USING THE MODIFIED DELPHI METHOD TO PROPOSE AND VALIDATE COMPONENTS OF A CHILD INJURY SURVEILLANCE SYSTEM FOR IRAN

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Using the Modified Delphi Method to Propose and Validate Components of a Child Injury Surveillance System for Iran

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Abstract

Background: Child injuries are a worldwide public health concern. An injury surveillance system (ISS) has a beneficial impact on child injury prevention, but an evidence-based consensus on frameworks is necessary to establish a child ISS.

Objectives: To investigate key components of a child ISS and to propose a framework for implementation.

Methods: Data were gathered through interview with experts using unstructured questions to identify child ISS functional components. Qualitative data was analyzed using content analysis method. Then, the Modified Delphi method was used to validate functional components. Based on the outcomes of the content analysis, a questionnaire with closed questions was developed to be presented to a group of experts. Consensus was achieved in two rounds.

Discussion: In round I, 117 items reached consensus. In round II, five items reached consensus and were incorporated into the final framework. Consensus was reached for 122 items comprising the final framework and representing seven key components: goals of the system, data sources, data set, coalition of stakeholders, data collection, data analysis, and data distribution. Each component consisted of several sub-components and respective elements.

Conclusion: This agreed framework will assist to standardize data collection, analysis, and distribution to detect child injury problem and provide evidence for preventive measures.

Keywords: Wounds and injuries, surveillance system, child, framework, consensus, Modified Delphi method

Introduction

Child injuries are an increasing global public health problem. Unintentional injuries of children aged one to 18 years-old are the major cause of death and hospitalization worldwide, with the likelihood of lifetime disabilities.[1] Intentional and unintentional injuries account for mortality of hundreds of thousands of children and disability of millions more children globally.[2] More than 95 percent of all fatal injuries in children occur in low and middle income countries (LMICs) where the magnitude of the problem is greater and injury data is more likely to be missing, as well as of lower quality or availablility.[3]

In Iran, with recent advances in providing timely, quality healthcare services to citizens, disease patterns have transitioned from communicable disease to non-communicable disease and injuries. Globally, Iran ranks fifth in road traffic mortality rates and also has the highest mortality rate in the Eastern Mediterranean region.[4] Iran has a population of more than 80 million people, among which 32 percent are younger than 19 years of age.[5] On average in Iran, 20.2 percent of deaths in children under five years-sold occurs because of unintentional injuries.[6] According to the results of a national injury registry, burn injuries account for 58.8 percent of injuries among children under seven-years-old.[7] Also, injuries are the highest cause of mortality in children 1to14 years-old.[8]

Injuries are preventable and the first step to preventing injuries is understanding the extent and magnitude of the problem.[2,9] Injury Surveillance Systems (ISSs), through ongoing systematic data collection, analysis, interpretation, and dissemination, help identify injury patterns, trends, and the magnitude of the problem, and provide necessary data for health policy makers to decide on preventive measures.[2,10]

Despite the fact that various studies have evaluated the usefulness of ISSs to provide data about injury trends and identify high risk groups, as well as prevention programs,[11-16] few countries have established formal injury surveillance systems because of various obstacles.[2] Obstacles identified in Iran include lack of political commitment, limited resources, poor management, and poor data collection procedures.[17] ISSs are are implemented mainly in high-income countries, while in LMICs where the magnitude of the problem is larger, often no formal data collection mechanism exists for child injury surveillance.

Although research has been conducted in the field of child injuries and prevention in Iran, the majority of this research is limited to epidemiologic studies[18-25] and less research has addressed the problem from a surveillance based point of view. There is lack of evidence in the body of knowledge in terms of ISS framework with respect to its key functional components. Examining the functional components of a child ISS is useful as it could contribute to a standard data collection system and more quality injury data. Thus, the aim of this study was to first identify and second to validate key functional components of a framework for child ISS in Iran, using interviews and the modified Delphi method respectively.

Materials and Methods

This research was carried out from January 2017 to June 2018 and involved two tandem steps, including 1.) identifying and collecting child ISS components through interviews with experts and 2.) validating the components using the modified Delphi method.

Identification of child ISS functional components

Identification of key components needed to build a child ISS for Iran was performed by means of interviews using an interview guide with unstructured questions. Participants were asked to express their opinion about key components of an ISS used to collect injury data on children in Iran. A snowball sampling technique was applied to identify experts, and interviews continued until data saturation was achieved. Thus, 14 experts in different fields of epidemiology, pediatrics, social medicine, safety promotion and injury prevention, and health information management were interviewed. Written informed consents to participate in this research as well as to record the interviews were obtained in the beginning of each interview session after instructions were given to the participants.

Recorded interviews were transcribed verbatim. Data were analyzed using content analysis methods. Transcriptions were reviewed by the main researcher and open coding for the smallest possible meaning unit took place. Codes were revised and classified in some selected groups and subgroups based on their similarities and differences. All codes were revised by a team member with experience and expertise in qualitative research.

Validation of child ISS functional components

This paper reports on a research study that employed the modified Delphi technique with a set of pre-selected items drawn from the interviews.[26] In the second step, based on the outcomes of the content analysis, a questionnaire with closed questions was developed to be presented to a group of experts. The questionnaire was subjected to scrutiny by a panel of experts and was pilot tested by a sample of injury prevention and control experts. Items were rated on a scale of 1=Very Important, 2=Important, 3=Moderately important, 4=Of Little Importance and 5=Unimportant. The questionnaire included 151 elements, which were divided into the following seven major components (some components included subcomponents as well). (**Table 1**)

- 11 items in goals of the system (e.g., to support injury prevention acts, to provide epidemiologic patterns of fatal injuries, to provide epidemiologic patterns of nonfatal injuries, to determine injury severity, etc.);
- 12 items in data sources (e.g., prehospital emergency, emergency department of general hospitals, emergency department of specialized hospitals with the priority of children hospitals, population-based surveys, etc.);
- 36 items in data set organized in eight subcomponents of identifiers, demographics, time related data, place related data, injury characteristics, injury context, parents' supervision and safety equipment's (e.g., national ID number, date of creation of the record, hospital name, etc.);
- 21 items in coalition of stakeholders organized in two subcomponents of members and leader (e.g., Ministry of Health and Medical Education, healthcare organizations/hospitals, forensic medicine, police, Ministry of Roads & Urban Development, etc.);
- 11 items in data collection organized in four subcomponents of ISS type, data collection

methods, data entry methods, and case definition (e.g., active data collection including data collection by child ISS officers; inactive data collection, including data collection by healthcare providers and facilities, a combination of both methods, etc.);
- 24 items in data analysis and interpretation organized in two subcomponents of indicators and analysis level (e.g., injury frequencies, injury percentages, injury rates, injury rates in special groups, adjusted injury rates, Years Lived with Disability (YLD), etc.); and
- 36 items in data distribution organized in three subcomponents of data distribution methods, audience, time intervals of reports (e.g., organizational newsletter, newspaper, mass media (TV and radio), social media (face book, twitter, Instagram, etc.), scientific papers published in journals and conferences, etc.).

