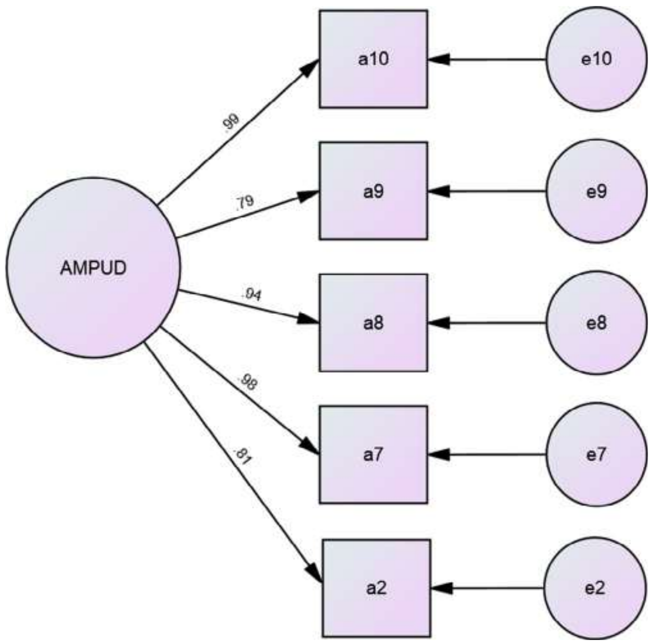

Fig. 2. Structural equation model showing the result of the confirmatory factor analysis of the factors in the Attitude towards Mobile Phone Use While Driving (AMPUD) scale; a represents factor items, e represents the error of the item variance.

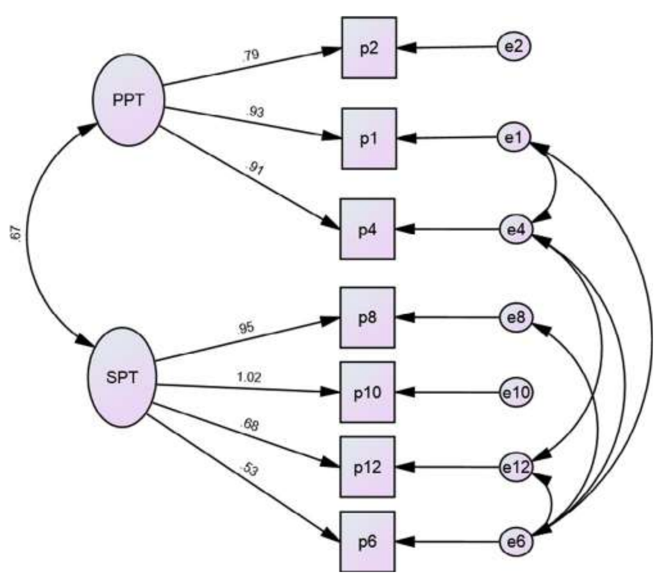

Fig. 3. Structural equation model showing the result of the confirmatory factor analysis of the factors in the Practice of Mobile Phone Use While Driving (PMPUD) scale. PPT: Primary Phone Tasks; SPT: Secondary Phone Tasks; p represents factor items, e represents the error of the item variance.

ested in and areas of continued policy development and experimental intervention (Braitman & McCartt, 2010; McCartt, Hellinga, & Bratiman, 2006). This study presents tools that can be used to observe driving behavior, measure mobile phone-related distracted driving interventions, and inform policies.

This study presents validated instruments that can measure knowledge of mobile phone hazards while driving, attitude towards mobile phone use while driving, and the practice of mobile phone use while driving. The design of this set of instruments follows the knowledge, attitude, and practice models, which provides an objective measure of the phenomenon of interest, establish a baseline from which effects of an intervention can be measured, and identifies areas of intervention (Gumicio et al., 2011). While a few studies have assessed the attitude toward cellphone and/or smartphone use while driving, the scale used in those studies were not validated (Baig et al., 2018; Harrison, 2011; Wang et al., 2009). Unlike knowledge of phone use hazards and attitude toward phone use while driving, the practice of mobile phone use while driving is well studied, though not cohesively as portrayed by the use of this instrument (Flynn, Taylor, & Pollard, 1992; Kim, Ghimire, Pant, & Yamashita, 2019; Ortiz, Ortiz-Peregrina, Castro, Casares-Lopez, & Salas, 2018). Furthermore, this study provides a uniform way to assess distracted driving behavior through a theoretically driven lens.

This study adds to the current crash injury prevention literature by providing reliable and validated instruments that assess phone-related distracted driving behavior. The instruments capture the additional domains of phone interactions that resulted from improved smartphone technology. Although validated among Nigerians, the items in the instrument are relevant, when retested, to other populations with increased phone-related distracted driving. Furthermore, the standalone nature of the KAP-modeled instrument makes for easy integration in other theoretical models such as the Theory of Planned Behavior.

This study must be considered in light of its limitations. Coverage error is likely as this study used a convenience sampling method due to the barriers in assessing some local government areas within the study area. While this study was conducted within the urban settlement in Ibadan, it is unknown if the driving behavior of those in the rural settlements differs from urban drivers. Selection bias is also likely as the study was restricted to English-speaking drivers. However, it is unlikely that language will significantly influence the knowledge, attitude, and practice of mobile phone use while driving. Additionally, nondifferential misclassification bias is likely as all responses are self-reported. Despite these limitations, this study represents the first validated instrument that measures the knowledge of mobile phone hazards while driving, the attitude towards mobile phone use while driving, and the practice of mobile phone use while driving among urban drivers in a developing African country.

6. Conclusion

This study provides a theoretically driven instrument that can be used to obtain population-based data on the knowledge of mobile phone hazards while driving, the attitude towards mobile phone use, and the pattern of mobile phone use while driving among Nigerian drivers. Assessing the knowledge, attitude, and practice of phone use while driving will help in determining the need and type of intervention to reduce mobile phone-related distracted driving. While this instrument was tested among Nigerians, further research is needed to assess the usability of this tool in other African countries and how the KAP model can be used to create behavioral interventions among Nigerians.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

The author wishes to acknowledge Jessica Hoyle, Department of Public Health Sciences, the University of North Carolina at Charlotte and Neema Olagbemiro, Department of Health Services

Research, the University of North Carolina at Charlotte, for their roles in proof-reading this manuscript. The author appreciates the instrument experts that validated the survey instruments.

Funding

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

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Oluwaseun Adeyemi, MBCh.B, MPH, MWACS, researches road accident prevention using a combination of human behavioral theories, spatial methods, and injury epidemiology to predict and provide information on road injury patterns in the United States and Nigeria. He is a recipient of several awards, including the American Public Health Association Presidential Award, the Lifesavers Traffic Scholar, and the Phi Beta Delta Honor Society for international scholars. He is a trained surgeon, and he is currently completing a doctoral degree in Public Health Science at the University of North Carolina at Charlotte.

Journal of Safety Research 77 (2021) 182–195

Contents lists available at ScienceDirect

Journal of Safety Research

journal homepage: www.elsevier.com/locate/jsr

Occupational injury rates among Norwegian farmers: A sociotechnical perspective

Kari Kjestveit [a,b,*], Oddfrid Aas [c], Kari Anne Holte [b]

[a] Faculty of Social Sciences, University of Stavanger, Postboks 8600 Forus, 4036 Stavanger, Norway
[b] Department for Social Science, NORCE – Norwegian Research Centre AS, Postboks 22 Nygårdstangen, 5838 Bergen, Norway
[c] Department of Occupational Medicine, St. Olav's Hospital, Postboks 3250 Sluppen, 7006 Trondheim, Norway

ARTICLE INFO

Article history:
Received 3 June 2020
Received in revised form 22 December 2020
Accepted 1 March 2021
Available online 22 March 2021

Keywords:
Agriculture
Injury risk
Sociotechnical system theory
Small enterprises
Safety
Climate

ABSTRACT

Introduction: This study addressed relative injury risk among Norwegian farmers, who are mostly self-employed and run small farm enterprises. The aim was to explore the relative importance of individual, enterprise, and work environment risks for occupational injury and to discuss the latent conditions for injuries using sociotechnical system theory. *Method:* Injury report and risk factors were collected through a survey among Norwegian farm owners in November 2012. The response rate was 40% (n = 2,967). Annual work hours were used to calculate injury rates within groups. Poisson regression using the log of hours worked as the offset variable allowed for the modeling of adjusted rate ratios for variables predictive of injury risk. Finally, safety climate measures were introduced to assess potential moderating effects on risk. *Results:* Results showed that the most important risk factors for injuries were the design of the workplace, type of production, and off-farm work hours. The main results remained unchanged when adding safety climate measures, but the measures moderated the injury risk for categories of predominant production and increased the risk for farmers working with family members and/or employees. An overall finding is how the risk factors were interrelated. *Conclusions*: The study identified large structural diversities within and between groups of farmers. The study drew attention to operating conditions rather than individual characteristics. The farmer's role (managerial responsibility) versus regulation and safety climate is important for discussions of injury risk. *Practical Applications:* We need to study subgroups to understand how regulation and structural changes affect work conditions and management within different work systems, conditioned by production. It is important to encourage actors in the political-economic system to become involved in issues that were found to affect the safety of farmers.

1. Introduction

National statistics indicate a substantial risk of fatal agricultural injuries (Norwegian Labour Inspection Authority, 2015). Nonfatal injury statistics are insufficient, in terms of both prevalence and circumstances, which is also an international concern (Donham & Thelin, 2016; Leigh, Du, & McCurdy, 2014; Solomon, Poole, Palmer, & Coggon, 2007). Moreover, studies of injury risk in farming lack information about exposure time (Jadhav, Achutan, Haynatzki, Rajaram, & Rautiainen, 2015), which makes it difficult to compare results and address preventive efforts, as these data are difficult to obtain. Various types of risk factors have been suggested for agricultural injuries, such as individual characteristics, activities, and production. Meanwhile, other studies emphasize risk factors that are less attached to activity or production, such as stressors and structural characteristics of the farm enterprise. These may serve as underlying features, also called latent conditions, through which agricultural injuries could be better understood. Using sociotechnical systems theory for discussing latent conditions in farming is an unexplored field.

The aim of this study is to assess the relevance of structural factors for occupational injuries among Norwegian farmers when controlling for work hours. The specific research questions are as follows:

1. What factors – in terms of individual and enterprise characteristics and work environment – predict injury risk among Norwegian self-employed farmers?
2. Do farmers' perceptions of safety climate affect the injury risk?

* Corresponding author.
E-mail address: kakj@norceresearch.no (K. Kjestveit).

https://doi.org/10.1016/j.jsr.2021.03.001
0022-4375/

The study has a multidisciplinary point of departure, which we find suitable for a discussion of occupational injuries in a wider perspective. Sociotechnical system theory is used to discuss the results in light of latent conditions in the farmers' work system (Smith & Carayon-Sainfort, 1989). The following sections will present current research on agricultural injuries, our theoretical point of departure, the Norwegian study context, and the conceptual approach.

1.1. Occupational injury risk within farming

It is well documented that farming is dangerous in terms of fatalities and injuries (Jadhav et al., 2015; Jadhav, Achutan, Haynatzki, Rajaram, & Rautiainen, 2016). At the individual level, risk factors for injuries are gender, age, physical health, and types of employment (Day et al., 2009; Horsburg, Feyer, & Langley, 2001; Jadhav, Achutan, Haynatzki, Rajaram, & Rautiainen, 2017; Rautiainen, Ledolter, Donham, Ohsfeldt, & Zwerling, 2009; Sprince et al., 2003; Virtanen, Notkola, Luukkonen, Eskola, & Kurppa, 2003). Studies also point to specific activities like handling animals, tractors, and other machinery as frequent direct causes of nonfatal injuries (Erkal, Gerberich, Ryan, Renier, & Alexander, 2008; Jadhav et al., 2017; Karttunen & Rautiainen, 2013; Solomon, 2002; Taattola et al., 2012; Virtanen et al., 2003). Moreover, numerous farm characteristics have been shown to be risk factors for injuries. One study found a difference between production types, with dairy farmers and pig farmers having the highest increased injury risk (Hartman et al., 2004). Factors like income level, field size, and occupational health service membership are risk factors for injuries (Rautinainen et al., 2009). Several studies have indicated that organizational aspects are important for risk, where injury risk is associated with being a full-time farmer and/or a farm owner (Jadhav et al., 2015), number of employees (Jadhav et al., 2017; Van den Broucke & Colémont, 2011), two operators and operators with fellows (Karttunen & Rautiainen, 2013), and cooperation with other farmers (Taattola et al., 2012). One study found single working farmers to be less at risk (Svendsen, Aas, & Hilt, 2014). Results are therefore inconclusive regarding the organizational aspects of farming. Heavy workloads, in terms of hours, have also been found to be a risk factor in several studies (Glasscock, Rasmussen, Carstensen, & Hansen, 2006; Hartman et al., 2004; Svendsen et al., 2014). Glasscock et al. (2006) found that stressors and stress symptoms like role conflict, economic concerns, administrative burden, and unpredictability are additional risk factors for injuries. Therefore, the status quo is indicative of how both organizational and managerial issues should be addressed to a higher extent than today when injury risks are studied in farming. Moreover, the effect of injury risk relative to exposure time (Jadhav et al., 2015) and off-farm work on injury represents a knowledge gap in this field (Jadhav et al., 2016).

1.2. Theoretical framework

Occupational injuries get little public attention (Lindøe, Engen, & Olsen, 2011) and are often viewed as individual accidents (Reason, 1997), where the worker is both the agent and the victim (Hovden, Albrechtsen, & Herrera, 2010). Thus, attempts are often made to explain occupational injuries through individual characteristics and direct causes. Direct causes or active failures are more visible than potential structural causes (latent conditions) of these events. Based on the worldwide changes in working life structures (e.g., technology and labor markets), Hovden et al. (2010) suggested that models derived from research in complex, high-risk, and socio-technical systems are also relevant for preventing occupational accidents, whose causes are influenced by external/contextual factors, like political climate and financial pressure (Rasmussen, 1997). Therefore, there is a need for discussing agricultural risk factors at a systemic level, moving away from the individual focus.

Sociotechnical system theory emphasizes the organization's interdependence of both the technical and social systems to obtain the most efficient results. This calls for addressing organizational design, such as the design of jobs and ways of organizing the work (Davis, Challenger, Jayewardene, & Clegg, 2014). Several sociotechnical models are in use, serving different purposes (e.g., Carayon, 2009; Leveson, 2004; Rasmussen, 1997; Smith & Carayon-Sainfort, 1989). However, all of them acknowledge that organizations and work systems depend on the environment by which they are regulated and otherwise influenced. Latent (underlying) conditions for accidents may therefore be economic constraints or production requirements that affect how the work is organized, as well as changes and irregularities within the system. A lack of awareness of the system mechanisms may itself be a latent condition, especially relevant in smaller work systems with few or no formal employees.