Although five to 10 experts are adequate for content validation[27], 16 experts representing epidemiology, pediatrics, social medicine, safety promotion and injury prevention, health information management, and medical informatics were invited to participate on the expert panel. In round one, 151 items organized in seven key functional components were distributed to the panel. Panel members were asked to rate the relative importance of individual items and make changes to the phrasing or substance of the items. The same voting method was used for round two. The research goal was to obtain consensus regarding what functional components and their respective elements (items) are important for establishing a child ISS in Iran. Round one presented a questionnaire to panel members, who completed and returned it to the researcher. The responses were analyzed and compiled to build the round two questionnaire. For each item, interquartile ranges were calculated as measures of dispersion and median scores were calculated as measures of central tendency. The combination of these indices was used to determine the degree of importance and consensus for each item. Items were accepted if they acquired more than 75 percent of collective consensus of (1=Very Important) and (2=Important). Collective consensus of items less than 50 percent and between 50 percent to 75 percent were removed and sent for the next round respectively.

Panelists were faculty members or researchers holding a PhD degree and medical specialists with established careers in the field of child injury prevention, injury surveillance, health information management, or medical informatics, with at least 10 years of experience working in the field. Panelist also had expertise in using injury surveillance systems.

Ethics approval for this study was provided by the Ethics Committee of Iran University of Medical Sciences.

Results

ISS component development

The outcome of the content analysis was 151 elements (items), which were categorized in seven major categories, including goal of the system, data sources, data set, coalition of stakeholders, data collection, data analysis and interpretation, and data use. Four of these major categories, including data set, coalition of stakeholders, data collection, data analysis and interpretation, and data distribution, comprised various subcomponents themselves. **Table 1** illustrates the seven major categories (components) of child ISS and a sample of its respective elements.

Insert Table 1 here.

Modified Delphi Round 1

After round one voting was completed and comments were summarized, redundant statements and statements sharing similar constructs were grouped and reduced. Specifically, 18 of 151 initial statements were combined and reduced to create nine statements that reached consensus and were accepted for the final framework. For example, the following two items were originally included in the list of statements for round one (goals of the system): 1.) to provide epidemiologic patterns of fatal injuries; and 2.) to provide epidemiologic patterns of nonfatal injuries. Both items received consensus (≥ 75 percent of respondents rated important/very important response (one or two) on the Likert scale for the element), were combined into a single statement to reduce redundancy, and accepted for the final framework. The revised element now reads "to provide epidemiologic patterns of fatal and nonfatal injuries." Of the 151 initial elements, 108 were deemed not redundant, reached consensus, and were accepted into the final child ISS framework without modification. In total, 117 elements from round one were accepted into the final framework.

Round one was also used to generate 18 new elements by the panelists. New elements were categorized in the following components: data sources, data set, coalition of stakeholders, and data distribution. Also, 25 out of 151 initial statements did not reach consensus after round 1. In total, 43 elements were sent to round two. **Figure 1** illustrates the results of the modified Delphi process.

Modified Delphi Round 2

In round two, five of 43 elements reached consensus and were accepted without modification (≥ 75 percent of respondents rated important/very important response (one or two) on the Likert scale for the element), and were accepted into the final child ISS framework. Thirty-eight of 43 elements did not reach consensus (≤ 50 percent of respondents rated important/very important response (one or two) on the Likert scale for the element) and were omitted from the final framework. The final child ISS framework consists of 7 major components and 122 elements: four related to goals, 8 related to data sources, 32 related to data set, 15 related to coalition of stakeholders, nine related to data collection, 19 related to data analysis and interpretation, and 36 related to data (**Table 2**).

Discussion

Child injuries are a worldwide public health concern requiring urgent attention. There seems to be a potential beneficial impact of the application of an injury surveillance system on special populations, such as children, in injury prevention.[17,28] In LMICs, in some cases, data pertinent to child injuries and violence are weakly gathered; in other cases collected injury related data is of less quality and/or is scattered between different organizations with reduced opportunities for access and linkage.[2] Thus, there is a need for evidence-based consensus on frameworks to establish child ISS for improving injury surveillance systems where there is agreement.

The current data collections for child injury in Iran is plagued with management barriers, weakness in data capture and usage, resource limitation, lack of coordination between different stakeholders, and lack of commitment to prevent injuries.[17]

Development of frameworks to establishing child ISS provide a step-by-step sequence that improves quality of data, data collection procedure, data dissemination, and coordination of injury prevention intervention across the entire continuum of injury chain prevention. This contributes to injury prevention and planning by identifying injury; detecting injury risk factors; monitoring the results of interventions; and identifying the best way to use available resources.[15] Although there is plenty of research in the field of child injuries in Iran, no research about establishing an injury surveillance system for children was found. Only WHO guidelines to establish injury surveillance systems was identified through a literature search.[15] Therefore, this study implores the use of a modified Delphi method to develop a framework for establishing a child ISS in an Iranian setting. The modified Delphi method was also used to build consensus around the components, elements, and description of such a system. A detailed description of the Delphi method was included in this study to improve the quality of the final consensus framework and to add a level of credibility to component development and selection process.[29]

To the best of our knowledge, this is the first use and reporting of a modified Delphi method to develop a framework for child ISS in an Iranian healthcare setting. Consensus was also reached for 122 elements representing seven major components (e.g., goals, data sources, data set, coalition of stakeholders, data collection, data analysis and interpretation, and data distribution) that could be used as a framework to establish a child ISS.

In agreement with the literature, this framework recommends that the goal of such a system not only should be providing the epidemiology pattern of child injuries but also, more importantly, providing adequate supporting data to help in designing injury interventions and surveillance purposes[15,30] a component that is lacking in most current data collections in Iran. Considering the variables in injury data sets in order to help gather the necessary information about child injury risk factors will make reaching this goal possible.[17] Variables proposed in the data sets of this framework, such as describing the injury event, activity of the patient child at the time of injury, parents' supervision, use of protective devices, and region of residence can provide the opportunity to analyze this data and identify possible child injury risk factors. Variables such as injury nature and injury mechanism based on ICD-10 also provide more structured data to analyze injury cause and the affected areas in more detail.[31]

Previous studies indicated that in the current injury data collection systems in Iran, deaths occurring at the injury scene, deaths occurring after leaving the emergency department (ED) for an operating ward, and deaths following hospital discharge are not registered at in hospitals' ED.[32-34] The same is true about injury patients who receive care at the scene of injury and do not go to an ED for further medical treatment.[32] It is estimated that this latter group makes up 30 percent of unintentional injuries in Iran.[17] Thus, current data collections fails to cover a considerable amount of fatal and non-fatal injury cases. Data sources proposed in this framework address this challenge by considering data from various existing injury mortality and morbidity data collections. For instance, prehospital emergency data is a valuable data source for injuries/death occurring at the scene and injuries/death that are not referred to a medical facility.[35]

The Forensic Medicine, National Death Registry, and 1-59 Month Child Death Surveillance are also important sources for death data because they gather considerable mortality data not registered at hospitals. Among these, the Forensic Medicine acts as the gold standard because death data is highly supported with death certificates and evidence. Police Department, Fire Department, and Red Crescent also have a substantial role in registering road traffic injuries, fire-related injuries, and injuries due to natural disasters, respectively. They can provide more details about what went wrong during the injury as well as injury risk factors, which are highly valuable when designing interventions.

Using different data sources leads not only to expanded data coverage but also to a 360-degree perspective on injury incidents, as various data sources gather a variety of information based on their organizational mission. The importance of considering a variety of data sources for data collection has been recognized in different literature.[14,30,36] WHO emphasizes postmortem or pathology reports, police reports, ED injury records, hospital inpatient records, trauma registries, ambulance records, community-based or household surveys, transportation department reports, records of car insurance companies, occupational safety or industrial, compensation records, rehabilitation centers, and national insurance schemes as potential sources of data[30] that each country can take into consideration based on its available resources.

Previous studies also indicate that current injury data collection in Iran is partially- electronic.[9] Data from all over the country are submitted to the Iran Ministry of Health and Medical Education (MOHME) for national data integration, quality control check, analysis, and dissemination for annual national reports.[4,32,37-39] Data collected in this way lacks timeliness, as it takes a complete year for

MOHME staff to complete this process.

The data collection method put forth in this framework solves this problem by considering a time interval of one month for the data collection process from identified data sources in order to ensure the data acquired from hospitals accurately record patients' outcome. It is important to note that the one-month time interval is considered for data collection, as it may take some time to investigate patients' real outcome after their discharge from hospital.

Prior studies in Iran have demonstrated that injury data are analyzed using descriptive statistics such as frequencies and percentages; more advanced analysis is not available.[40] This guideline highlights the importance of considering analytical statistics and geographic-based analysis to demonstrate black spots or spot maps for child injuries. Application of global positioning systems (GPS) could provide the needed geographical data for improved analysis.

Research also specifies that child injury reports are not well communicated through the healthcare system and stakeholders in the country. Evaluation studies have revealed that data usage is the weakest part of this system in Iran.[40] The ultimate goal of every injury surveillance system is to provide data for action. Designing, implementing, monitoring, and evaluating interventions aimed at preventing childhood injuries is only possible when the required data for identifying causes of the problem as well as factors are well communicated between different stakeholders.[30]

Thus, identifying the major child injury stakeholders as well as the means to distribute child injury reports are major keys in injury prevention programs. The proposed framework has identified a group of stakeholders from different involved organizations such as related offices of MOHME, forensic medicine, police, Ministry of Roads and Urban Development, insurance companies, representative from provincial governments, municipality, fire department, Red Crescent organization, standard organization, media, and NGOs to act as a focal point for establishing child injury interventions and further inter-organizational cooperation.

Different distribution means have been also identified in this framework to be employed for extended data dissemination to make data available. All of the following may contribute to the dissemination of injury information to stakeholders and to society at large: Organizational newsletters, newspapers, mass media (TV and radio), social media (Facebook, Twitter, Instagram, etc.), scientific papers published in journals and delivered at conferences, educational leaflets and pamphlets for patients in healthcare centers and hospitals, and discussion of child injury data in meetings and on websites of related offices affiliated to the Ministry of Health. Child injury strategies can be employed using these different methods.

Although Iran took significant steps to develop and promote the ED surveillance system, based on an evaluation in 2009,[40] it was revealed that the system requires major modifications in data collection and dissemination processes to make it more operative and useful for injury prevention activities. Many researchers even believe that the system may not be a candidate for an injury surveillance system, as it does not comply with the formal standard definition of an injury surveillance system in terms of ongoing systematic and regular injury data collection process and data usage.[15,41]

Limitations

This study has some limitations. Firstly, the opinions of experts in this study are based on the available resources and capacity of each data source, which is responsible for injury data collection. This could affect the amount of data which is to be collected. In this respect, although further variables with more focus on parents' supervision at the time of injury as well as variables for parents' and the child's activity at the time of injury with a proper classification were suggested, they were not approved by the experts to be included in the final data set. The main concern was that the recognized data sources are not of the required capacity to gather information on a large data set due to different reasons, such as human resource limitations, time limitation, and physical and financial limitations.[17] In addition, environments such as EDs are of a highly- stressed nature with a great focus of delivering emergency services to patients requiring immediate care, making the data registration process less of a priority. Instead, experts agreed on collecting such data through routine and systematic population-based surveys. Secondly, injury is a multi-factorial health problem requiring cooperation and coordination between different stakeholders and organizations. Although, based on the results of this study, a coalition of stakeholders was agreed upon, this does not guarantee collaboration of the identified organizations in the coalition in practice. Hence, legislation should provide this commitment.

Conclusion

The purpose of this study was to provide a framework on the major components, elements, and their description of a child ISS in an Iranian setting in order to standardize child injury data collection procedures and assist in designing evidence-based injury prevention interventions for health policy-makers. The framework is also meant to accomplish the following: 1.) improve the coordination and cooperation between the stakeholders; 2.) increase the efficiency of data sharing and access; and 3.) increase the early adoption of appropriate prevention intervention. This framework serves as the first step to informing public health policy-makers about the ideal structure of a child ISS in Iran. The next step is to compare the current state of child injury surveillance to the ideal state, represented by this framework. This will identify gaps in data collection, data analysis and data dissemination with the ultimate goal of proposing a solution that can help narrow the gap between the ideal state and the current state. This framework should also be recurrently reviewed to ensure consensus remains consistent with current injury surveillance literature and national guidelines.

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Declaration of Interest Statement

The authors report no conflict of interest.

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Table 1. Content analysis results demonstrating seven major components of child ISS with their respective subcomponents/elements

Row	Components	Subcomponents/ elements

1	Goals	(1) to support injury prevention acts (2) to provide epidemiologic patterns of fatal injuries (3) to provide epidemiologic patterns of nonfatal injuries (4) to determine injury severity (5) to determine injury burden (fatal injuries) (6) to determine injury burden (nonfatal injuries) (7) to analyze fatal injury mechanism (8) to analyze nonfatal injury mechanism (9) to analyze fatal injury nature (10) to analyze nonfatal injury nature (11) to evaluate the effectiveness of injury interventions
2	Data sources	(1) emergency department (general hospitals) (2) emergency department (specialized hospitals with the priority of children hospitals) (3) population-based surveys (4) trauma registry (5) national death registry (6) 1-59 month children death surveillance (7) National Organization for Civil (8) Statistical Center of Iran (9) insurance companies (10) Ministry of Roads & Urban Development (11) police (12) forensic medicine

3	Data set	identifiers	(1) national ID number, (2) date of creation of the record, (3) hospital name
		demographics	(4) name, (5) date of birth, (6) gender, (7) address of residence place, (8) postal code, (9) race/ ethnicity, (10) education level, (11) occupation, (12) BAC
		time of injury related data	(13) date of injury/ death, (14) time of injury/ death, (15) date of visit, (16) time of visit, (17) date of examination by a doctor, (18) time of examination by a doctor
		place of injury related data	(19) injury place (home, outside of home, RTI, work, other, unknown), (20) if home, the exact place in home, (21) if outside of home, the exact place, (22) if RTI, the exact place, (23) if work, the exact place, (24) postal address of injury place
		injury characteristics	(25) body part, (26) external cause based on ICD-10, (27) injury nature based on ICD-10, (28) injury severity, (29) patient's outcome, (30) injury description (a free text field to describe what went wrong)
		injury context	(31) any involved products, (32) patient's activity at the time of injury (a free text field to describe patient's activity)
		safety equipment	(33) use of safety tools, (34) color of the clothes
		(35) injury intention	
		(36) costs	
4	Coalition of stakeholders	Members of the coalition	(1) Ministry of Health and Medical Education, (2) healthcare organizations/ hospitals, (3) forensic medicine, (4) police, (5) Ministry of Roads & Urban Development, (6) Plan and Budget Organization, (7) Ministry of Education, (8) Ministry of Science, Research and Technology, (9) State Welfare Organization of Iran, (10) Iranian Social Security Organization, (11) insurance companies, (12) NGOs, (13) Legislature of Iran, (14) the Executive (government), (15) Judicial System of Iran, (16) Iran Broadcasting Organization, (17) state governors, (18) mayors, (19) fire departments, (20) standard organization
		leadership of the coalition	(21) Ministry of Health and Medical Education