When studying farmers and agriculture, an appropriate model for understanding safety is the model described by Carayon et al. (2015), integrating the "balance theory of job design for stress reduction" (Smith & Carayon-Sainfort, 1989). This model places the worker in the center of the work system, and the work system is seen as *the local context in which work activities are performed,* embedded within a larger sociotechnical context, involving organizational structural elements and the external environment including regulatory regimes (Carayon et al., 2015). The "sharp end" refers to the area where the worker/operator faces the physical and technical challenges of the production (Reason, 1997), and while "sharp end" operators in other industry productions may be bounded by procedures set by others, the center position in the model (Carayon et al., 2015) gives a high degree of influence over the current work situation. Seeing the worker in the center, we believe, makes this model practically focused and compatible with unpredictability. First, worldwide agriculture is dominated by family farming[1] (Donham & Thelin, 2016), agricultural enterprises are small (<50 employees) and micro (<10 employees)[2], and the owner is the main worker (i.e., the leader-owner), which is similar to small and micro enterprises in general (Hasle, Limborg, Kallehave, Klitgaard, & Andersen, 2012). Second, due to technological development and high employment costs, Northern Europe and Scandinavia lead the world in the level of automated milking systems (AMS), requiring fewer employees (de Koning & Rodenburg, 2004; Hansen, 2015), making the farmer him/herself highly exposed to the technological changes. In Carayon's model (2015), technology is equally weighted with other elements of the system (organization, task, environment, individual), and the worker is to a greater degree an agent with the power to act, compared to other models (e.g., Rasmussen, 1997) and might reflect farmers covering roles as workers, owners, and leaders. Moreover, farming is in general characterized by small-scale, manual, linear, and somewhat transparent work, which can therefore be defined as the "sharp end" (Reason, 1997) (Fig. 1).

Within a system perspective, addressing the farmer as a manager becomes critical; hence, the literature on small enterprises and the management of OHS is relevant. Small enterprises have restricted resources for handling occupational health and safety (hereafter, OHS) (Champoux & Brun, 2003; Hasle & Limborg, 2006), often resulting in a lack of formal documentation and man-

[1] http://www.fao.org/3/a-i4036e.pdf. The state of food and agriculture 2014 (in brief) by the Food and Agriculture Organization of the United Nations. Downloaded June 14, 2017.

[2] http://ec.europa.eu/growth/smes/business-friendly-environment/sme-definition/index_en.htm.

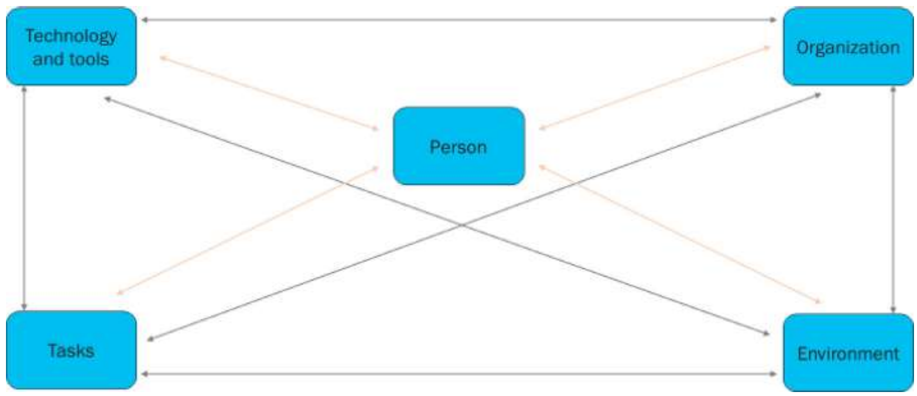

Fig. 1. The work system (Smith & Carayon-Sainfort, 1989).

agerial responsibility for these matters (Hasle & Limborg, 2006; MacEachen et al., 2010; Sorensen, Hasle & Bach, 2007). The OHS responsibility may even be redistributed to the worker (Hasle et al., 2012), and leader-owners often face dilemmas between interests of the enterprise (economy, survival) and workers' interests (future work, health, and safety) (Hasle et al., 2012; Vickers, James, Smallbone, & Baldock, 2005). Moreover, in farm enterprises, risk is more accepted, but also harder to detect (Storstad, Holte, & Aas, 2013), and animal husbandry makes the work environment unpredictable (Follo et al., 2016). Furthermore, cross-sectorial studies indicate that industries with a low degree of formal organization and where safety pressure from external stakeholders is low have fewer incentives for systematic safety improvements (Gaupset, 2000; Lindøe et al., 2011; Vickers et al., 2005).

Current research and quotes from Norwegian farmers (unpublished data) support the impression that farmers are not perceived as managers (by others or themselves) and that the farm is seldom referred to as an enterprise as such. Moreover, as industries and organizations change, the awareness of the unsolved challenges regarding workplace safety increases, motivating continuous efforts to understand the underlying mechanisms of occupational injuries. Knowing that choices made in the work system are heavily influenced by external factors pinpoints the irony of personalizing agricultural injuries and calls for efforts to address emergent risks on a systemic level (Carayon et al., 2015). Accordingly, external factors should be given more attention regarding their impact on structural factors and decisions made by the farmer as a manager, pointing to laws and regulations, authorities, stakeholders, etc.

2. Study context

Norwegian agriculture mainly consists of self-employed farmers (Statistics Norway, 2016a), although they often receive help from family (Logstein, 2012), which is rarely displayed in formal statistics. In recent decades, structural changes have reduced the number of holdings, farmers, and man-labor years (Statistics Norway, 2016b). Yet, holdings are larger and more efficient, and there has not been an overall reduction in the production of agricultural products (Statistics Norway, 2016b). However, cold and wet climates, large areas with steep terrain, and small and scattered fields challenge the development of modern agricultural production. The increased use of AMS (de Koning & Rodenburg, 2004; Hansen, 2015) may have had an impact on how the industry is organized, in terms of each farmer's workload, number of employees, and degree of cooperation with other farmers (Statistics Norway, 2016b).

In a system perspective, Norwegian agriculture differs from other countries, particularly in terms of political arrangements (Rommetvedt & Veggeland, 2017). It constitutes a political-economic system, including the government, the parliament, political parties, public administration, corporate organizations, producers, and the individual as a consumer and a voter (Rommetvedt, 2002). In matters of promoting agricultural interests in policy-making farm-owners are represented through two associations (Norwegian Farmers' Union and the Association for Smallholders), and the farm economy is heavily dependent on the annual negotiations between them and the government (Farsund, 2002). When it comes to OHS regulations, self-employed farmers are not subject to the regulations outlined in the Working Environment Act (2005) unless they are considered employers. When they are an employer, the requirements relate to safety training for and security of the employees, but not the employer him/herself[3]. Detailed OHS regulations relate more to the use of machinery and quality of products than requirements for safe work. Little formalization is put on farmers' solutions for practical work or for managing workplace safety.

In addition, most agricultural producers are certified according to the Norwegian Agricultural Quality System and Food Branding Foundation (Norwegian abbreviation: KSL). The KSL includes OHS and performs farm audits at given intervals, depending on type of production (Holte & Follo, 2018). The farm economy is partly dependent on satisfactory quality results, because the farm can be "punished" through lower prices for the products they deliver, which makes the KSL an important external factor influencing the farmer's work system.

3. Conceptual approach

The conceptual model (Fig. 2) is based on a combination of demographic and enterprise characteristics as well as variables related to work environment. Each of these three groups of variables is treated as independent risk factors for being injured during work. Because work hours are controlled for, individual variables are equally interesting as variables related to the farm as an enterprise/organization. Physical and quantitative demands are known to increase the risk of injuries (Cantley, Tessier-Sherman, Slade, Galusha, & Cullen, 2016; Hollander & Bell, 2010; Kjestveit, Tharaldsen, & Holte, 2011; Treiber, 2009) and are included as work environment variables, in addition to workplace design. Off-farm work hours are included as an independent variable, representing an aspect of the overall job demand. We called the first search for predictors (horizontal arrows) Model 1.

[3] The Working Environment Act (2005): §2-1, §2-2.

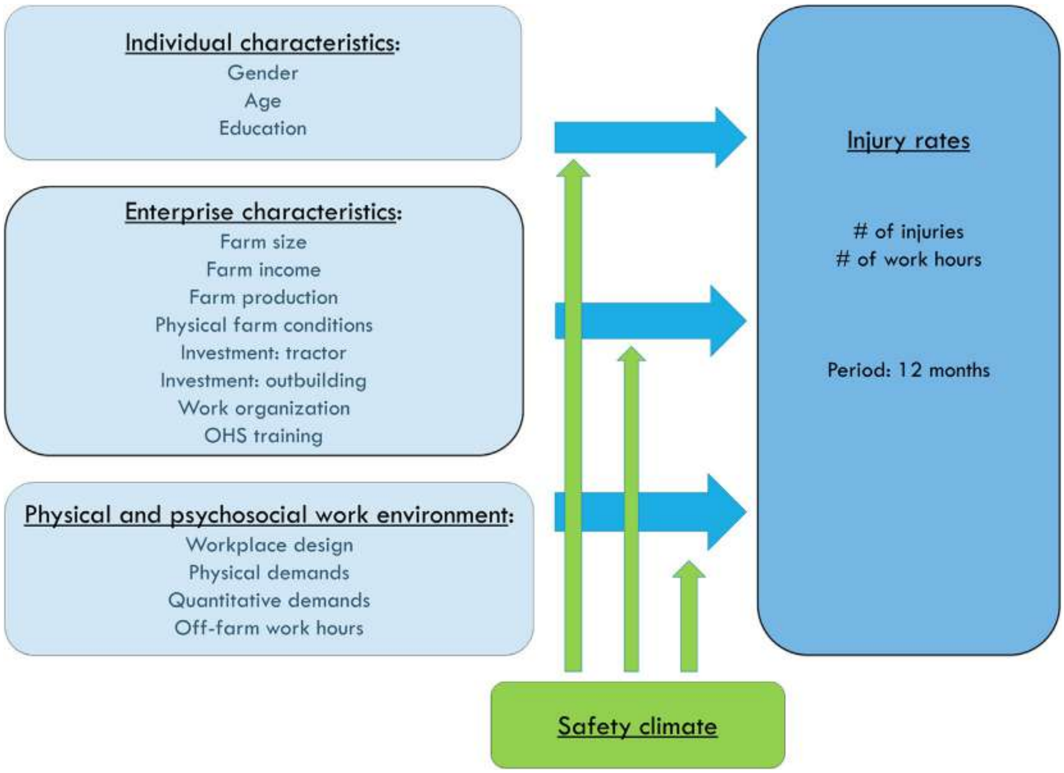

Fig. 2. Conceptual model — searching for predictors.

Safety culture is increasingly recognized as important for injury prevention within agriculture (McNamara et al., 2018; Törner et al., 2002) and should also be considered when using sociotechnical system theory (Carayon et al., 2015). Because culture is difficult to measure, safety climate assessments are performed for this purpose, as it gives a snapshot of the prevailing situation (Mearns, Whitaker, & Flin, 2003). A favorable safety climate is found to correlate positively with safety behavior and the reduction of injuries among employees in large companies (e.g., Ajslev et al., 2017; Antonsen, 2009; Dahl & Kongsvik, 2018; Mearns et al., 2003; Neal & Griffin, 2006; Treiber, 2009). Agriculture and other small-scale industries that miss formal organizational structures, management, and co-workers are perceived as having less fit to safety climate measures. Therefore, we have partly borrowed and partly developed suitable variables to include in our measures of safety climate, as described in section 4.1.5. A discussion of how safety climate assessments affect the main results is of special interest in our study because having what could be called a "good" safety culture is about handling risk, which is essential in workplaces characterized by unpredictability (Grote, 2012). High-risk organizations typically aim to reduce uncertainty because their survival is dependent on low accident rates (Grote, 2012). Where elimination is difficult, the focus must lie on coping with uncertainty (Grote, 2012).

To investigate the potential in joint cultural elements, the found predictors in Model 1 were tested again by including indexes for safety climate. The repeated version of the model while including safety climate (vertical arrows) was called Model 2.

4. Materials and methods

The study was designed as a national survey among farm owners who were 18 years or older. The questionnaire covered individual and enterprise characteristics, such as age, education, marital status, farm income, work hours, employees, machinery, health and worries, physical and psychosocial work environment, injuries, and safety climate.

4.1. Population and data collection procedures

Study participants were recruited through the registry of producers in the Norwegian Agricultural Authority, where persons who perform agricultural production and who apply for farm production subsidies are registered. The registry allows only one person per farm enterprise (i.e., the farm owner). In 2012, there were 43,917 agricultural enterprises registered, and 7,500 random units were drawn as a study sample.

A paper questionnaire was post mailed to the participants in November 2012, with an online option for answering. Reminders were sent out four weeks later. Ultimately, 59 questionnaires were returned due to unknown address and the like, giving a net sample of 7,441 farmers. Sentio Research Norge AS performed the actual data collection.

To ensure adequate treatment of the independent variables, some variables were refined, and indexes for work environment and safety climate were prepared. Details are given in the following subsections.

4.1.1. Self-reported work environment

Fourteen items on the questionnaire measured physical and quantitative work demands; these were subject to exploratory factor analysis with Oblimin rotation. Dissimilar response categories (8 items + 6 items) limited the options for indexes, but three indexes obtained satisfactory coherence (Cronbach's alpha): (1) workplace design, which includes three questions related to cramped space, bad lighting, and bothersome equipment (yes/no; Cronbach's alpha = 0.653); (2) physical demands, which include three questions related to demands for heavy lifting and repetitive movements, as well as work in bent, twisted, or any other strained positions (yes/no; Cronbach's alpha = 0.626); and (3) quantitative demands, which include three questions related to demands of a high work pace, very hard work, and too much work effort (yes/often; yes/sometimes; no/seldom; no/hardly ever; Cronbach's alpha = 0.772). The questions stem from Karasek and Theorell's (1990) work, and this index has also been used in other studies (Bjerkan, 2010; Logstein, 2016).

4.1.2. Predominant production

Details related to farm production were given directly through the registry of producers and revealed an overlap of production types (see Fig. 3). Mutually exclusive categories of predominant farm production were created using the following principles: (a) dairy cattle superseded all else; (b) other cattle superseded anything but dairy cattle; (c) due to being almost omnipresent, fodder was not excluded from other productions unless the respondent only produced fodder; (d) fodder and grain were set as distinct categories; and (e) the "other" category included other combinations and productions with a prevalence <5% (horses, fruit and vegetables, pigs, poultry, and fur farming).

4.1.3. Work organization

The farmers were asked to report annual work hours at the farm performed by people other than themselves. Based on this information, three categories of work organization were constructed: (a) the lone farmer, who had no one to help with farm work; (b) the family farmer, who worked together with his/her spouse and/or other family members; and (c) the farmer who hired one or more employees and/or relief workers, irrespective of family.

4.1.4. Other workplace characteristics

The variable *Physical farm conditions* was based on a question where the respondents could tick off one or several difficulties regarding farm condtions outdoor. Except for one response (No difficult farm conditions), six categories referred to difficulties regarding small, scattered, and/or uneven fields, long distances to fields, road/railroad crossings with fodder and/or livestock, challenging roads/bridges to fields, and steep terrain. A sumscore was used to reorganize into three final categories (≤1 difficulty = not very complicated; 2–3 difficulties = complicated; 4–6 difficulties = very complicated).