5	Data collection	ISS type	(1) comprehensive child ISS
		data collection method	(2) active including data collection by child ISS officers, (3) inactive including data collection by healthcare providers and facilities, (4) a combination of both methods
		data entry method	(5) paper- based, (6) electronic (off-line), (7) online
		case definition	(8) the first visit of one person
		data entry criteria	(9) International Classification of Disease- 10th revision codes including (S00-S99), (T00-T78), (V01-X59), (X60-X84), (X85-Y09), (Y10-Y34), (Y35-Y36) and other injury related codes
		data entry time interval	(10) Monthly data registration, as it needs at least a complete month to determine patients' final outcome
		classification	(11) International Classification of Disease- 10th revision
6	Data analysis and interpretation	indicators	(1) injury frequencies, (2) injury percentages, (3) injury rates, (4) injury rates in special groups, (5) adjusted injury rates, (6) Years Lived with Disability (YLD), (7) death frequencies, (8) death percentages, (9) death rates, (10) death rates in special groups, (11) adjusted death rates, (12) Years of potential life lost (YPLL), (13) Disability-Adjusted Life Year (DALY), (14) admission rates, (15) disability rates, (16) trends over time, (17) direct costs, (18) indirect costs, (19) costs payable to relatives, (20) geographical analysis using GPS data to create spot map, (21) area or choropleth map, (22) black spots
		analysis level	(23) national and (24) provincial

7	Data distribution	data distribution methods	(1) organizational newsletter, (2) newspaper, (3) mass media (TV and radio), (4) social media (face book, twitter, Instagram, etc.), (5) scientific papers published in journals and conferences, (6) educational leaflet and pamphlet in healthcare centers and hospitals for patients, (7) reports and governmental documents, (8) discussion of child injury data/ reports in meetings, (9) websites of related offices affiliated to Ministry of Health as well as coalition of stakeholders
		audience	(10) Ministry of Health and Medical Education, (11) healthcare organizations/ hospitals, (12) forensic medicine, (13) police, (14) Ministry of Roads & Urban Development, (15) Plan and Budget Organization, (16) Ministry of Education, (17) Ministry of Science, Research and Technology, (18) State Welfare Organization of Iran, (19) Iranian Social Security Organization, (20) insurance companies, (21) NGOs, (22) Legislature of Iran, (23) the Executive (government), (24) Judicial System of Iran, (25) Iran Broadcasting Organization, (26) the public, (27) journalists, (28) researchers, (29) fire department, (30) Standard Organization, (31) municipalities
		time intervals of reports	(32) weekly, (33) monthly, (34) quarterly, (35) every six months, and (36) annual reports based on the type of the audience

Figure 1 Modified Delphi process and the results of each round

Table 2 child ISS framework comprising 7 major components and 122 elements

Goals
(1) to support injury prevention acts
(2) to provide epidemiologic patterns of fatal and nonfatal injuries
(3) to analyze fatal and nonfatal injury mechanism
(4) to analyze fatal and nonfatal injury nature
Data sources
(1) prehospital emergency
(2) emergency department of general and specialized hospitals with the priority of children hospitals
(3) national death registry
(4) 1-59 month children death surveillance
(5) police
(6) forensic medicine
(7) fire department

(8) red crescent

Data set

identifiers	(1) national ID number, (2) date of creation of the record, (3) hospital name
demographics	(4) name, (5) date of birth, (6) gender, (7) address of residence place, (8) postal code
time of injury related data	(9) date of injury/ death, (10) time of injury/ death, (11) date of visit, (12) time of visit, (13) date of examination by a doctor, (14) time of examination by a doctor
place of injury related data	(15) injury place (home, outside of home, RTI, work, other, unknown), (16) if home the exact place in home, (17) if outside of home the exact place, (18) if RTI the exact place, (19) if work the exact place, (20) postal address of injury place
injury characteristics	(21) body part, (22) external cause based on ICD- 10, (23) injury nature based on ICD- 10, (24) injury severity, (25) patients' outcome, (26) injury description (a free text field to describe what went wrong)
injury context	(27) any involved products, (28) patient's activity at the time of injury (a free text field to describe patient's activity)
safety equipment	(29) use of safety tools, (30) color of the clothes

(31) injury intention

(32) parent's supervision

Coalition of stakeholders

Members of the coalition	(1) Ministry of Health and Medical Education, (2) healthcare organizations/ hospitals, (3) forensic medicine, (4) police, (5) Ministry of Roads & Urban Development, (6) insurance companies, (7) NGOs, (8) Legislature of Iran, (9) Iran Broadcasting Organization, (10) state governors, (11) mayors, (12) fire departments, (13) standard organization, (14) red crescent
leadership of the coalition	(15) Ministry of Health and Medical Education

Data collection

ISS type	(1) comprehensive child ISS
data collection method	(2) active including data collection by child ISS officers, (3) inactive including data collection by healthcare providers and facilities, (4) a combination of both methods
data entry method	(5) online
case definition	(6) the first visit of one person
data entry criteria	(7) International Classification of Disease- 10th revision codes including (S00-S99), (T00-T78), (V01-X59), (X60-X84), (X85-Y09), (Y10-Y34), (Y35-Y36) and other injury related codes

data entry time interval	(8) Monthly data registration as it needs at least a complete month to determine patients' final outcome
classification	(9) International Classification of Disease- 10th revision
Data analysis and interpretation	
indicators	(1) injury/ death frequencies, (2) injury/ death percentages, (3) injury/ death rates, (4) injury/ death rates in special groups, (5) adjusted injury/ death rates, (6) Years Lived with Disability (YLD), (7) Years of potential life lost (YPLL), (8) Disability-Adjusted Life Year (DALY), (9) admission rates, (10) disability rates, (11) trends over time, (12) direct costs, (13) indirect costs, (14) costs payable to relatives, (15) geographical analysis using GPS data to create spot map, (16) area or choropleth map, (17) black spots
analysis level	(18) national and (19) provincial
Data distribution	
data distribution methods	(1) organizational newsletter, (2) newspaper, (3) mass media (TV and radio), (4) social media (face book, twitter, Instagram, etc.), (5) scientific papers published in journals and conferences, (6) educational leaflet and pamphlet in healthcare centers and hospitals for patients, (7) reports and governmental documents, (8) discussion of child injury data/ reports in meetings, (9) websites of related offices affiliated to Ministry of Health as well as coalition of stakeholders
audience	(10) Ministry of Health and Medical Education, (11) healthcare organizations/ hospitals, (12) forensic medicine, (13) police, (14) Ministry of Roads & Urban Development, (15) Plan and Budget Organization, (16) Ministry of Education, (17) Ministry of Science, Research and Technology, (18) State Welfare Organization of Iran, (19) Iranian Social Security Organization, (20) insurance companies, (21) NGOs, (22) Legislature of Iran, (23) the Executive (government), (24) Judicial System of Iran, (25) Iran Broadcasting Organization, (26) the public, (27) journalists, (28) researchers, (29) fire department, (30) Standard Organization, (31) municipalities
time intervals of reports	(32) monthly, (33) quarterly, (34) every six months, and (35) annual reports based on the type of the audience, (36) ad hoc reports such as injuries on special occasions, national festivals, etc.

There are no comments yet.

A SIMULATION STUDY OF CORONAVIRUS AS AN EPIDEMIC DISEASE USING AGENT-BASED MODELING

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A Simulation Study of Coronavirus as an Epidemic Disease Using Agent-Based Modeling

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Abstract

At the end of 2019, the world faced the novel coronavirus, and with it fear of economic collapse and mass fatalities. Simulation systems can be used to monitor the behavior of the virus. Simulation provides an abstract representation of reality by conveying details and characteristics of reality in a simple application. One of the most important ways to simulate is agent-based modeling. The health information professional plays an important role in developing these models. In this research, we simulate the spread of COVID-19 in a region restricted to a population with specific demographic characteristics and social relationships. This study aims to clarify the effects of preventative techniques that suppress the spread of epidemics, such as quarantines, social distancing, and reduced mass transit.

Keywords: COVID-19, coronavirus, agent-based modeling, SIR model, epidemic diseases

Introduction

Coronaviruses are a large family of viruses that typically cause respiratory illnesses. COVID-19 is a zoonotic coronavirus, meaning it can transmit between and among humans and animals. Coronaviruses are often transmitted through the exudates or by contacting the surfaces of infected bodies and is often associated with colds, especially in the winter season.[1]

Prior to 2019, two types of coronavirus caused serious epidemics. The first was the 2002-2004 outbreak of severe acute respiratory syndrome (SARS), caused by the SARS-CoV strain, which infected 8,000 and killed 774 in 29 countries. The second major outbreak was caused by Middle East Respiratory Syndrome (MERS-CoV), which was first discovered in Saudi Arabia; in the initial outbreak, 1,841 people were infected and 652 died.[1]

In December 2019, cases of acute pneumonia were detected in a wet market in Wuhan, the capital of the Hubei Province, with a population of 11 million. On January 7, 2020, a novel coronavirus—later named COVID-19—was identified, and the first death was recorded.[2]

The new strain belongs to the extended family of coronaviruses, which includes six strains that target the human respiratory system. The incubation period for this virus is believed to be two to 14 days.[1]

COVID-19 mainly threatens people managing chronic respiratory diseases with a weakened immunity, and the elderly. It is transmitted through close contact with the infected person. It is also transmitted with droplets or aerosol. Symptoms of the disease include shortness of breath, coughing, headache, acute pneumonia, in addition to a fever, which is one of the most common symptoms.[3,4]

By the middle of May 2020, the world began talking about 4.5 million infections and half a million deaths but to some extent, there are also nearly 2 million recovered cases and the largest number of the infections exist in the USA.[2]

Figure 1 illustrates the number of cases distributed around the world until May 22, 2020, as taken from the "worldometers.info" website2, figured using Tableau software.[5]

Computer models can provide comprehensive insight into the behavior of disease outbreaks by simulating the spread of infections over populations with different geographic and demographic characteristics.[6] Computer models can improve the representation and understanding of complex social structures with real-world communication networks that decide the dynamics of transmission, which in turn will be cost-effective as compared with real-time experiments.[7]

One of the most reliable modeling approaches is agent-based modeling, which is a method that can deal with advanced modeling and simulations related to pandemics. Pandemic agent-based modeling re-creates the entire population and its dynamics by the integration of social systems, the heterogeneous fashion of interactions and communities on a single person's level.[8]

Agent-base modeling simulates a real-time environment (organized system) in an abstract representation, where the main element in this system is the agent (e.g., person, virus, first responders, etc.). The second main element in the model is the factors of each agent, which represent the agent's characteristics and they are usually taken from real-time experiments (facts about the nature of agents). The third element is the links between agents that work by the values of the selected factors (e.g., a virus infects a person whose respiratory system is compromised by another chronic respiratory condition, such as COPD). And finally, all these elements must be behaving in a predetermined environment.[9,10] There are many applications for agent-based modeling. However, in this work, we are limited to the epidemic applications.

One of the most prominent mathematical agent-based models is the Susceptible-Infectious-Recovered (SIR) model, which is based on ordinary differential equations.[11] The model assumes that all the people inside the community are initially equally susceptible to be infected by the virus and that they will have a seasonal immunity after recovery once the infection subsides.[11]

In this study, our main aim is to extend the SIR model to COVID-19 and its factors such as age, gender, smoking status and isolation tendency. Our contribution starts with collecting data about

Coronavirus as it is still a novel virus with unknown behavior since the way of getting infected is still unpredictable and unknown. Additionally, the severity of the disease is heavily dependent on the person's age and health status. We also aim to study the effect of the controlling procedures to limit the epidemiological effect over closed populations. This paper is structured as follows: the second section lists the most related works about the epidemic disease simulations with agent-based modeling. The third section provides the proposed model, and model validation. Section four talks about the epidemic controlling procedures that might be undertaken. Experiments and results are discussed in section five. And finally, section six provides the conclusion of this work.

It is also important to point out that health informatics and information management professionals should work closely with epidemiologists, computer scientists, and biostatisticians to examine pandemics and epidemics using agent-based modeling. It takes a team with different subject matter expertise to examine this pandemic from all perspectives that involve data, computer systems, and population health.

Related Works

One of the most popular agent-based models is the BIOWar, which is a computer model that consists of many computational models for diverse types of environments such as social networks, epidemic disease transmission, weather forecasting, urban areas and the effects of bioterrorist attacks.[12] BIOWar is also one of the models that adapts the SIR model and uses its main concepts to build its model.

Ge et al., studied H1N1 influenza inside an artificial classroom, in which the agents are students and teachers.[13] This study considers that there exist some social relations between students and they have some common paths of movement and contact with others. The features they included in their study were age, gender, immunity, and agent activity inside the social network.

Khalil et al., studied H1N1 influenza in 1,000 individuals in an Egyptian society.[14] They have analyzed the Egypt census data of 2006, where they determined the distribution of the population based on the census records. They also considered the social relations based on the person's social types (e.g., sibling, child, other families, coworker, etc.). They combined multiple features, including those for the environment, human interactions, and disease characteristics. They adopted the SIR model and customized it to have many more categories for the agents such as (S) Susceptible, (C) in Contact, (E) Exposed, (I) Infectious, (Q) Quarantined, (NQ) Not Quarantined, (D) Dead, (R) Recovered, and (M) Immunized. Unlike Ge, et. al, they selected the contact to be random.[13]

Another study on the H1N1 was presented by Luo et al.[15] This study built an artificial society of a town with a population of 1,500 people considered as agents, to study the propagation rules. The model focused on public transportation as being a high-rate infection area with densely connected agents and movements. They performed experiments with several cases, such as the lack of people's actions, the closing of major places, and epidemic control surveillance.

The spread of influenza virus infection was simulated in a hospital Emergency Department in Winnipeg, Canada, by adapting the SIR model.[16] Researchers divided the agent's types into patients and healthcare workers and inanimate objects (e.g., chairs) that can transmit the virus. The collection of features they used were a group of topography, agent characteristics, behaviors, and interactions. Their method is different than others as the agent moves inside the model in predetermined actions in a circular order controlled by the random arrival of patients.

Also, Hackl et al.,[17] studied the spread of influenza within mass transit systems in Zurich, Switzerland. Their main agent included individuals who move inside the transit system. They used basic socio-demographic data, housing locations, and the activity schedule for each of these people. In contrast to other research, they did not consider the effects of the vaccination existence, immunity, virus incubation periods, age distribution, and gender.

Chickenpox (varicella-zoster virus), also considered an epidemic virus, was studied by Rafferty et al.[18] This study was conducted in an urban center and rural regions in Alberta, Canada. The authors used a wide range of properties for the model, including population size, mortality and fertility rates, initial cell-mediated immunity, force of reactivation, duration, probability of infection, connection range, and others.