The degree of mechanization on the farm was self-assessed by the farmer through a specific question with three response categories (high degree; middle degree; low degree).

Respondents were asked for age of tractors. We chose to use the newest tractor as an indication of investment (>5 years = old; ≤5 years = new). The equivalent was done for outbuildings, where a split at 12 years was set to correspond to the year that AMS was first introduced in Norway. In the outbuilding question, one was to name the year of construction or re-construction, and the newest year was used in the analysis.

4.1.5. Assessments of safety climate

The questionnaire contained 40 statements regarding safety climate. The statements were partly based on Almås (1982) ($n = 5$), Törner et al. (2002) ($n = 5$), NOSACQ-50 (Kines et al., 2011) ($n = 3$), and the Petroleum Safety Authority Norway's (2014) Risk Level Project ($n = 5$). The remaining statements ($n = 22$) were developed by the project group to cover topics that emerged from qualitative interviews conducted in the overall Accidents in Norwegian Agriculture (AINA) project (unpublished data).

An exploratory factor analysis was conducted using principal axis factoring and Oblimin rotation, and items with correlations <0.3 were excluded. In general, the correlations were low (<0.4), and different solutions for missing values were used to look for correlation patterns. Five indexes were suggested in the model, but only three were found to be adequate. In total, 20 items were included in the indexes. *Safety System* (Climate 1) measured the respondents' attitudes towards a systematic safety approach, including safety audits. *Accept/Normalization* (Climate 2) measured the attitude towards the farmers' own possibilities to affect injuries and safety level. *Safety Practice* (Climate 3) measured the actual safety behavior, as perceived by the respondents (Table 1).

4.2. Data analyses

The quantitative analyses are described in five steps. All statistical analyses were made using SPSS version 25.0. Goodness of fit was tested using Pearson's chi square/df.

First, a 12-month injury prevalence for farmers was calculated. The number of injuries was based on two questions regarding occurrence and number of accidental injuries in relation to farm work during the past 12 months. In addition, injuries that were described in detail in a second questionnaire[4] were included if they were reported to occur in 2012, corresponding to the preceding 12 months. Reporting being "injured" with no information about frequency was coded as a single injury. Outliers were Winsorized (Yang, Xie, & Goh, 2011) and replaced with the nearest "non-suspect" value, which in this case was six. See Table 2 for the distribution of injuries.

Second, the material was explored using descriptive statistics. Correlations between the independent variables were investigated, and cross-tabulations with chi-square tests were made for variables of special interest.

In the third step, crude injury rates for all independent variable categories were calculated and expressed as injuries per 100,000 hours worked. Thereafter, crude rate ratios were calculated, using the category with the lowest crude rate within each variable as a reference category. Self-reported work hours at the farm during the preceding 12 months (string variable) were used to indicate work hours. When reporting their own work hours, the respondents were given the example of 1,700 hours as the annual workload for an industrial worker; 5% and 95% percentiles were used to eliminate extreme values, which resulted in an interval of 150–3,400 ($n = 2,605$, missing = 362, mean = 1,435, SD = 899).

Step four consisted of calculating adjusted rate ratios. A Poisson regression was used because of a count outcome and low injury prevalence (Agresti, 2013; Coxe, West, & Aiken, 2009). Crude rate ratios (CRR) were used as selection criteria for the regression analysis. Variables with 0.8 < CRR < 1.2, as well as variables with <15% impact on other variables, were left out. The outcome (injuries) is relative to work hours, thus *Log (work hours)* was the link function in our model. To clarify, variables whose categories obtained *p*-values <0.05 were kept in the model even if the overall variable did not meet this criterion. Confidence limit ratios (CLRs) were reported for the final variables (see Table 3).

In the final and fifth step, step four was repeated for the revealed risk factors and for indexes for safety climate. These were added to detect moderating effects on injury risk.

5. Results

5.1. Presenting the sample

Of 7,441 farmers approached, 2,967 responded, giving a response rate of 40%. The respondents were found to be represen-

[4] The second questionnaire contained questions specifically aimed at the circumstances of accidents and injuries that had occurred at the farm during the preceding 5 years and was a supplement to the injury questions in the first questionnaire.

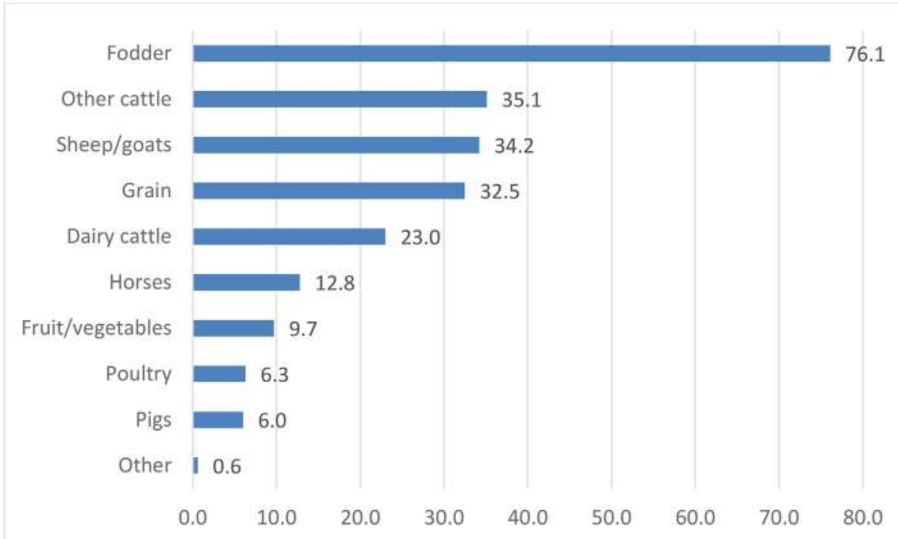

Fig. 3. Production at the farm (%; several categories possible, so the total >100).

Table 1
Safety climate indexes.

#	Index name	Cronbach's Alpha	# of items
1	Safety System	0.738	7
2	Accept/Normalization	0.700	6
3	Safety Practice	0.716	7

tative in terms of age, geographical belonging, and type of production (Storstad et al., 2013). Production characteristics are given in Fig. 3, showing that there was a heterogeneity and overlap regarding productions and that 76% of the farms produced fodder. For practical reasons, fodder was therefore not excluded from animal-related activity when constructing mutually exclusive predominant production categories (Fig. 4).

Work hours at the farm were unevenly distributed, as were off-farm work hours. Both entities are shown in Fig. 5. Cross-tabulations were made for work organization*work hours, predominant production*work hours, and predominant production*off-farm work hours, and the chi-square tests were all significant at the $p = 0.000$ level.

Thirty percent of respondents reported being full-time farmers (i.e., no other paid work). In terms of work organization, workers with hired help had the highest prevalence of full-time farmers (39%), while family farmers had the lowest (22%). In terms of predominant production, full-time farmers were most common among dairy farmers (51 %), followed by sheep/goat and other/mix (28 %). Grain producers had the lowest prevalence of full-time farmers (16%) and the highest prevalence of full-time off-farm work (47%).

Furthermore, 59% of family farmers worked more than 850 hours/year off farm, followed by lone farmers (52%) and farmers with hired help (34%). A higher percentage of farmers with workers said that they were full-time farmers (39%), followed by lone farmers (30%) and family farmers (22%). The chi-square test was statistically significant with $p < 0.005$.

All correlations between independent variables are <|0.3|.

5.2. Injury prevalence and rates

Only 6.7% of respondents had been injured in an occupational farm accident during the preceding 12 months, irrespective of the number and work hours (see Table 2 for injury distribution). Crude rates (CR) and CRR for independent variables are presented in Table 3. High CRRs (>2.0) were found for age (<35, 35–44, 45–54), certain types of predominant production (other cattle, fodder, and other/mixed production), education (university), work organization (family farm, relief/other workers, and family), physical farm conditions (very complicated), and workplace design (highly challenging).

5.3. Regression results

Poisson regression analyses used injury rates results for modeling (see Table 3 for details). Goodness-of-fit tables showed that Pearson's chi square/df = 2.011, which indicated overdispersion. Deviance was therefore scaled with Pearson's chi square in the adjusted model.

5.3.1. Model 1: Testing independent variables

Results from the adjusted model (Adj RR) are shown in Table 3. Only workplace design had an overall significant model effect ($p = 0.012$). Respondents with highly challenging design faced an injury risk 2.23 times greater than the risk of respondents who reported good design ($p = 0.009$, CLR = 2.85). Predominant production had a borderline non-significant model effect ($p = 0.056$); however, three of the response categories had significantly higher injury risk than the reference category (Adj RR/p-value): other cattle (2.56/0.028), fodder (3.36/0.015), and other/mixed production (2.91/0.007). High CLRs (>4.8) were observed for all three categories.

Table 2
Injury prevalence, total sample ($n = 2967$).

# Injuries	0	1	2	3	4	5	6	Missing	Total
Frequency	2707	166	15	6	3	3	4	63	2967
Percent	91.2	5.6	0.5	0.2	0.1	0.1	0.1	2.1	100

Table 3
Crude rates and regression results: model 1 (independent variables) and model 2 (adding safety climate).

Variables and categories (n*)	# Injuries**	# Hours worked	Crude rate (CI 95 %)	Crude Rate Ratio (RR) (CI 95 %)	Model 1			Model 2		
					Adj RR (CI 95 %)	CLR***	p-value	Adj RR (CI 95 %)	CLR***	p-value
Age										
<35 (158)	30	222,405	13.5 (8.7–18.3)	4.14 (2.2–7.8)						
35–44 (499)	53	639,810	8.3 (6.1–10.5)	2.34 (1.3–4.2)						
45–54 (873)	93	1,147,970	8.1 (6.5–9.7)	2.35 (1.3–4.1)						
55–64 (897)	72	1,186,208	6.1 (4.7–7.5)	1.71 (0.96–3.0)						
≥65 (438)	16	438,926	3.6 (1.9–5.4)	1						
Missing (102)	*1*									
Gender										
Female (358)	32	393,604	8.1 (5.3–10.9)	1.22 (0.8–1.8)	1.31 (0.7–2.3)	1.60	0.358	1.25 (0.7–2.1)	1.38	0.402
Male (2575)	229	3,298,184	6.9 (6.0–7.8)	1	1			1		
Missing (34)	*4*									
Education										
University (700)	64	731,729	8.7 (6.6–10.9)	2.06 (1.3–3.3)						
Upper secondary (academic) (382)	36	500,539	7.2 (4.8–9.5)	1.59 (0.9–2.7)						
Upper secondary (voc./agric.) (1385)	138	1,894,267	7.3 (6.1–8.5)	1.66 (1.1–2.6)						
Primary/secondary school (432)	24	535,582	4.5 (2.7–6.3)	1						
Missing (68)	*3*									
Income****										
No/negative income (312)	16	268,352	6.0 (3.0–8.9)	1.01 (0.6–1.8)	0.68 (0.3–1.8)	1.56	0.440	0.73 (0.3–1.8)	1.47	0.484
1–49999 NOK (513)	30	355,928	8.4 (5.4–11.4)	1.38 (0.9–2.2)	1.31 (0.6–2.9)	2.33	0.508	1.19 (0.6–2.5)	1.91	0.650
50–99999 NOK (492)	44	444,671	9.9 (7.0–12.8)	1.76 (1.2–2.6)	1.86 (0.96–3.6)	2.65	0.068	1.79 (0.97–3.3)	2.33	0.064
100000–199999 NOK (629)	66	895,577	7.4 (5.6–9.1)	1.33 (0.9–1.9)	1.38 (0.8–2.4)	1.58	0.250	1.51 (0.9–2.5)	1.55	0.101
≥ 400,000 NOK (297)	37	527,591	7.0 (4.8–9.3)	1.12 (0.7–1.7)	1.00 (0.5–1.9)	1.38	0.993	1.00 (0.6–1.8)	1.23	0.989
200000–399999 NOK (658)	69	1,186,473	5.8 (4.4–7.2)	1	1			1		
Missing (66)	*3*									
Mechanization										
High degree (732)	70	913,135	7.7 (5.9–9.5)	1.07 (0.7–1.6)						
Medium degree (1707)	159	2,263,383	7.0 (5.9–8.1)	0.98 (0.7–1.4)						
Low degree (418)	34	471,017	7.2 (4.8–9.6)	1						
Missing (110)	*2*									
Predominant work										
Other cattle (not dairy) (360)	47	489,721	9.6 (6.9–12.3)	2.70 (1.6–4.6)	2.56 (1.1–5.9)	4.82	0.028	2.32 (1.1–4.9)	3.82	0.027
Fodder (only) (222)	18	189,261	9.5 (5.1–13.9)	2.60 (1.4–5.0)	3.36 (1.3–9.0)	7.69	0.015	2.90 (1.2–7.1)	5.86	0.019
Other/mixed production (704)	80	865,347	9.2 (7.2–11.3)	2.51 (1.5–4.2)	2.91 (1.3–6.3)	5.00	0.007	2.65 (1.3–5.4)	4.04	0.006
Dairy cattle (683)	88	1,355,303	6.5 (5.1–7.8)	1.64 (1.0–2.7)	2.19 (0.97–5.0)	4.01	0.060	1.99 (0.96–4.2)	3.20	0.066
Grain (only) (459)	11	265,876	4.1 (1.7–6.6)	1.07 (0.5–2.3)	1.17 (0.4–3.8)	3.47	0.799	1.23 (0.4–3.6)	3.15	0.698
Sheep/goats (510)	19	542,679	3.5 (1.9–5.1)	1	1			1		
Missing (29)	2									
Farm size										
< 50 da (356)	21	268,469	7.8 (4.5–11.2)	1.42 (0.9–2.3)	1.61 (0.8–3.4)	2.59	0.204	1.79 (0.9–3.5)	2.54	0.084
50–99 da (529)	30	454,913	6.6 (4.2–9.0)	1.04 (0.7–1.6)	1.05 (0.5–2.0)	1.51	0.885	1.15 (0.6–2.1)	1.49	0.664
250–499 da (641)	79	1,069,314	7.4 (5.8–9.0)	1.26 (0.9–1.7)	1.24 (0.8–2.0)	1.27	0.398	1.20 (0.8–1.9)	1.13	0.429
≥ 500 da (263)	48	413,072	11.6 (8.3–14.9)	1.99 (1.4–2.9)	1.81 (0.96–3.4)	2.43	0.065	1.62 (0.9–2.9)	1.98	0.105
100–249 da (1139)	84	1,508,359	5.6 (4.4–6.8)	1	1			1		
Missing (39)	*3*									
Joint operation										
Yes (115)	14	172,817	8.1 (3.9–12.3)	1.23 (0.7–2.1)						
No/missing (2852)	251	3,566,620	7.0 (6.2–7.9)	1						

Table 3 (*continued*)