EpiSims is an agent-based simulation tool that studies the population movability based on the census of people using a set of parameters to simulate the progress of the transmission of an epidemic disease between the infected and susceptible people.[19] It has been built based on the Transportation Analysis and Simulation System (TRAN- SIMS).[20]

TRANSIMS is a model built to predict the social networks of the population by assuming that the transportation infrastructure controls people's intentions regarding where or when to carry out their activities. EpiSims was applied to Portland, Oregon, where people are carrying out their activities such as, studying, working, or shopping and they are moving between several locations and thus exposing themselves to various viral infections.

Proposed Model

In this study, we extend the SIR model and propose an agent-based model to simulate the spread of COVID-19 in an urban area. The environment that we are studying is two urban neighborhoods separated by crossings (A and B), where there are many options for movement and communication between people in both regions. Also, there are two groups of people, represented in either squares or circles, and are geographically divided by a border. These individuals are randomly moving around their environment.

The individual's health status is represented by the colors of agents. We used four colors: white is uninfected, red is infected, green is recovered, and blue are immune. When a person is recovered, it is permanently immune to the virus. The other type of agent we have is the health official or ambulance worker, symbolized by yellow, who patrols the environment for people who are ill. Once a person comes in contact with an infected agent, the ambulance will immediately deliver the infected person to the hospital inside his region of residence. An illustration is provided in **Figure 2**.

SIR Model Extended

We used the SIR model as a base model to develop our proposed agent-based model, by extending extra states of the agents to be more realistic and related to the characteristics of COVID-19. Also, we used random distribution for the movements between agents and then the infection would be random. The agents traverse a series of classes showing the states of the disease over the infection duration. In the declaration of the state's classes, we followed the model presented by Khalil et al.,[14] where they also adapted the SIR model. The first class is Susceptible (S), which is the state of the person that is not in contact with other people in the environment and each person is initialized to this class with a 0.1 probability to be infected.

The second class is Contact (C), where people are in contact with each other, randomly or in predetermined links. Since the infection is controllable with a percentage, we will assume that the next state of the agent after the contact will remain Susceptible (S) or will become Infected (I) based on that infection chance, which basically depends on the immunity level of the person.

After that, if the infected individuals are still moving around and contacting the other susceptible people, they also will be exposed to the danger of being infected. Hence, there must be a controlling procedure by quarantining the infected individuals driven by a probability of isolation tendency.

In this state, the types of class would be Quarantine (Q), which is divided into two types (at the hospital or at home). And in case the person is not quarantined, his class would be Non-Quarantine (NQ). If people are not quarantined, they would not have adequate health care, so they would be exposed to the danger of death and their classification would be (D). People who have been quarantined in hospitals are assumed to have perfect healthcare, and they are expected to recover from the disease five times faster than people who are quarantined in their homes.

If people have finished the quarantine period with a high recovery chance, they will move to the Recovered (R) class. This recovery chance depends on the demographic properties assigned randomly to the individuals. At the end of the infection period, the person will recover from the disease and become a cured person with a state class named Cured (Cu). **Figure 3** presents the chart of our proposed model, and **Figure 4** illustrates the sequence flow chart.

Our model reflects the behavior of a group of people with various characteristics, such as gender, age, immune ability, and smoking, who live in a closed area.

There are two types of agents. The first is ordinary people. The other is the paramedic. The characteristics mentioned above are randomly distributed to all people, while the paramedics have no specific characteristics since they are considered immune assuming they wear personal protective equipment (PPE) that prevents them from contracting the virus. In our model, we study the behavior of normal people. So, we excluded the paramedics from our model and we just added them to accelerate patients' transmission to hospitals and to prevent people's contact while transmission to hospitals. Therefore, we expect that the paramedics are not going to be infected, as we are studying the behavior of the people not the medical staff. The environment contains a certain number of randomly distributed residents who move in a period of time, measured in days, to suit the average period of the disease.

The ordinary individuals in this model could fall into many different categories listed as follows:

- Infection chance: probability that the disease would be transmitted from one individual to another.
- Recovery chance: probability of an individual to recover once the infection period ends.
- Average recovery time: the time needed (on average) for an individual to The actual individual's recovery time is pulled from a normal distribution centered around the average recovery time at its mean, with a standard deviation of a quarter of the average recovery time in days.
- Average isolation tendency: the average tendency of individuals to isolate themselves and to not spread the infection.
- Average hospital tendency represents the average tendency of a person to go to a hospital when sick. If the infected individual is predefined as a "hospital goer", then he will be isolated in the hospital, and the recovery time is half the time of the normal average recovery period because he will get better medication and
- Cured: probability of the person to get better and be healthy, and hence be immune from the virus infection again.
- The number of males
- Smoking percentage
- Mortality rates: from Meters et al.[2] and being normalized into proportions consistent with the population on which our model was applied.

In addition, there are two conditions that might be used to control the behavior of the model, the first one is the" LINKs", and when this option is ON, there will be random links to represent the social network of individuals. In this case, the disease will spread twice as fast. However, when the option is OFF, then the disease will spread with equal probability between people who are moving around. The other condition is the "TRAVEL", when this option is on, then the people can travel between the two separate regions and the population will be mixed. There is also the Travel Tendency feature, which will be active when the Travel option is turned on. This feature indicates 1 percent of individuals to travel per each unit of time.

Model Validation

Often, because of the lack of reliable field data and the lack of the real position of the individual cases, epidemiological modeling is very difficult to verify. Hence, we adopt the SIR model to develop and validate our proposed model because it has solid mathematical assumptions and has been validated for many real epidemic scenarios.

We have validated our proposed model by experimenting with the same parameters on both the SIR model and our model. Then we aligned the plot that resulted from both of them to check the behavior for each of the disease types: Susceptible, Infected, and Recovered.

Khalil et al.[14] used Mathematica[21], which is a computer program widely used in the fields of mathematics, engineering, and various sciences, to simulate the SIR model with the following variables: duration of infection=15 days; initial immune=0; and initial infection chance=0.01.

Results are shown in **Figure 5**. The original SIR model[11] showed that same behavior in **Figure 6**. The same values of the previously mentioned parameters were used in our proposed model, assuming that there is no quarantining. Results are shown in **Figure 7**. We can notice that the three behaviors are not perfectly matched, but at the end, our model matches the general behavior of the SIR model.

We can hypothesize that the difference is related to (a) the different allocation of community demography information such as sex, age, and smoking and (b) the random variable allocation for the infection time which is the infection chance where the SIR model uses deterministic values. We can also notice that in our model, the number of non-infected people starts to increase after a while because we are adding them back to the (not infected counter).

Epidemic Controlling Procedures

Suppression procedures are often applied to control epidemic diseases, but only after the disease reaches the highest level of outbreak. This would bring chaos among individuals, especially after a large number of deaths and this is what we are seeing across the world today with COVID-19.

Therefore, a course of events should be predicted in epidemiological situations to ensure the control of the situation before reaching a high peak of the outbreak. One of the most important methods of this control is to quarantine infected patients inside their homes or in private hospitals.

Additionally, it also is preferable to reduce the movements resulting from the behavior in the practical life or the social life network where uninfected persons are required to limit their relationships and movements to ensure that no infection is transmitted to them. In the worst cases, people of a particular city or neighborhood are required to remain within the range of their city and not move to other cities and preventing other individuals from other cities to enter. Furthermore, people who are at risk of infection (susceptible) are advised to exercise healthy habits that increase pathological resistance (immunity) such as adequate sleep, exercise, and smoking cessation.

Experiments and Results

In this study, we focus on the controlling strategies that could be taken during epidemic situations. We have built multiple scenarios in our model using NetLogo software to simulate the effect of each strategy.[22] The population we used is 1,000 persons and the infection chance is 25 percent (this means each person has a chance less than or equal to 25 percent of contracting the virus based on their immunity), recovery chance is 25 percent, average recovery time is 15 days, intra-mobility (movements inside the city range) is 60 percent, the ages were randomly distributed, and smoking was also randomly distributed.

The controlling strategies include:

- Applying the model without any controlling procedures and without considering any relationships between people or traveling between the two regions
- Applying the model with average isolation tendency = 10 percent
- Applying the model with an average hospital going tendency = 10 percent
- Applying the model with adding a cured chance = 20 percent
- Applying the model with employing the paramedics = two persons
- Applying the model with relationships between people (a)without applying controlling procedures, (b)with applying controlling procedures
- Applying the model with allowing the travel between the two regions with travel tendency

= 60 percent%, (a)with links, (b)without links, (c)without controlling procedures

The results of the scenarios are plotted and listed in Figures 8-14. We notice from the plots that the peak of the infection changes based on the application of the controlling strategies. Also, as controlling strategies are implemented, the epidemic duration is decreased.

For Scenario 1 (**Figure 8**), the peak of the epidemic started early from day number seven. Since the values of the parameters are random, we conducted the experiment five times and noticed that the values are very close. The number of deaths was between 100 and 150, where we can predict that poor controlling of such a disease can yield high mortality rates.

In the second scenario, shown in **Figure 9**, we did the home isolation option by 10 percent, the peak of the infection was on the tenth day, which means that it has reduced the prevalence of infection with comparison to the first scenario. The number of deaths did not diminish too much, but it ranged between 100 and 120 people.

The third scenario (**Figure 10**) was about adding both home and hospital isolation with 10% each. The peak of the infection was also on the tenth day since we did not alter the basic parameters of the model. This experiment was to check the effect of hospital isolation, where we suppose that the healthcare provided in the hospital is better than home isolation, as it limits the person's communication with his surroundings completely, to reduce the spread of infection. The number of deaths was reduced to the range of 90 to 100.

For the fourth experimental scenario (**Figure 11**), we assumed that people have been cured and they are safe from being infected again with a chance of 20 percent. We noticed that the peak of infection was on day five, but with a lower number of infections. The number of deaths was also reduced to 75 to 95. We tried to increase the immunity for 25 percent, 30 percent and so forth, and we found that the number of infections and deaths decreased.

In the fifth scenario (**Figure 12**), we added the possibility of ambulance personnel transporting infected people to hospitals. This will accelerate the process of transferring patients to the hospital, in addition to reducing the infection rate, as ambulance personnel are designed in this model, so that they would be isolated with PPE from infection. The number of deaths was decreased at a tiny level but still in the same range of scenario four.

The sixth scenario was to apply the LINKs option, which indicates the relationships among the community. First, we applied these links without applying controlling procedures (**Figure 13 a**), then with controlling procedures in place (**Figure 13 b**).

The first try resulted in epidemic, where the rise in infection occurred on the sixth day, as the number of infected people at that time was more than half of the community, and the number of deaths rose to 150.

This situation looks like the first scenario with more rapid infection spreading related to social network interactions. The second part of this experiment was much less dangerous than the first, because the necessary precautions—isolation and the presence of ambulance personnel—are in place. The number of infected people also reached its peak on the sixth day, but with fewer infections, so that the largest number of infections was up to 423, and the number of deaths decreased to 85 to 95.

The final scenario allowed travel between both regions and applied controlling procedures on people traveling. The first experiment was to allow the traveling between two regions with applying the LINKs and with the existence of the controlling procedures. This situation means that people from region A will contact people from region B whom they linked with only. This assumption can let us predict that the mobility would not be chaos, but it will be directed by the social network between the two communities. In this experiment the peak of the infection was on day seven, the number of infections was about 450 cases only 75 to95 out of them have died (**Figure 14a**). The second experiment was to allow the mobility but without links limits, which means that the people will move between the two regions in a total random chaos but with controlling procedures. The peak of infection was on day six, the number of deaths was around 70 to 90 people (**Figure 14b**). The third experiment was to study the community with traveling but without links or controlling procedures. The situation was totally epidemic, where the number of infections was more than 50 percent and the number of deaths was around 200 (**Figure 14c**).

Discussion

We have discussed the mechanisms for controlling epidemiological conditions. Through the results that we obtained for multiple scenarios and after repeating every scenario more than five times, we found that the implementation of isolation policies can result in significant reductions in death rates.

In addition, the process of separating people and limiting their social relations can lead to a clear effect of reducing the infection rates in society. Mobility ratios also have an impact on the spread of infection, whether it is going only according to social proximity or a random way. And we have noticed that the failure to take preventive measures can cause a rapid increase in the spread of the infection, as we are seeing in some countries across the world.

Countries are now heading to apply difficult coercive measures to cities and urban residents, at the peak time of the spread of the disease. This behavior is correct, but it must be taken in the necessary time so that the peak of spread can be controlled before reaching the stage of the outbreak and the high death numbers, which is the goal of simulation models.

Health informatics and information management professionals can aid in the early detection of such outbreaks since they are the ones dealing with health data every day. As health information professionals scour the electronic health record, they can establish trends in clinical documentation, coded data, and quality measures that can relate to signs and common symptoms of the virus. All of this information is used in building the agent-based modeling that was previously described. Health information professionals, working with other members of the healthcare team can be at the epicenter of pandemics since they have data at their fingertips that is crucial to building simulation models that can be used to slow the progress of a devastating illness such as COVID-19.

Conclusion

In this work, we studied COVID-19 on a closed community using agent-based modeling. We matched the details of the model with the current status of the disease, considering that there is some ambiguity in the details of this disease as the infection rate varies from one country to another and from one community to another. We did an extension of a mathematically proven basic model (SIR) so that we added other scenarios to the model to represent the stages of disease transmission, infection, and recovery. The main contribution of this work lies in reviewing the main data of the disease and in representing the results of the controlling measures in cases of the spread of epidemic diseases, such as COVID-19. We also found that health information professionals working with epidemiologists, computer scientists, and statisticians can aid in the development of the simulation models by providing accurate data to assist in the development of such models. Finally, we found that staying home and hospital isolation policies, in addition to preventing travel between cities, will reduce the prevalence and thus reduce the deaths.

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SIMILARITIES AND DIFFERENCES BETWEEN RURAL AND URBAN TELEMEDICINE UTILIZATION

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Similarities and Differences Between Rural and Urban Telemedicine Utilization

By Lincoln R. Sheets, MD, PhD; Emmanuelle Wallach, MS; Saif Khairat, PhD, MPH; Rachel Mutrux, BA; Karen Edison, MD; and Mirna Becevic, PhD

Abstract

Telemedicine has traditionally been used in rural areas, but the recent development of mHealth solutions has led to a growth in urban telemedicine services. The aim of this study was to determine whether urban and rural patients in a large academic medical center use telemedicine to access different healthcare specialties at different rates. This retrospective cohort study examined all telemedicine visits dated 2008-2017 at a large academic medical center. Visits were classified by clinical specialty. Teledermatology, child telepsychiatry, and adult telepsychiatry made up 97 percent of telemedicine visits.