Variables and categories (n*)	# Injuries**	# Hours worked	Crude rate (CI 95 %)	Crude Rate Ratio (RR) (CI 95 %)	Model 1			Model 2		
					Adj RR (CI 95 %)	CLR***	p-value	Adj RR (CI 95 %)	CLR***	p-value
Investment: Tractor										
Old (>5 years) (1870)	170	2,150,626	7.9 (6.7–9.1)	1.24 (0.95–1.6)						
New (≤5 years) (930)	88	1,403,565	6.3 (5.0–7.6)	1						
Missing (167)	*7*									
Investment: Outbuilding										
New (≤12 years) (855)	100	1,237,265	8.1 (6.5–9.7)	1.14 (0.9–1.5)						
Old (>12 years) (1999)	164	2,418,757	6.8 (5.7–7.8)	1						
Missing (113)	*1*									
Work organization										
Relief/other workers and family (1210)	146	1,983,819	7.4 (6.2–8.6)	2.29 (1.3–4.1)	1.93 (0.8–4.8)	4.01	0.157	2.52 (0.99–6.4)	5.43	0.053
Family farm (1177)	97	1,262,679	7.7 (6.2–9.2)	2.44 (1.3–4.5)	1.77 (0.7–4.4)	3.67	0.221	2.41 (0.9–6.1)	5.20	0.066
No help (533)	13	404,939	3.2 (1.5–5.0)	1	1			1		
Missing (47)	*9*									
Physical farm conditions										
Very complicated (671)	94	1,019,282	9.2 (7.4–11.1)	2.05 (1.5–2.9)						
Complicated (1147)	117	1,498,790	7.8 (6.4–9.2)	1.65 (1.2–2.3)						
Not very complicated (1091)	52	1,166,145	4.5 (3.2–5.7)	1						
Missing (58)	*2*									
OHS training										
Yes (1302)	149	1,867,447	8.0 (6.7–9.3)	1.26 (0.98–1.6)						
No/missing (1665)	116	1,871,990	6.2 (5.1–7.3)	1						
Workplace Design										
Highly challenging (3 items) (885)	139	1,235,102	11.3 (9.4–13.1)	2.77 (1.8–4.2)	2.23 (1.2–4.1)	2.85	0.009	2.01 (1.1–3.6)	2.43	0.017
Challenging (2 items) (628)	55	799,032	6.9 (5.1–8.7)	1.78 (1.1–2.8)	1.66 (0.9–3.2)	2.35	0.131	1.59 (0.9–3.0)	2.09	0.139
Moderate (1 item) (648)	35	804,460	4.4 (2.9–5.8)	1.1 (0.7–1.8)	1.04 (0.5–2.2)	1.66	0.917	1.05 (0.5–2.1)	1.55	0.897
Good (no items) (629)	31	740,949	4.2 (2.7–5.7)	1	1			1		
Missing (177)	*5*									
Physical demands										
Very high (4 items) (581)	39	508,336	7.7 (5.3–10.1)	1.32 (0.8–2.1)						
High (3 items) (871)	118	1,372,409	8.6 (7.0–10.1)	1.55 (1.1–2.2)						
Moderate (2 items) (744)	65	971,633	6.7 (5.1–8.3)	1.14 (0.8–1.7)						
Little (1 item) (579)	40	710,128	5.6 (3.9–7.4)	1						
Missing (192)	*3*									
Quantitative demands										
High demands (1549)	187	2,323,110	8.0 (6.9–9.2)	1.41 (1.1–1.9)						
Low demands (1254)	72	1,270,500	5.7 (4.4–7.0)	1						
Missing (164)	*6*									
Work hours off-farm										
< 200 hours (290)	40	500,483	8.0 (5.5–10.5)	1.29 (0.9–1.9)	1.19 (0.7–2.1)	1.47	0.566	1.21 (0.7–2.1)	1.33	0.470
200–849 hours (330)	32	511,056	6.3 (4.1–8.4)	1.00 (0.7–1.5)	0.79 (0.4–1.5)	1.14	0.492	0.82 (0.4–1.5)	1.05	0.511
850–1699 hours (563)	38	562,499	6.8 (4.6–8.9)	1.13 (0.8–1.7)	1.12 (0.6–2.1)	1.44	0.710	1.16 (0.7–2.0)	1.31	0.602
≥ 1700 hours (741)	56	525,635	10.7 (7.9–13.4)	1.72 (1.2–2.4)	1.83 (1.02–3.3)	2.28	0.045	1.74 (1.01–3.0)	2.00	0.046
No work elsewhere (834)	88	1,386,217	6.3 (5.0–7.7)	1	1					
Missing (209)	*11*									
Climate 1: Safety system										
Above mean (positive) (1448)	146	1,821,236	8.0 (6.7–9.3)	1.36 (1.1–1.8)				1.44 (0.99–2.1)	1.07	0.050
Below mean (1412)	112	1,787,197	6.3 (5.1–7.4)	1				1		

(*continued on next page*)

Table 3 (*continued*)

Variables and categories (n*)	# Injuries**	# Hours worked	Crude rate (CI 95 %)	Crude Rate Ratio (RR) (CI 95 %)	Model 1			Model 2		
					Adj RR (CI 95 %)	CLR***	p-value	Adj RR (CI 95 %)	CLR***	p-value
Missing (107)	7									
Climate 2: Accept/normalization										
Below mean (1412)	190	1,919,713	9.9 (8.5–11.3)	2.41 (1.8–3.2)				2.33 (1.6–3.5)	1.92	0.000
Above mean (positive) (1510)	75	1,789,540	4.2 (3.2–5.1)	1				1		
Missing (45)	*0*									
Climate 3: Safety practice										
Above mean (1420)	141	1,803,151	7.8 (6.5–9.1)	1.13 (0.9–1.4)						
Below mean (positive) (1400)	121	1,765,776	6.9 (5.6–8.1)	1						
Missing (147)	3									

Note. *Total number of respondents, $n = 2967$, **Total number of injuries = 265, ***CLR = Confidence Limit Ratio (upper-lower), ****NOK = Norwegian kroner.

Work hours (off-farm) had a non-significant model effect. However, respondents who annually worked >1700 hours off farm had a significantly higher injury risk compared to the reference group (no work elsewhere) (Adj RR = 1.83; $p = 0.045$; CLR = 2.28).

Relatively high Adj RR, although non-significant, was found for categories of the confounders farm size (<49 da, ≥500 da), income (50–99,999 NOK), and work organization (family farm, relief/other workers).

5.3.2. Model 2: Testing moderating effects of safety climate

Adding safety climate indexes did not change the main results from Model 1. However, it resulted in nearly a 10% decrease in injury risk for highly challenging workplace design. The injury risk was also reduced for categories of predominant production, with the largest change for farmers with fodder (13.7%). Among all the variables (predictors and confounders) in Model 1, the change in percent was largest for work organization. Within this variable, farmers with relief/other workers and family showed a 30.6% increase in Adj RR, whereas the increase was 36.2% among family farmers. In addition, adding safety climate changed the relevance of farm size (borderline non-significant). In Model 1, farmers with large farms (≥500 da) had the highest injury risk, followed by farmers with the smallest farms (<50 da). In Model 2, these two categories had changed places, and the effect was >10%.

Looking at the safety climate indexes themselves, acceptance/normalization (Climate 2) was a significant predictor of injury ($p = 0.000$), and respondents who expressed the most acceptance/normalization of accidents had twice the risk of injuries compared to the reference group. Safety system (Climate 1) was a borderline non-significant predictor for injury ($p = 0.050$), with the highest risk for respondents who had positive assessments of the safety system.

6. Discussion

In this study, we explored occupational injury risk among Norwegian farm owners through the calculation of CRRs and Poisson regression, with work hours as the offset. The main findings were that the poor physical design of farmers' workplaces served as the most significant independent predictor of injury. We also found a higher injury risk for certain categories of predominant production, for extensive work off farm, and for farmers working with family/employees. When including the safety climate, the risk for farmers with family and/or employees increased. For predictors related to workplace design and production, adding the safety climate reduced the injury risk. Isolated farmers expressing high degrees of acceptance/normalization of accidents had more than twice the risk of injury compared to the reference group.

In this section, we discuss how these results are new contributions to the understanding of injury risk among farmers and more thoroughly address how our findings enhance our systematic understanding of managing risk in agriculture.

6.1. New contributions regarding risk factors

In this study we calculated rates not often seen in studies within agriculture; therefore, the results are not directly comparable to others. As discussed in Section 1.1, previous research found that dairy production represented high injury risk due to the heavy workload and animal contact. In our study, dairy farmers were mostly full-time farmers, having the highest number of work hours at the farm, resulting in a medium level of injury rate. Full-time farming gives more continuity than having additional work off farm; it also involves somewhat routinized work tasks, which has been suggested to lower the injury risk (Van der Broucke &

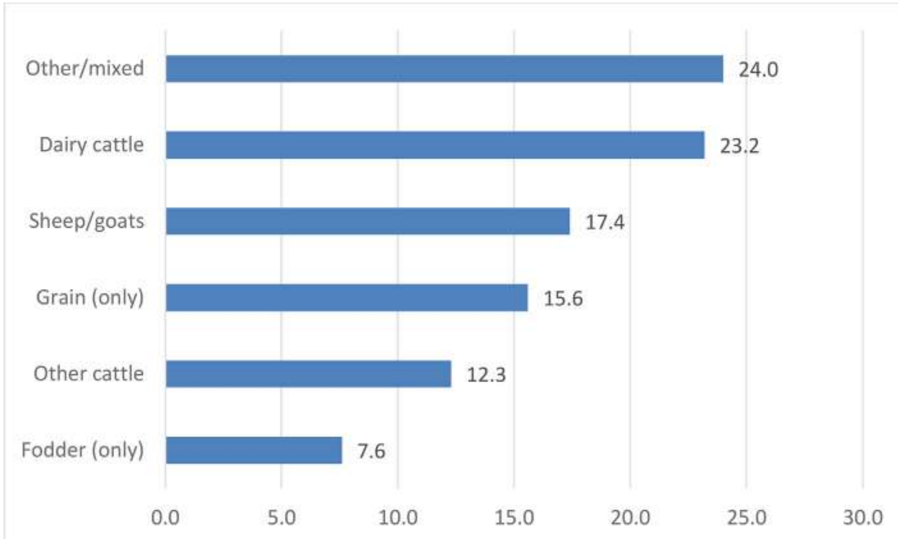

Fig. 4. Predominant farm production (%): Refined variable with mutual exclusive categories. (Note: Fodder is only excluded from "Grain (only)" because ¾ of all the farms produce fodder).

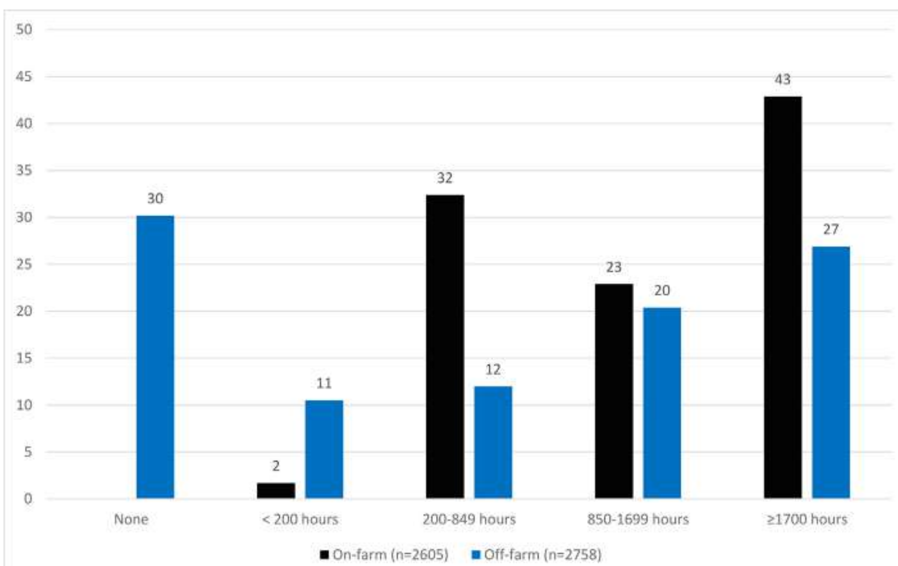

Fig. 5. Farm owners' annual work hours: on-farm (refined for regression) and off-farm (original) (%).

Colémont, 2011). Although the danger of handling large animals is still present, it seems that this is "evened out" by exposure time. Furthermore, dairy production is strictly constrained through quality standards, which will be further dealt with in Section 6.2. The producers of fodder (only), other/mixed, and other cattle (not dairy) all had higher injury risk than dairy farmers. These farmers also worked less on the farm and had more off-farm work hours than dairy farmers. No other studies could be found that combined on- and off-farm work hours. Compared to those with the farm as the only workplace, we found an almost two-fold risk of occupational injury for farmers working more than 1,700 h off farm. As a large amount of on-farm work hours is associated with a high injury risk (Hartman et al., 2004; Jadhav et al., 2015; Svendsen et al., 2014; Van den Broucke & Colémont, 2011), independent of where you work, the amount of work (i.e., total workload) is significant.

Another new contribution of this study is the finding that injury risk is reduced for all predictors of injury when controlling for safety climate. We found the largest risk-reducing effect for farmers with fodder production, followed by farmers with challenging workplace design. It is hard to find corresponding research designs to confirm or contradict these results. A Swedish survey among farmers included safety climate, showing that work pressure was positively correlated with perceived risk, risk acceptance, and injury experience but negatively correlated with engagement in safety work (Törner et al., 2002). Farmers who had several employees reported more safety activity, which was explained by the farmers' legal obligations as employers. More safety activity was also reported by those with injury experience (Törner et al., 2002). We know from other sectors that safety climate is important for safety behavior and outcomes, but these studies rarely include the perspective and challenges of small enterprises.

Our main predictor, the physical design of the workplace, to our knowledge, has not been found as a risk factor in other studies within agriculture. The overall findings, including the lack of individual characteristics as predictors for injuries, raise the need for highlighting organizational and managerial issues as well as a sociotechnical system perspective as an approach when discussing findings.

6.2. Managing risk on different levels

The model described by Carayon et al. (2015) defines the work system as the local context in which work activities are performed, although it is heavily influenced by external factors like legislation, markets, political direction, and so forth (i.e., the national context). The national context for Norwegian farmers is well described in the political-economic system model by Rommetvedt (2002), which enables us to discuss risk management in a wide perspective. Our study fits the description of "mesoergonomics," introduced by Karsh, Waterson, and Holden (2014), as it refers to the study of variables in two or more levels, having ergonomic constructs as the dependent variable. External levels (e.g., government, policy makers, and regulatory bodies) have lately received more attention in studies of causalities, herein also calling for interdisciplinarity (Karsh et al., 2014).

A part of organizational decisions is deciding on what and how to produce, thereby affecting the overall latent condition for injuries through the implications it directs in the work system (Carayon et al., 2015; Reason, 1997). An example of such mechanisms is given in Holte, Follo, Kjestveit, and Stræte (2019), where implementing AMS affects workplace design, activity level, and the distribution of work tasks. Although change in technology is the farmers' decision, it is indirectly influenced by political incentives and subsidies related to modern production methods (Ministry of Agriculture and Food, 2016). This is also evident for workplace design, which is an independent injury risk factor in our analyses, although it is affected by production through general standards and for livestock husbandry in particular[5]. This demonstrates how production (tasks, technology, organization) is a latent condition for injuries because investments in technology and/or buildings affect the physical environment. However, regarding modernization and investments, the old age of outbuildings is surprisingly not a risk factor for injury. An interpretation of this is that poor workplace design may be found in new environments as well, which calls for considering OHS issues altogether (individual, environment, tasks, technology, organization) when investing and modernizing. Design is therefore an embedded risk factor when national policy enforces larger, more efficient farms (Ministry of Agriculture and Food, 2016).

The impact from regulation varies due to system characteristics (literally: type of production). In other sectors, regulation as such has shown positive effects on safety practices and injuries (Andersen et al., 2019; Lindøe & Olsen, 2004; Vickers et al., 2005). Safety climate may reflect these practices and the underlying culture (Mearns et al., 2003), and Carayon et al. (2015) recommended including safety climate when discussing organizational aspects of sociotechnical system theory and workplace safety. Our results indicate that safety climate is even more important for injury risk in less regulated productions. Fodder production has relatively low documentation requirements compared to, for example, animal husbandry, which may explain why the risk for this category of farmers is more affected when safety climate is controlled for. These farmers are also more likely to work alone. If the farm production entails fewer system requirements, documentation and auditing may be perceived as an unnecessary burden (Holte & Follo, 2018). The same reasoning can be used for the use of family and/or hired help at the farm. Observing the impact of safety climate on injury risk demonstrates the importance of organizational factors (climate) when working together compared to working alone.

Based on our analyses, we argue that farmers may play two roles: (1) owner and manager of the enterprise, making them responsible for daily work, planning, resource allocation, and strategic decisions, or (2) a "worker," tackling consequences due to externally given policies and regulations, indirectly influencing through collective channels (farmers' organizations, etc.). In the first role, the farmer is supposed to perform active risk management, while in the second role, the farmer is coping with risk. The positive correlation found between injuries and normalization (Climate 2) indicates that coping with risk (Grote, 2012) is closer to what farmers do than risk management (role 1). The results that showed safety climate plays a larger role for farmers with hired help and family than for lone farmers also underscores this anticipation. The same goes for the finding of the old age of outbuildings not being a risk factor for injury, indicating a lack of OHS focus regarding new investments, as previously described. Coping with risk is associated with flexibility in decisions and actions among those in the "sharp end," where plans and task standardizations are few (Grote, 2012). They use tacit knowledge and operational freedom in handling unpredictability (Grote, 2012). This may be linked to the culture of accepting injuries as a normal part of their work. Moreover, from the qualitative interviews in this project we know that animal husbandry in particular makes the work environment unpredictable (Follo et al., 2016). Hence, our findings also correspond to existing knowledge regarding small enterprises, where day-to-day challenges are the focus due to restricted resources (Champoux & Brun, 2003; Vickers et al., 2005). Similar reasoning can be used for the finding of farmers with managerial responsibility having higher injury risk. They might not allocate work tasks associated with risk to employees, but instead perform these tasks themselves; hence, this is a way of coping with risk without actively managing risk. Moreover, eliminating risk requires knowledge, work task standardization, and a clear distribution of responsibility (Grote, 2012), which is hard to find in small enterprises (Hasle & Limborg, 2006; MacEachen et al., 2010; Sorensen et al., 2007). For farmers, being a manager may increase the injury risk through the factors found by Glasscock et al. (2006): work overload/time pressure, role conflict, economic concerns, administrative burden, and unpredictability. It may further reduce farmers' continuity on their own farm efforts, as illustrated by the higher risk for those having a full position (or more) off farm.

Our results indicate that injury risk emerges due to specific aspects embedded at the systemic level (Carayon et al., 2015). Therefore, we claim that farms need to be managed according to their context and that efforts to increase OHS need to reflect the heterogeneity of the industry. Moreover, the shift from small to larger farms is a relatively new trend in Norwegian agriculture. This raises the question of whether the ongoing industry changes may actually give an even higher risk of injury because of the new complexity and the lack of awareness regarding latent conditions in the work systems. Taken together, we therefore need to raise awareness of the managerial aspects of running a farm enterprise while taking external aspects into consideration. The political-economic system is an important contributing factor regarding strategic choices in Norwegian agriculture (Farsund, 2002; Rommetvedt, 2002; Rommetvedt & Veggeland, 2017). Both governmental bodies and the industry should be attentive to the effects of these choices because larger farm sizes have been found

[5] Loose housing is required for cattle from 2024 to 2034 depending on when the existing outbuilding was built (https://lovdata.no/dokument/LTI/forskrift/2013–08-07–955).

to increase injury risk (Rautiainen et al., 2009). Despite our results being indicative, policies, regulations, funding programs, training programs, and planning and design, as part of the strategic choices, will be of significant importance in the years to come to ensure promotion of OHS in agriculture. Moreover, research that deepens our understanding of the complexity and interdependencies is highly needed.

6.3. Limitations and methodological considerations

The questionnaire was sent to 7,500 farmers, or 17% of the total population of farmers applying for subsidies in the national registry of farm producers in 2012 (Directorate of Agriculture, 2020). The quality of the final data set was strengthened by extracting farm production details directly from this registry. The survey sample was confirmed to be representative in terms of geographical distribution and type of production (Storstad et al., 2013).

There is always a risk of recall bias using questionnaire surveys. However, unpublished data from qualitative in-depth interviews in the project enabled us to use mixed methods in the interpretation of the results. Furthermore, the unique sample size increased the validity by enabling strict criteria for missing values in, for example, sum-score variables and indexes based on factor analysis.

In our study, 6.7% of the respondents reported having had an occupational injury during the preceding 12 months, which corresponds to results in other studies (Jadhav et al., 2017; Rautiainen et al., 2009; Van den Broucke & Colémont, 2011). Still, the prevalence is lower than we expected. Our qualitative interviews indicate that farmers have trouble remembering smaller injuries and that small ones are not counted. As the questionnaire did not include a definition of severity, we regarded the injury incidence as fairly trustworthy as a demonstration of the underreporting of injuries from which agriculture suffer. The confidence intervals of some of the results are rather wide, especially for categories of predominant production. We anticipate this to be a statement of the heterogeneity of the sample and a consequence of the struggle of isolating productions from each other. The results are nonetheless important because of the link to work hours (exposure), and they can serve as a starting point for further research.

The study is based on data collected in 2012 and may be considered somewhat old. This paper argues that the trend of modernizing Norwegian agriculture is an ongoing process, starting before 2012 and we find that our data fulfills the purpose of describing an industry in transformation. The inclusion of annual work hours and safety climate makes the data highly valuable for a sociotechnical discussion of latent conditions, irrespectively of its age.

7. Conclusions and practical applications

This study improves existing knowledge regarding injury risk factors in agriculture as the combination of a systematic approach and work hours illuminated injury causes that are more complex and interrelated than those most frequently presented in published research. The results point to the importance of studying physical design of workplaces as a separate topic as well as studying subgroups of farmers based on diversities in work tasks, technology, work organization, and so forth. Less heterogeneity in subgroups will make work system characteristics easier to detect and understand, which will increase the practical use of study results in injury prevention.

Our initial anticipation was that latent conditions affect occupational injuries in the way they are treated by the farmer, which our study results confirmed. The predictors of injury and CRRs point to organizational complexity and call for sociotechnical understanding. According to our study, risk factors are highly interrelated in the work system and difficult to separate from each other. This sector needs to raise awareness regarding work system dynamics, especially when it comes to the external influence and for design issues in particular. In addition, farmers need support when it comes to detecting and understanding risk mechanisms in their own work systems.

Funding and ethics

The overall AINA project is financed by the Research Council of Norway and the Research Funding for Agriculture and the Food Industry (grant numbers 208053/I10 and 208053/E40). *Declarations of interest:* none.

This study was approved by the Regional Committees for Medical and Health Research Ethics — Central Norway (number 2011/2239, later 2011/2239-26). Anonymity of the respondents was ensured through the use of an external actor when drawing the respondent sample. We found no ethical constraints for publishing these results.

Acknowledgements

Partners in the AINA project were Ruralis, the Department of Occupational Medicine at St. Olav's Hospital, and the Norwegian Research Centre (NORCE), all located in Norway. Project members who were not authors contributed to the data collection and methodological discussions: Gro Follo, Oddveig Storstad, Brit Logstein, Reidar Almås, and Bjørn Hilt. Professor Ole Andreas H. Engen of the University of Stavanger supervised the main author during the writing process. We are especially grateful for Professor Hester J. Lipscomb (PhD, Duke University Medical Center) and Professor Ashley Schoenfisch (PhD, Duke University Nursing School) for sharing their experiences with Poisson regression, giving methodological advice, and providing outstanding hospitality.

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Kari Kjestveit has a MSc in Societal Safety and Risk Management from the University of Stavanger and works as a senior researcher at NORCE. Kjestveit is mainly engaged in projects regarding OHS within different sectors, herein construction, petroleum, and agriculture. Other research topics are, safety culture, small enterprises, regulation, and sociotechnical system theory.

Oddfrid Aas is a medical doctor at the Department of Occupational Medicine at St. Olav's Hospital in Trondheim. She works mainly within occupational medicine and has engaged in several research projects covering farmers and agriculture.

Kari Anne Holte has a PhD (Dr.Ing.) in Ergonomics from Norwegian University of Science and Technology (NTNU) in Trondheim. She works as a chief scientist at NORCE, where she is mainly engaged in research projects regarding OHS, ergonomics, and sociotechnical system theory. Holte has extensive experience from project management in industry projects and projects funded by the Norwegian Research Council.

Journal of Safety Research 77 (2021) 40–45

Contents lists available at ScienceDirect

Journal of Safety Research

journal homepage: www.elsevier.com/locate/jsr

On-road driving test performance in veterans: Effects of age, clinical diagnosis and cognitive measures

John P.K. Bernstein [a,b,*], Tonya Rich [b], Stefanie McKnight [b], Julie Mehr [b], John Ferguson [b,d], Adriana Hughes [b,c,e]

[a] Department of Clinical Psychology, Louisiana State University, Baton Rouge, LA, United States
[b] Minneapolis Veterans Affairs Health Care System, Minneapolis, MN, United States
[c] Oregon Center for Aging & Technology, Portland, OR, United States
[d] Department of Rehabilitation Medicine, University of Minnesota, MN, United States
[e] Department of Psychiatry, University of Minnesota, Minneapolis, MN, United States

ARTICLE INFO

Article history:
Received 5 June 2020
Received in revised form 27 November 2020
Accepted 29 January 2021
Available online 23 February 2021

Keywords:
Driving
Older adults
Cognition
Processing speed
Attention

ABSTRACT

Introduction: Veterans are at heightened risk of being in a motor-vehicle crash and many fail on-road driving evaluations, particularly as they age. This may be due in part to the high prevalence of age-associated conditions impacting cognition in this population, including neurodegenerative diseases (e.g., Alzheimer's Disease) and acquired neurological conditions (e.g., cerebrovascular accident). However, understanding of the impact of referral diagnosis, age and cognition on Veterans' on-road driving performance is limited. *Methods:* 109 Veterans were referred for a driving evaluation (mean age = 72.0, SD = 11.5) at a driving assessment clinic at the Minneapolis Veterans Affairs Healthcare System. Of the 109 Veterans enrolled, 44 were referred due to a neurodegenerative disease, 37 due to an acquired neurological condition, and 28 due to a non-neurological condition (e.g., vision loss). Veterans completed collection of health history information and administration of cognitive tests assessing visual attention, processing speed, and executive functioning, as well as a standardized, on-road driving evaluation. *Results:* A total of 17.9% of Veterans failed the on-road evaluation. Clinical diagnostic group was not associated with failure rate. Age was not associated with failure rates in the full sample or within diagnostic groups. After controlling for age, poorer processing speed and selective/divided attention were associated with higher failure rates in the full sample. No cognitive tests were associated with failure rates within diagnostic groups. *Conclusion:* Referral diagnosis and age alone are not reliable predictors of Veterans' driving performance. Cognitive performance, specifically speed of processing and attention, may be helpful in screening Veterans' driving safety. *Practical Applications*: Clinicians tasked with assessing Veterans' driving safety should take into account cognitive performance, particularly processing speed and attention, when making decisions regarding driving safety. Age and referral diagnosis, while helpful information, are insufficient to predict outcomes on driving evaluations.

1. Introduction

Motor-vehicle crashes are one of the most common causes of mortality among U.S. military members and Veterans, accounting for almost one third of all fatalities annually (Krahl, Jankosky, Thomas, & Hooper, 2010; Krull, Jones, Dellinger, Yore, & Amoroso, 2004). In comparison to civilians, Veterans are at increased risk of motor-vehicle accidents and related fatalities (Lincoln et al., 2006; Woodall, Jacobson, & Crum-Cianflone, 2014).

Additionally, the aging Veteran population is predisposed to both neurodegenerative disease (e.g., Alzheimer's Disease, Parkinson's Disease) and acquired neurological conditions such as stroke, seizure, and traumatic brain injury (TBI) (Flanagan, Hibbard, & Gordon, 2005; Sibener et al., 2014). Studies have also shown that TBI and post-traumatic stress disorder (PTSD), conditions that are more prevalent in the Veteran population, are associated with higher risk for cognitive decline and dementia in older age, thus potentially increasing their risk above age alone (Barnes et al., 2014).

Both neurodegenerative disease and acquired conditions have an impact on cognitive abilities and may undermine driving safety (Fitten et al., 1995; Reger et al., 2004; Ross, Ponsford, Di Stefano, &

* Corresponding author at: Department of Clinical Psychology, Louisiana State University, Baton Rouge, LA, United States.

E-mail address: jberns16@u.rochester.edu (J.P.K. Bernstein).

https://doi.org/10.1016/j.jsr.2021.01.005
0022-4375/

Spitz, 2015). Despite this, in some cases, those with acquired conditions are able to return to driving following recovery and resolution of symptoms, while this is more uncommon in those with neurodegenerative diseases (Pietrapiana et al., 2005). Evidence from the civilian literature suggests that those with neurodegenerative disease may have higher failure rates than those with acquired conditions (e.g., 37% to 56% failure rate in patients with dementia, 21% to 33% failure rate in patients with TBI) (Berndt, Clark, & May, 2008; Lincoln, Radford, Lee, & Reay, 2006; McKay, Liew, Schönberger, Ross, & Ponsford, 2016; Ross et al., 2015). As a result, it is unsurprising that on-road evaluations are often recommended following a diagnosis of a neurodegenerative disease or acquired neurological condition (Bernstein, Calamia, Meth, & Tranel, 2019).

Decrements in sensory abilities, physical functioning, and mental health may also be partially responsible for heightened crash risk in Veterans. Reduced physical capacities (e.g., amputation, orthopedic injuries) and sensory abilities (e.g., vision) are commonplace in older adulthood and may be cause for driving-related difficulties (Boulias, Meikle, Pauley, & Devlin, 2006; Owsley & McGwin Jr, 2010). Additionally, mental health conditions (e.g., PTSD) are overrepresented in the Veteran population and may lead to difficulties with self-regulation of emotions as well as impulsive symptoms, which in turn may be expressed in the form of dangerous driving behaviors when behind the wheel (Lew et al., 2011; Wickens, Toplak, & Wiesenthal, 2008). Psychotherapy and medication may be helpful in reducing these mental health symptoms to the point where the patient is capable of safe driving (Verster, Veldhuijzen, & Volkerts, 2005).

On-road driving evaluations are considered the "gold standard" in the assessment of safe driving (Korner-Bitensky, Bitensky, Sofer, Man-Son-Hing, & Gelinas, 2006). However, they are also expensive to administer, often non-covered by medical insurance, time consuming, and may risk the safety of both the participant and evaluator. As a result, a multitude of research has explored cost-effective, objective alternative measures that may be administered in a timely manner in a clinic or office setting. Driving simulators represent one such approach; however, it should be noted that simulators are subject to several limitations, such as being usually unable to capture the full range of components encountered in a typical driving environment (e.g., in-car distractions, speed limits) and inducing simulator sickness in some individuals (Bernstein, Calamia, De Vito, Cherry, & Keller, 2020; Kawano et al., 2012). Cognitive performance measures are one of the most thoroughly studied types of measures in this area, with results from prior studies suggesting that executive function, attention, visuospatial abilities, and memory may all be linked to driving performance in older adults (Mathias & Lucas, 2009; Reger et al., 2004). In what is to our knowledge the only study examining associations between cognitive performance and on-road driving performance in a Veteran sample, Niewoehner and colleagues (2012) found that measures assessing visual search, psychomotor speed, and executive functioning were the best predictors of on-road driving performance (Niewoehner et al., 2012). Notably, analyses were solely conducted with Niewoehner's full sample and not within diagnostic groups, limiting understanding of how findings may translate to Veterans with particular diagnoses.

As noted previously, a variety of clinical diagnoses may impede driving safety and thus be grounds for conducting an on-road driving evaluation. However, despite Veterans being at heightened risk for these conditions and having higher rates of automobile crash, specific diagnostic population failure rates haven't been reported in a Veteran sample. Moreover, despite extensive work suggesting that age and cognition negatively impact on-road driving performance (Lee, Cameron, & Lee, 2003), none have examined how these factors may vary in their predictive utility depending on the Veteran's referral diagnosis. Such an investigation is warranted given that younger age may be beneficial for some clinical groups (e.g., brain plasticity in those recovering from brain injury) and not others (e.g., those with an orthopedic injury), as well as given that cognitive batteries administered for driving evaluation purposes are often largely the same irrespective of referral diagnosis. The aims of the present study were: (1) to determine whether Veterans' passing rates on an on-road driving evaluation vary as a function of their age and clinical diagnostic group (i.e., neurodegenerative disease, acquired neurological condition or another diagnosis), and (2) to assess whether age and cognitive measures in the domains of visual attention, processing speed, and executive functioning predict passing rates within each clinical diagnostic group.

2. Methods

2.1. Participants & procedures

Participants were military Veterans seen at an occupational therapy driving rehab clinic housed at the Minneapolis Veterans Affairs (VA) Healthcare System. Referrals were received from across the medical center as well as VA satellite community-based outpatient clinics from throughout the region. For the purposes of the present study, all participants were grouped into one of three condition groups: (1) Neurodegenerative Disorder ($n = 44$); (2) Neurological Event ($n = 37$); and (3) Non-Neurological or Neurodegenerative Condition (Non-Neuro) ($n = 28$). Participants in the neurodegenerative disorder group had a primary referral diagnosis of Alzheimer's Disease ($n = 31$), Parkinson's Disease ($n = 10$), Multiple Sclerosis ($n = 2$), or Amyotrophic Lateral Sclerosis ($n = 1$). Participants in the neurological event group had a primary referral diagnosis of cerebrovascular accident (CVA) ($n = 27$), TBI ($n = 9$), or seizure disorder ($n = 1$). Non-neuro participants had a primary referral diagnosis of cardiovascular condition (e.g., heart attack) ($n = 4$), chemo radiation ($n = 1$), diabetes mellitus ($n = 5$), essential tremor ($n = 1$), family concerns ($n = 2$), glaucoma/vision loss ($n = 2$), mental health (e.g., PTSD, anxiety) ($n = 5$), orthopedic injury ($n = 3$), or other miscellaneous musculoskeletal injuries ($n = 5$).

The driving evaluations included an in-clinic pre-driving screen. Veterans who passed the screen subsequently completed an on-road evaluation a maximum of three months later. The pre-driving screen lasted approximately 45–60 min, was conducted by an occupational therapist (OT), and included a patient interview with a review of the Veteran's driving history, visual evaluation, motor evaluation, and cognitive evaluation. Cognitive measures included: the Trail-Making Test Part A (Reitan, 1958), a speeded measure of sustained attention and visual scanning in which the participant draws a line between a set of numbered circles (1–25) in ascending numerical order; Trail-Making Test Part B (Reitan, 1958), a measure of divided attention and set-shifting in which the participant draws a line between a set of circles labeled with either numbers (1–13) or letters (A-L) in an ordered, alternating fashion (i.e., 1, A, 2, B, 3, C, etc.); and the Useful Field of View (UFOV) (Sekuler & Ball, 1986), a measure of visual processing speed, sustained and divided attention in which participants identify the type or location of an object presented very briefly on a computer screen. Other tests of cognition, visual and motor abilities were also administered as part of the evaluation but were not included in the present study's analyses given low frequency of administration or homogeneity in performance. Therapists used clinical reasoning to determine which additional tests were appropriate to administer depending on diagnosis and patient background. The criteria to pass the pre-screen and move on to an on-road assessment were cognitive testing with no or mild cognitive impairment and no obvious red flags identified in the clinical interview (e.g., history of recent accidents, getting lost in familiar areas, strong family objection to continuing to drive).

Veterans who passed the driving pre-screen subsequently completed a 90-minute on-road driving evaluation with an OT. On-road evaluations included assessment of driving safety in a standardized, progressively more difficult set of contexts, with Veterans beginning by driving in a parking lot, and proceeding to local roads, intersections, and finally highways. The total route was approximately 13 miles in length. Veterans who demonstrated unsafe driving behaviors (e.g., near-misses, difficulties staying in one lane) were directed back to the medical center parking lot or were instructed to pull over and stop so the OT could take over driving. On-road assessment outcomes were coded as "fail" (i.e., driving rehabilitation specialist recommended the Veteran retire from driving), "pass with restrictions" (e.g. driving limited to familiar areas, daytime driving only, residential driving only, etc.), or "pass with no restrictions" (i.e., full driving in all conditions is allowed). Given a low frequency of individuals who received an outcome of "pass with no restrictions," the present study grouped all Veterans who passed the on-road evaluation into a single "pass" group, irrespective of whether they were given restrictions. Assessments were conducted using a government vehicle with automatic transmission and an instructor brake with the OT sitting in the passenger's seat. They were conducted year-round during daylight hours but were postponed in the event of inclement weather (e.g., slippery conditions).

Inclusion criteria for the present study included passing the pre-driving screen and completing an on-road driving evaluation from July 2018 to July 2019.

In total, 114 Veterans completed the pre-driving screen appointment during the study period and were cleared to complete the on-road evaluation. Of these, five Veterans were cleared to complete the on-road evaluation but did not do so within the study period and thus were excluded from analyses. Thus, data from a total of 109 Veterans were included in analyses.

2.2. Analyses

Given that data pertaining to specific driving errors committed during the on-road evaluation was unavailable, on-road performance was coded as a binary pass/fail variable. To allow for comparisons based on age, median age for the full sample (72) was first computed to serve as a cutoff, and frequency data were then used separately for the "younger" and "older" age groups. Participants of the median age were included in the older age group. In total, 54 participants were included in the younger group (ages 53 –71), and 55 were included in the older group (ages 72–91).

Descriptive statistics were used to provide rates of on-road evaluation failure within the full sample and each of the three diagnostic groups. Kruskal–Wallis tests were used to examine differences in failure rates between the diagnostic groups and between participants of younger and older age. Chi square analyses were used to determine whether failure rates were significantly different between the younger and older participants in each diagnostic group. A binary logistic regression model was used to examine associations between cognitive performance and on-road performance in the entire sample as well as within each diagnostic group separately. Continuously measured age was entered in step 1 as a control variable in regression analyses given prior literature suggesting an effect of age on driving-related outcomes (Lee et al., 2003), while raw Trails A time, raw Trails B time, and UFOV score were simultaneously entered as predictor variables in step 2.

3. Results

3.1. Effects of diagnostic group, age and cognition on driving performance in full sample

Demographic and test information in both the full sample and within each of the diagnostic groups may be found in Table 1. In total, 17.9% ($n = 19$) of the sample failed the on-road test. Although there was no significant difference in failure rates between the diagnostic groups [Kruskal–Wallis test statistic = 2.00 (2, $N = 109$, $p > .05$)], descriptively, Veterans with a neurodegenerative disorder had the highest rate of failure on the on-road test (23.8%), followed by the neurological event group (16.7%), and the non-neuro group (10.7%). Additionally, while there was no significant difference in failure rates between those of younger versus older age [Kruskal–Wallis test statistic = 0.57, (1, $N = 109$, $p > .05$), descriptively, Veterans of older age had a higher failure rate than those of younger age (20.8% vs. 15.1%).

Demographic and test information in the older and younger groups may be found in Table 2. Within the full sample, a binary logistic regression indicated that after controlling for age, poorer UFOV performance was associated with higher likelihood of failing the on-road test ($X^2(4) = 11.95$, $B = -0.88$, $p < .05$). Neither Trails A nor Trails B time was associated with likelihood of failing the on-road test (both $p > .05$).

3.2. Effects of age and cognition on driving performance within diagnostic groups

Chi square analyses indicated no significant differences in failure rates between older and younger Veterans in the neurodegenerative disorder group [X^2,(1, $N = 42$) = 0.53, $p > .05$], neurological event group [X^2,(1, $N = 36$) = 0.02, $p > .05$] and non-neurological group [X^2,(1, $N = 28$) = 0.55, $p > .05$]. Descriptively, older Veterans were more likely than younger Veterans to fail the on-road test in both the neurodegenerative disorder group (28.6% vs. 19.0%) and the non-neurological group (15.4% vs. 6.7%). In contrast, older Veterans were less likely than younger Veterans to fail the on-road test in the neurological event group (15.8% vs. 17.6%). Within individual diagnostic groups, binary logistic regression analyses indicated that after controlling for age, no cognitive test scores were significantly associated with on-road test performance (all $p > .05$).

4. Discussion

This study examined the effects of clinical diagnostic group, age, and driving pre-screen cognitive measures on failure rates on an on-road evaluation in a Veteran population referred for driving assessments. At odds with prior work (Berndt et al., 2008; Lincoln et al., 2006; McKay et al., 2016; Ross et al., 2015), we found no significant difference in failure rates among diagnostic groups. Descriptively in our sample, the greatest failure frequency was observed in Veterans with neurodegenerative disorders, although differences in failure rates between diagnostic groups were not statistically significant. One possible explanation is that overall clinical presentation and disease severity may be more relevant to driving performance than a particular diagnosis (Frittelli et al., 2009; Ross et al., 2015). Thus, while providers may glean some information concerning a Veteran's likely driving safety based on their clinical diagnosis (e.g., in Veterans with a neurodegenerative disease; Brown & Ott, 2004), the context of the diagnosis (e.g., presence of other health conditions) and its implications for Veterans' overall functioning must be considered.

In our sample, we did not observe an effect of age on the outcome of the on-road assessment in either our full sample or within

Table 1
Sample Demographics and Test Data by Diagnostic Group.

	Full Sample (n = 109)	Neurodegenerative Disorder (n = 44)	Acquired Neuro Condition (n = 37)	Non-Neuro Condition (n = 28)
Age, mean (SD)	72.0 (11.5)	74.9 (8.5)	69.2 (13.6)	71.0 (11.9)
Gender, male n (%)	107 (98.2%)	44 (100.0%)	36 (97.3%)	27 (96.4%)
Race, n (%)				
Caucasian	97 (93.3%)	42 (97.7%)	32 (91.4%)	23 (88.5%)
Black/African-American	6 (5.8%)	1 (2.3%)	2 (5.7%)	3 (11.5%)
Asian-American	1 (1.0%)	0 (0.0%)	1 (2.9%)	0 (0.0%)
MoCA score, mean (SD)	22.4 (4.0)	21.0 (4.1)	24.7 (3.4)	23.6 (2.1)
On-road evaluation failures, n (%)	19 (17.9%)	10 (23.8%)	6 (16.7%)	3 (10.7%)
Cognitive Performance				
Trails A seconds, mean (SD)	46.3 (19.9)	49.2 (16.9)	45.0 (25.1)	43.5 (16.5)
Trails B seconds, mean (SD)	142.7 (65.2)	162.1 (71.3)	128.5 (61.6)	135.8 (57.6)
UFOV score, mean (SD)	2.6 (1.2)	2.9 (1.4)	2.3 (1.0)	2.4 (1.1)

Note: MoCA = Montreal Cognitive Assessment; UFOV = Useful Field of View; SD = Standard Deviation; Neuro = Neurological.

Table 2
Sample Demographics and Test Data by Age Group.

	Younger Group (n = 54)	Older Group (n = 55)
Age, mean (SD)	63.9 (10.0)	79.8 (6.2)
Gender, male n (%)	52 (96.3%)	55 (100.0%)
Race, n (%)		
Caucasian	43 (86.0%)	54 (100.0%)
Black/African-American	6 (12.0%)	0 (0.0%)
Asian-American	1 (2.0%)	0 (0.0%)
MoCA score, mean (SD)	22.6 (3.0)	22.3 (4.5)
On-road evaluation failures, n (%)	8 (15.1%)	11 (20.8%)
Trails A seconds, mean (SD)	42.9 (15.4)	49.7 (23.2)
Trails B seconds, mean (SD)	138.6 (70.8)	147.0 (59.3)
UFOV score, mean (SD)	2.2 (1.2)	3.0 (1.2)

Note: MoCA = Montreal Cognitive Assessment; UFOV = Useful Field of View; SD = Standard Deviation.

diagnostic groups. Our findings differ from previous studies in which greater age was identified as a significant predictor of driving safety and performance (Lee et al., 2003), although it is worth noting that studies are not universal in detecting this effect (Pope, Bell, & Stavrinos, 2017). As a result, some have suggested that driving-specific procedural memories and automaticity may mask the effect of age-related cognitive and sensory decrements on driving safety in those with extensive driving experience (e.g., older adults; Bieliauskas, Roper, Trobe, & Lacy, 1998; Strayer & Drew, 2004). This reliance on procedural memory may be particularly prevalent in Veterans, many of whom (10.2%) work in the transportation and material moving industry after serving (US Bureau of Labor, 2016).

This study also assessed the predictive utility of several well-established cognitive performance measures previously found to relate to driving safety and commonly used in driving evaluations (Anstey et al., 2005). Consistent with prior research, we observed that facets of cognitive functioning significantly predicted driving failure rate in the full sample after controlling for age. These results, in combination with the noted absence of statistically significant differences among diagnostic groups in failure rates, are broadly in line with past work highlighting that cognition may be a stronger correlate with on-road driving performance than age or diagnosis (Fitten et al., 1995). The present study specifically identified the UFOV as being a strong predictor of driving performance. The UFOV has been hypothesized to be a cognitively more demanding task than paper and pencil screening tools, including Trails A and B (Bowers et al., 2013). Notably, although the UFOV was a predictor of failure rates in our full sample, it was not associated with failure rates within any individual diagnostic group. This is somewhat surprising given prior investigations, which have demonstrated the UFOV's predictive utility within individual populations, such as Alzheimer's Disease and TBI (Novack et al., 2006; Silva, Laks, & Engelhardt, 2009). It is possible that diagnostic heterogeneity within groups may have limited the sensitivity of the UFOV in these cases. Altogether, our results suggest that while cognitive tests such as UFOV have value, clinicians must be cautious of over-interpreting the findings of performance screening tools.

With rapid advancements in technology, new approaches are being explored in research settings to assess driving performance. One promising approach is sensor-based driving monitoring, which uses a small device that is plugged into a person's vehicle and records driving data such as driving speed, acceleration, braking, GPS locations, and driving routes (Seelye et al., 2017). Sensor-based driving monitoring allows for passive monitoring of a person's driving behaviors. The driving data can be remotely accessed and represents typical, real-world driving performance in a person's natural environment. In the future, passive driving monitoring could serve as a supplement to traditional clinic-based driving assessments to assess daily driving in adults who are cognitively healthy and who have mild cognitive impairments, and then inform the individual, family, or clinicians at the earliest sign of meaningful changes in driving habits including self-regulation of driving (e.g., reducing frequency and distance or avoiding complex driving settings) and risky driving behaviors (e.g., hard braking, speeding, and navigational abilities). Early detection of driving changes could facilitate early targeted intervention and planning for driving modifications to promote safety and independence. Compared to conventional driving assessment methods (e.g., road tests and simulators), sensors are low-cost and, in the future, may be more accessible to a larger population of individuals who have barriers to accessing specialty driver rehab assessment due to geographic, health, or socioeconomic barriers.

4.1. Limitations

Our VA Medical Center serves a diagnostically diverse population through our polytrauma rehabilitation services. As a result, despite efforts to group Veterans by diagnostic category, variability in diagnoses within diagnostic groups may have prevented detection of group differences. The non-neurological group was particularly diagnostically diverse, as it included participants who were referred for various injuries, cardiovascular conditions/events, and sensory changes, among others. As such, future work exploring Veterans' on-road driving should recruit samples with a more narrow set of referral diagnoses. Diagnostic groups were also relatively small, which further limited our statistical power. Additionally, our sample was predominantly Caucasian and male, which may limit generalizability to Veterans with these backgrounds. Furthermore, some variables typically associated with risk of on-road driving test failure, such as number of previous accidents and circumstances of those accidents, were not systematically collected given the time-limited nature of evaluations.

With regard to the measures used, although the cognitive screening tools included in this study provide some insights into cognitive functions presumed necessary for safe driving, in-person clinical testing using paper–pencil measures inherently provides added structure to the testing task that cannot simulate the unpredictable nature of real-world driving environments. While the OTs administering the on-road driving tests utilized a standardized course as well as took into account observed unsafe driving behaviors when determining outcomes, the frequency of such behaviors was unavailable for analyses, as data were not collected for research purposes. As a result, the present study solely evaluated outcomes on a binary basis (i.e., pass/fail) and was unable to examine outcomes in greater depth. Future studies should record this information in order to provide a more nuanced understanding of Veterans' on-road driving performance. Finally, while the OTs had extensive experience administering the on-road tests, biases may have still impacted the outcome of an evaluation. Pairing clinical on-road tests with technology-assisted methods that more objectively assess driving safety, such as those noted earlier, may be helpful in this regard.

4.2. Conclusions

Although considered an important factor in assessing driving safety, diagnostic category is not independently predictive of Veterans' on-road failure rates, and age does not modify this relationship. Cognitive performance, specifically in the areas of processing speed and/or selective and divided attention, may be useful in screening for driving safety in this population. Larger studies that incorporate a wider array of information collected in clinic to screen for Veterans' driving safety are warranted.

Conflicts of interest

All authors report no conflicts of interest.

Acknowledgements

We thank the Veterans who participated in this study. We also thank Jessica Kiecker, OTR/L, DRS and David Lawler, OTR/L, CDRS who completed a portion of the pre-screens and the on-road assessments.

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John PK Bernstein, MA is a graduate student at Louisiana State University and a predoctoral psychology intern at the Minneapolis VA Healthcare System.

Tonya Rich, PhD, OTR/L is a clinical researcher and occupational therapist in the department of occupational therapy at the Minneapolis VA Health Care system and an assistant professor at the University of Minnesota.

Stefanie McKnight is an undergraduate occupational therapy student at the University of Minnesota.

Julie Mehr, MA is an occupational therapist at the Minneapolis VA Healthcare System.

John Ferguson, PhD is a research scientist and assistant professor at the University of Minnesota and at the Minneapolis VA Healthcare System.

Adriana Hughes, PhD is a staff neuropsychologist and clinical investigator at the Minneapolis VA Healthcare System and an assistant professor at the University of Minnesota.

Journal of Safety Research 77 (2021) 61–66

Contents lists available at ScienceDirect

Journal of Safety Research

journal homepage: www.elsevier.com/locate/jsr

Parents' work injuries and children's mental health: The moderating role of children's work centrality

Nick Turner [a,*], Steve Granger [a], Sean Tucker [b], Connie Deng [a], E. Kevin Kelloway [c]

[a] *University of Calgary, Canada*
[b] *University of Regina, Canada*
[c] *Saint Mary's University, Canada*

ARTICLE INFO

Article history:
Received 22 March 2020
Received in revised form 17 September 2020
Accepted 3 February 2021
Available online 16 March 2021

Keywords:
Injuries
Mental health
Parents
Work centrality
Young workers

ABSTRACT

Introduction: The purpose of this study is to explore the relationship between parents' work-related injuries and their children's mental health, and whether children's work centrality – the extent to which a child believes work will play an important part in their life – exacerbates or buffers this relationship. *Method:* We argue that high work centrality can exacerbate the relationship between parental work injuries and children's mental health, with parental work injuries acting as identity-threatening stressors; in contrast, high work centrality may buffer this relationship, with parental work injuries acting as identity-confirming stressors. We test this relationship with a sample of Canadian children (N = 4,884, 46.2% female, M age = 13.67 years). *Results:* Children whose parents had experienced more frequent lost-time work-related injuries reported worse mental health with high work centrality buffering this negative relationship. *Conclusions:* Our study highlights the vicarious effects of work injuries on salient others, specifically parental work injuries on children's mental health, as well as the role of work centrality in shaping children's sense-making and expectations about the consequences of work.

1. Introduction

Occupational injuries negatively affect workers, co-workers, employers, and the families of injured workers. Research on the consequences of a work-related injury on the injured person's family highlights changes in family functioning, with potentially negative consequences for children (Kosny, Newnam, & Collie, 2018; Sachs & Ellenberg, 1994). Changes in family functioning can have negative consequences for children (Dembe, 2001, 2005; Keogh, Nuwayhid, Gordon, & Gucer, 2000), including adverse physical health effects (Asfaw et al., 2012, 2016) as well as declines in mental health (Hisle-Gorman, Susi, & Gorman, 2019).

The current study investigates the mental health consequences for children of parents who are injured at work, as well as how children's early beliefs about the importance of work affects this relationship. We predict that observing parents who are off work due to a work-related injury is associated with lower quality mental health. Parents who have paid employment outside the home are often the first point of contact about the world of work for many children, with children learning much from indirectly experiencing the positive and negative consequences of their parents' work (Mortimer, 2003; Preves & Mortimer, 2013). We argue in this paper that the interaction between formative experiences related to work, namely frequency of parents' work-related injuries, and a child's own work centrality predicts additional variance in that child's mental health. What is unclear is whether the parental work injury-child work centrality relationship has adverse or protective effects on a child's mental health. In the current study, we use data from a large sample of Canadian school children to explore the main and interactive effects of parental work injuries and work centrality on children's mental health.

2. Literature review

2.1. Work injuries and mental health

Research shows that employees who experience a work-related physical injury, and require time away from work to heal are at greater risk of experiencing a mental illness (Jones, Koehoorn, Bultmann, & McLeod, 2017; Orchard, Carnide, Mustard, & Smith, 2020). However, little is known about the potential spillover of parental work-related time-loss injuries on children's psychological wellbeing. Sachs and Ellenberg (1994) describe a range of family outcomes of a work-injured parent including role changes (e.g.,

* Corresponding author at: Haskayne School of Business, University of Calgary, 2500 University Drive NW, Calgary, Alberta, Canada.
E-mail address: Nicholas.Turner@ucalgary.ca (N. Turner).

https://doi.org/10.1016/j.jsr.2021.02.002
0022-4375/

the injured parent may not be able to carry out childcare), communication changes (e.g., the nature of the parent's interaction with children changes), changes in intimacy (e.g., increased emotional distance with children and lack of family cohesiveness as a result of parental injury), and changes with boundaries (e.g., children taking on more household responsibilities during recuperation and assisting the parent with rehabilitation). More recently, Hisle-Gorman et al. (2019) found that children of parents in the military who sustained an injury required more mental health care and increased psychiatric medication use after their parents' injuries. Analogously, we hypothesized that children of parents who experienced lost-time (severe) work injuries would report poorer quality mental health than those children whose parents had not experienced lost-time work injuries.

2.2. Children's vicarious experiences of work and development of work centrality

Childhood and early adolescence comprise the life stages when self-concepts and values about work develop, shaping expectations about what work means and its importance (Cemalcilar, Jensen, & Tosun, 2019; Kittel, Kalleitner, & Tsakloglou, 2019). The experience of working part-time or odd jobs while going to school (e.g., babysitting, helping in a family business, lawn mowing, casual service work) is one important way this occurs. Data from a nationally-representative sample of Canadian children in 2002 suggest over half of Grade 5 children (9–10 year olds) held at least one odd job for pay at the time of the survey, with the proportion of part-time job holders rising to almost 90% among those in Grade 9 (13–14 year olds; Bergenwall, Kelloway, & Barling, 2014). Furthermore, Mortimer (2003) cohort study found that teenagers who were "most invested" (i.e., greater number of total months working and total cumulative hours) in work while going to school developed stronger extrinsic work values (e.g., the importance of earning money or job security) than those who did not work while going to school. More work experience and stronger work values contribute to a more clearly defined work identity, with variation in the extent to which work becomes more or less central to children's self-concepts.

The centrality of work to self-concept, or work centrality, is defined as the extent to which work plays and will play a principal role in the lives of individuals (Paullay, Alliger, & Stone-Romero, 1994). Further, work centrality is relatively consistent and stable in adults once it develops rather than differing from job-to-job (e.g., Harpaz & Fu, 2002). Prior to working part-time, however, development of work centrality in children comes from learning about the work experiences of salient others, such as parents (Kittel et al., 2019). Substantial evidence points to how parents' work experience indirectly shapes their children's attitudes and outcomes. For instance, parental job insecurity is related to children's work and life beliefs (e.g., lower humanistic work beliefs and higher beliefs in an unjust world; Barling, Dupre, & Hepburn, 1998; Barling & Mendelson, 1999), as well as higher cognitive distraction (Barling, Zacharatos, & Hepburn, 1999) and lower academic performance (Barling & Mendelson, 1999). Furthermore, Lim and Kim (2014) show that parental frustration stemming from work is related to lower work centrality of children via non-supportive parenting behavior. These vicarious experiences of work via parents involves children being directly affected by aspects of their parents' work; in the current study, we investigate the consequences of parents' work injuries on children's mental health. More specifically, we argue that the psychological strain of parents' work injuries experienced by children may be contingent on the extent to which children see work as central to their self-concepts.

2.3. Stress appraisal, work centrality, and mental health

A key feature of many models of psychological stress (e.g., Lazarus & Folkman, 1984) is the subjective appraisal of stressors, such that the same stressor can be perceived by different people as ranging from innocuous to harmful or threatening. A vital factor in the subjective appraisal of stress is "an important or valued self-conception" (Thoits, 2013, p. 361). The subjective appraisal of stress between individuals based on the conditional role of an important self-concept gives rise to competing hypotheses.

In the current context, we argue that the extent to which a child sees work as important to their self-concept can increase the likelihood that a parental work injury is perceived to be harmful or threatening. The more a child identifies with work, the higher the potential a parental work injury as an adverse work event can engender psychological harm because it threatens a domain important to a child's self-concept. In the same way albeit with an adult working sample, Martire, Stephens, and Townsend (2000) showed that high work centrality exacerbated the association between employee stress and depressive symptoms: the relationship between employee stress and depressive symptoms was strengthened as they perceived work-related stress as identity-threatening. Parental work injuries may therefore be an identity-threatening stressor, with higher work centrality exacerbating the relationship between parental work injury and a child's mental health.

An alternative hypothesis is that a parental work injury could be considered identity-confirming by children. Through this lens, high work centrality acts as a personal resource for making sense of and coping with a parental work injury. Work centrality may play a role in offsetting the psychological strain associated with a parent's work injury by anchoring a child's expectations. Children with high work centrality may be more likely to see a parent's work-caused injury as identity-confirming, enabling appraisal of the parental work injury with fewer negative emotions and associating work injuries with the belief that "this is just the way work is." Parental work injuries may therefore be an identity-confirming stressor, with higher work centrality buffering the relationship between parental work injury and a child's mental health.

In the present study, we examined whether the relationship between parental work injuries and children's mental health varied by level of children's work centrality–whether it served to intensify or cushion the adverse relationship between parental injuries and children's mental health (see Fig. 1).

3. Method and measures

3.1. Participants and procedure

Between September 2013 and July 2014, 5,330 participants (54% male) primarily from the Canadian province of Ontario voluntarily responded to a short survey before taking *Passport to Safety Challenge for Teens* (Canada, 2019), an online occupational safety

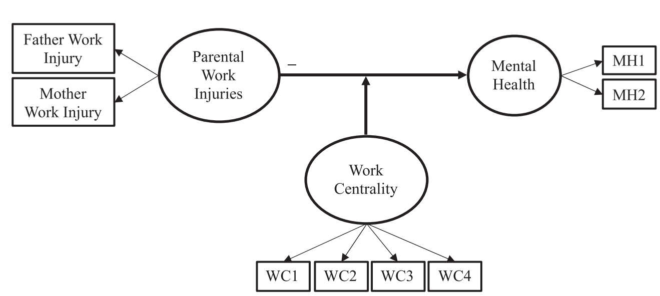

Fig. 1. Study model.

module voluntarily selected by hundreds of teachers and school boards across Canada (mainly the province of Ontario) for use in in junior high school and high school classes to raise students' awareness about young workers' rights and responsibilities and workplace hazards. The curriculum for the *Challenge for Teens* module variously covers employer responsibilities, worker rights and responsibilities, work hazard information systems, dealing with work hazards, and other general workplace safety provisions. We removed 446 participants from the sample who reported being under the age of 10 years old or whose age was missing. Among the remaining participants (N = 4,884), 46.2% were female, the average age was 13.67 years old (SD = 1.21, range: 10–18 years), and approximately 36% of the sample were employed part-time at the time of the survey.

The short survey appeared before participants logged into the *Challenge for Teens* curriculum. It was designed to be completed in under a minute and was restricted to only a few items. Each school year we included different items in the short survey. Data from other items collected from different school years' surveys have been reported in other articles (e.g., 2011–2012 in Tucker, Diekrager, Turner, & Kelloway, 2014; Turner, Tucker, & Kelloway, 2015; 2012–2013 in Pek, Turner, Tucker, Kelloway, & Morrish, 2017; 2012–2013 and 2014–2015 in Tucker, Pek, Morrish, & Ruf, 2015); readers can get more information about *Passport to Safety* resources from these sources.

3.2. Measures

3.2.1. Parental work injuries

We measured parental experience of workplace injuries by asking all respondents how frequently their mother and father (each in a separate item) had experienced lost-time work injuries (i.e., "How many times has your mother [father] been forced to take time off work due to a work-related injury?"). The two items about parents used a response scale 'never' (0), 'once' (1), 'twice' (2), 'three times' (3), and 'four or more times' (4), with an addition of a 'does not apply/unsure' option. We used two items as manifest indicators of a latent variable to reflect the vicarious experience of parental workplace injuries.

3.2.2. Mental health

We used two items from the General Health Questionnaire (Shevlin & Adamson, 2005) social dysfunction sub-scale as an indicator of mental health. The items had the root "How much of the time, during the last month, have you..." at the front of each item: "enjoyed day-to-day activities" and "been able to concentrate." The response scale was a five-point scale, ranging (coded as) from never (1) to always (5), with higher scores indicating better mental health. We used these two items as indicators of a mental health latent variable.

3.2.3. Work centrality

We adapted four items from Paullay et al. (1994) measure of work centrality by including the root "I expect..." at the front of each item: "work will be very central to my existence," "that the major satisfaction in my life will come from work," "the most important things that will happen to me will involve my work," and "I would probably keep working even if I didn't need the money." Although this work centrality scale has evidenced subsequent validity and reliability (e.g., Hirschfeld & Feild, 2000), these properties are based on working adult samples, not adolescent samples. The four items used here had high face validity and as a set had a Flesch-Kincaid Grade Level score (i.e., a function of average word length of each item and average number of syllables per word) of 5.8, several school grades below the reading level of the average respondent (i.e., Grade 8/9). The response scale was a five-point scale, ranging (coded as) from strongly disagree (1) to strongly agree (5), with higher scores representing work being a more central part of the respondent's self-concept. We used the four items as indicators of a work centrality latent variable.

3.2.4. Demographic variables

Respondents reported their gender (female = 0; male = 1), their age (in years), and whether or not they were employed at the time of the survey.

4. Results

4.1. Data analysis strategy

We used the two-step latent moderated structural equation method (LMS; Klein & Moosbrugger, 2000; Maslowsky, Jager, & Hemken, 2015) with XWITH and full information maximum likelihood with robust standard errors in Mplus (Muthén & Muthén, 1998, 2012) to test the relationship among parental work injuries, work centrality, and their interaction on children's mental health. This involved first testing a model without the latent interaction as a comparison model and as a means of examining the main effects. In a second model (i.e., the hypothesized model), we created a cross-product term between the latent variables of parental work injuries and work centrality. The latent interaction variable would be deemed significant based on a likelihood ratio test when comparing the models. Estimation of the measurement model prior to the structural equation modeling suggested good fit (χ^2 = 162.41, $p < 0.001$, comparative fit index = 0.97, Tucker-Lewis index = 0.95, root mean square error of approximation = 0.03 [95% CI: 0.03, 0.04]; Browne & Cudeck, 1993).

4.2. Parental work injuries, work centrality, and children's mental health

Table 1 reports employment status of the sample by age, Table 2 reports descriptive statistics and zero-order correlations for the sample, and Table 3 reports results from the structural equation model we described above. Approximately half of the respondents at the modal age of 13 years reported being employed at the time of the survey, with percentages of part-time employment for participants aged between 10 and 12 years ranging from 38% to 44% (see Table 1). We found that the parental experience of injury was negatively related to children's mental health ($r = -0.09$, $p < 0.001$; see Table 2). This finding is replicated in our multivariate model: parental experience of injury was negatively related to children's mental health ($b = -0.19$, SE = 0.03, $p < 0.001$, 95% CI: -0.26, -0.13), controlling for age and gender (see Table 3). Further, there was a significant interaction between parental injuries and work centrality (b = 0.12, SE = 0.02, $p < 0.001$, 95% CI: 0.06, 0.18), with

Table 1
Frequency and percentage of employment status by age of participants.

	Age of participants (in years)								
	10	11	12	13	14	15	16	17	18
Employed	20 (42%)	45 (38%)	182 (44%)	808 (49%)	495 (34%)	166 (18%)	21 (9%)	2 (40%)	1 (13%)
Unemployed	28 (58%)	73 (62%)	232 (56%)	847 (51%)	984 (66%)	762 (82%)	208 (91%)	3 (60%)	7 (87%)

Table 2
Means, standard deviations, and zero-order correlations between study variables.

	M	*SD*	1	2	3	4
1. Age	13.67	1.17	–			
2. Gender	0.54	0.50	0.02	–		
3. Parental Work Injuries	0.71	0.92	−0.02	−0.01	–	
4. Work Centrality	3.38	0.79	−0.01	0.03*	0.05**	–
5. Mental Health	3.79	0.75	0.02	0.13***	−0.09***	0.13***

Note: N = 4,884. Gender: female = 0, male = 1.
* $p < 0.05$.
** $p < 0.01$.
*** $p < 0.001$.

Table 3
Parental work injury and work centrality on children's mental health, controlling for age and gender (N = 4,842).

	Comparison model					Hypothesized model				
				95% *CI*					95% *CI*	
Variable	*b*	*SE*	*p*	*LL*	*UL*	*b*	*SE*	*p*	*LL*	*UL*
Age	0.02	0.02	0.439	−0.02	0.05	0.02	0.02	0.454	−0.02	0.05
Gender	0.17	0.02	0.000	0.13	0.21	0.17	0.02	0.000	0.13	0.21
Parental Work Injuries	−0.19	0.03	0.000	−0.26	−0.13	−0.23	0.03	0.000	−0.30	−0.17
Work Centrality	0.21	0.02	0.000	0.17	0.26	0.23	0.02	0.000	0.18	0.27
Parental Work Injuries × Work Centrality						0.12	0.03	0.000	0.06	0.18

Note: outcome = mental health (lower scores represent worse mental health); gender: 0 = female, 1 = male.

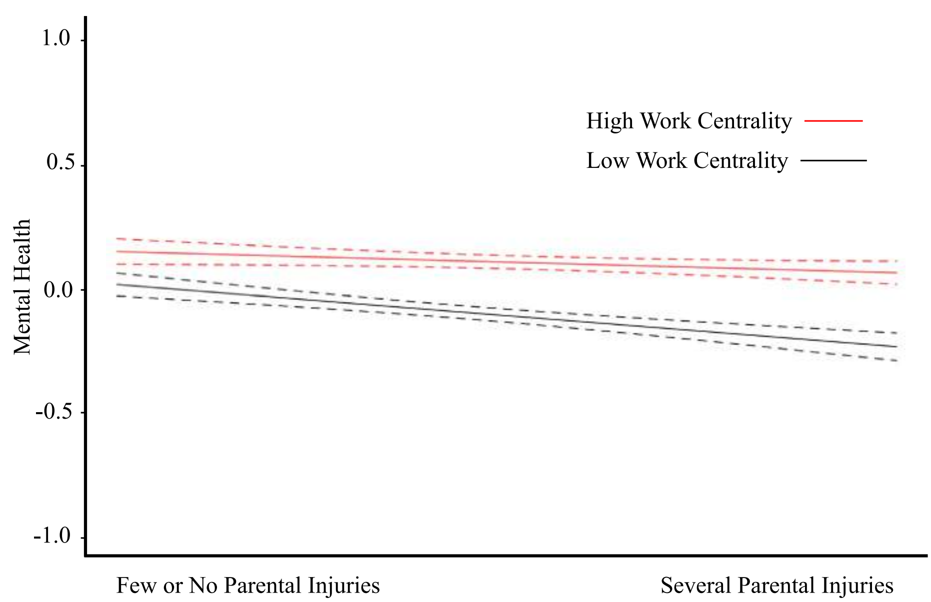

Fig. 2. The latent interaction between parental work injuries and work centrality on children's' mental health, controlling for age and gender. Dotted lines represent 95% confidence bands.

the comparison model representing a significant loss in fit relative to the interaction model (χ^2 = 5.38, p = 0.020).[1] Plotting the interaction (see Fig. 2) revealed that parental work injuries were related to worse mental health among children who reported low work centrality. Assessment of the interaction reveals that the coefficient for parental work injuries had a stronger negative relationship with mental health when work centrality was low (b = −0.12, SE = 0.02, $p < 0.001$, 95% CI: −0.17, −0.08) than when work centrality was high (b = −0.04, SE = 0.02, p = 0.039, 95% CI: −0.08, −0.00), in support of the buffering hypothesis.

5. Discussion

The current study investigated the relationship between parents' work-related lost-time injuries and their children's mental health. We found that parental job-related injuries were associated with lower child mental health controlling for child age and gender. Further, higher levels of work centrality were related to better mental health and the interaction between parental job-related injuries and work centrality was significant. The significant interaction supports the notion that work centrality is a personal

[1] There was no significant difference in the interaction effect between those employed at the time of survey and those not employed at the time of survey. We thank an anonymous reviewer for asking us to test this possibility.

resource that might enable children who identify with work more to see parental injuries in a less negative light than children who identify with work less.

The current findings have several implications worth noting. First, although we cannot determine from the current findings whether parental work injuries and decrements in children's mental health co-occur, parents should be cognizant of their children's mental health when parents experience a work-related injury. This may open a dialogue between parents and children about the nature of work, particularly the importance of physical safety at work, as well as anticipating possible changes in family functioning that may occur in the case of parental injury (Kosny et al., 2018). Second, and relatedly, exploring a family climate for work safety may be a helpful extension of family climate for road safety (e.g., Taubman-Ben-Ari & Katz-Ben-Ami, 2013) in understanding how children make sense of their parents' and ultimately their own work safety related experience. As children gain their own experience of work, part of which may unfortunately involve getting injured at work, we anticipate that the influence of parents' work experience in shaping children's work centrality and mental health will diminish. The relative importance of work-based and family-based safety climate remains an area for future research.

5.1. Study limitations

Four limitations of this research are worth noting. First, the survey instrument was short and conducted at a single time point, leading to potential shortcomings in the type and quality of data collected. Although we asked participants about the number of their parents' lost-time work injuries, we do not have detailed descriptions of the nature of the injuries experienced (i.e., physical, psychological, duration of injuries, or length of recuperation); the extent to which the participants had (i.e., single- or two-parent families) or identified with one or both of their parents (indicating a possible salience of injuries of one parent over the other); or a baseline measure of children's mental health. Further, the ordinal measures of parental injuries, the two-item measure of mental health, and the four-item measure of work centrality are likely not as valid as the full versions of the measures.

Second, there is a possibility that children (as young as 10 years old in this sample) may not comprehend the work centrality items used (e.g., "I expect work will be very central to my existence") in the same way adults do. Paullay et al. (1994) items were developed with employed adults and it is common to develop child-appropriate scales for constructs ordinarily completed by adults (e.g., adolescent versions of mental health measures, Luthar, Ebbert, & Kumar, in press). As such, the extent to which participants made sense of work centrality items in the same way across the eight-year age range is unclear, despite the items being likely understandable by the average respondent's reading level.

Third, children often report being unaware of parental trauma, including serious life-threatening accidents, with more accurate knowledge of fathers' trauma than mothers' trauma (Duarte et al., 2019). This calls into question the extent to which children may be unintentionally under-reporting parental work injuries, and in turn the underestimation of the relationship between parental work injuries and children's mental health.

Finally, family socioeconomic status may be an unmeasured confound in this study, serving as a plausible alternative explanation of the findings.[2] Parents who are at risk of work-related injuries are more likely to have physical-oriented jobs, which are not paid as well as with non-physical-oriented jobs (Yuma-Guerrero, Orsi, Lee, & Cubbin, 2018). Lower family income is a measure of lower socioeconomic status, which has been linked with children's mental health problems (Reiss, 2013), as well as both lower parental transmission of work centrality and mean levels of work centrality among children (Kittel et al., 2019). Future research needs to consider the relationship between and among these three variables and socioeconomic status of the family.

6. Conclusion

In conclusion, the current findings show the relationship between more frequent parental injuries and children's mental health, and that this relationship may be buffered in children with high work centrality. These findings have implications for how children are socialized directly and vicariously into the world of work, and more specifically the extent to which parents' work experiences such as injuries may differentially affect children's mental health.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

We presented an earlier version of this paper at the 19th Congress of the European Association for Work and Organizational Psychology, Turin, Italy. We thank Jayne Morrish and Parachute Canada for providing access to Passport to Safety and financial support from the Canadian Centre for Advanced Leadership in Business. Morteza Charkhabi, Sharon Clarke, Zhanna Lyubykh, Simon Pek, Natalie Valle, Ivana Vranjes, and Julie Weatherhead all provided helpful comments at various stages of this research.

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[2] We thank an anonymous reviewer for suggesting this point.

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Nick Turner, PhD (Sheffield) is Professor and Distinguished Research Chair at the Haskayne School of Business, University of Calgary, Canada. His research focuses on work design, transformational leadership, and occupational health and safety.

Steve Granger, MSc (Manitoba) is a PhD candidate in the Haskayne School of Business, University of Calgary, Canada. His research focuses on workplace safety, proactivity, and resilience among gig workers.

Sean Tucker, PhD (Queen's) is Associate Professor of Human Resource Management at the Faculty of Business Administration, University of Regina, Canada. His research focuses on change in young worker safety behaviors across time, the influence of executive leadership on frontline employee safety behaviors and injuries, and predictors of young worker injury under reporting.

Connie Deng, MSc (Sheffield) is Research Associate at the Canadian Centre for Advanced Leadership in Business, Haskayne School of Business, University of Calgary, Canada. Her research focuses on workplace safety and teamworking.

E. Kevin Kelloway, PhD (Queen's) is Professor and Tier 1 Canada Research Chair in Occupational Health Psychology in the Department of Psychology, Saint Mary's University, Halifax, Canada. He is a prolific researcher, an experienced consultant, and a popular speaker.