Rural patients were more likely to have multiple telehealth visits. A significant difference was observed between rural and urban use of telemedicine, both in terms of specialties and demographics. This suggests that health systems should consider adjusting resources and training to meet the different needs of these two populations. In particular, telemedicine may offer help for the nationwide maldistribution of adolescent psychiatry providers.

Keywords: Telemedicine, rural health, urban health, healthcare disparities

Introduction

For more than 30 years, telemedicine has been used as a platform that supports patient-centered care, bringing the care to the patient's location and supporting local economic development. Telemedicine has traditionally been used in rural areas, because of its obvious advantages in reducing unnecessary travel and improving access to specialty care for patients from underserved regions.[1] In fact, a recent study found family physicians practicing in rural areas were twice as likely to refer their patients to use telemedicine as their urban counterparts.[2] However, telemedicine use is not limited to rural areas; though less widely advertised, a few telemedicine programs focus on underserved urban populations.[3]

At the same time, recent rapid development of eHealth, or "organization and delivery of health services and information using the Internet and related technologies"[4] and mHealth, or "medical and public health practice supported by mobile devices",[5] solutions has supported the growth of urban telemedicine services. The convenience of disruptive technologies, such as easy-to-use video-conferencing applications, will likely reduce the differences between telemedicine utilization in rural and urban areas in the near future.[6] It has been suggested that telemedicine and eHealth can help reduce geographic disparities in the treatment of mental illness[7] and diabetes.[8] However, a better understanding is needed of how specific telemedicine services are used by rural and urban patients, and if certain specialties have higher utilization rates than others. This information can be used for better resource allocation and a more data-driven approach to improving access to care.

The University of Missouri (MU) Missouri Telehealth Network (MTN) has been providing telemedicine services to Missourians since 1994. With more than 100 telemedicine sites across the state, its mission is to improve access to care for all Missourians and provide distant live-interactive continuing medical education for clinicians. The MTN also provides operational, legal, regulatory and research support to telemedicine sites, and conducts program evaluation and research.[9]

Missouri faces a serious healthcare crisis: a recent America's Health Rankings report positioned Missouri 39th out of 50 states in the assessment of the nation's health.[10] Some of the challenges indicated in this report are high prevalence of frequent mental distress, and increased rates of obesity, diabetes, and sexually transmitted diseases.[10] However, Missouri is also ranked 36th in the country on measures of access to care.[11,12] A primarily rural state (over 97 percent of land is considered rural)[13], Missouri's barriers to access to care are hardly limited to geographic isolation. High poverty rates, coupled by strong community norms (such as stigma for mental health and psychiatric care) affect how and where Missourians seek medical care maybe even more so than their physical location or geographic isolation. The aim of this project was to study differences in telemedicine use between rural and urban patients when accessing healthcare specialties. In addition, we wanted to learn more about telemedicine patient demographics, in terms of age and sex.

Methods

Data collection

University of Missouri Health Care (UMHC) has been a leader in providing telemedicine services to patients from all over Missouri for more than 20 years. Centrally located, the UMHC's team approach to comprehensive medical care supports its mission to save and improve lives, and serve as Missouri's premier academic health center.[14] With only three metropolitan areas with large medical centers in the state, Missouri has no counties classified as 100 percent urban, and over 97 percent of the land area is classified as rural.[13] UMHC conducted a retrospective cohort study to help highlight the differences between rural and urban patient usage of telemedicine services by UMHC over the past ten years. IBM Cognos/Analyzer (https://www.ibm.com/products/cognos-analytics[15]) was used to access de-identified telemedicine claims data from January 1, 2008, through December 31, 2017. These were provider-submitted claims that did not discriminate by insurance type or ability to pay, and included every telemedicine visit through an UMHC location during the ten-year study period.

The following data points were collected:

- Provider location and date of visit
- Provider name and specialty
- Patient ZIP code (to classify subjects as rural or urban)
- Patient age and gender
- Primary diagnostic code (to identify the purpose of the visit)

The Federal Office of Rural Health Policy (FOHRP)'s definition of rural locations was used to classify patients by their ZIP code.[16] The visits were categorized according to provider specialty:

- Teledermatology (including dermatopathology)
- Child telepsychiatry visits that involved patients up to age 21, and general telepsychiatry visits that involved patients younger than 18 years of age
- Adult telepsychiatry visits that involved patients 18 years of age or older
- Other: other specialties that provided telemedicine services (anesthesiology, child development, endocrinology, family practice, neurology, orthopedic oncology, pediatric hematology/oncology, vascular surgery), which comprised less than 5 percent of all visits

Data Analysis

The following were computed for each classification: the mean age of patients at the time of visit, the proportion of male patients, the proportion of patients in a pediatric (0-17 years old), adult (18-64 years old), and elderly (65 years old and older) cohort, as well as the mean number of visits and mean number of diagnoses for each patient. The numbers for rural and urban were then compared via two-sample hypothesis tests using the Z-test for means and proportions and the F-test for variances. Variances were compared before means to ensure that the correct test statistic was used; the sample sizes were all large enough for the Z-test. We report both the confidence intervals (CI) and *p*-values. This analysis was conducted in Excel (https://products.office.com/en-us/excel).

In addition, the analysis included a multinomial logistic regression, with the specialty as the outcome, and three predictor variables: gender (male or female), location (rural or urban), and age at time of visit (a continuous variable). This was supplemented with logistic regressions looking at binary outcomes: teledermatology or not, child telepsychiatry or not, adult telepsychiatry or not, and telepsychiatry or not telepsychiatry (without age restrictions). A regression analysis looked at the effect of gender, location, and age at time of visit on the number of visits and diagnoses per patient. STATA (www.stata.com) was used for these analyses.

Ethics Approval

Institutional Review Board approval was obtained from the University of Missouri Institutional Review Board.

Results

A total of 2,198 unique patients used telemedicine services during the study period. Of those, 1,420 (65%) were from rural areas, and 778 (35%) were from urban areas. The total number of visits was 5,411, with 3,582 (66%) from rural areas and 1,829 (34%) from urban areas (**Figure 1** and **Figure 2**). Interestingly, rural inhabitants make almost 37 percent of the total Missouri population, which implies that rural patients were almost four times as likely to utilize telemedicine services as their urban counterparts. Only 18 patients came from outside Missouri: six from rural areas in neighboring Kansas, Iowa, and Oklahoma; and 12 came from urban areas.

Telepsychiatry had the highest number of total (3,365, or 63.5%) and unique visits (1,061, or 48.3%), **Table 1** and **Table 2**. The second-most-used specialty was teledermatology, with 1,824 (33.7%) visits and 1,062 (48.3%) unique patients. Child telepsychiatry, adult telepsychiatry, and teledermatology combined to make up 97 percent of all visits. Another 1 percent of visits were for telemedicine visits for "opioid dependence in remission." The remaining 2 percent of visits were telemedicine visits for surgical follow-up, chronic pain, autism, and other conditions. **Figure 3** shows the distribution of unique patients by age, gender, and specialty.

Rural vs. urban populations

Overall, the rural patient population was older than the urban population (average age of 31, and 95% confidence interval , in rural areas, and average age of 21, and 95% CI , in urban areas; $p < 0.001$) and had a larger proportion of females than the urban population (45% female, and 95% CI , in rural areas, and 35%, and 95% CI , in urban areas; $p < 0.001$). The difference between rural and urban areas in the proportions of pediatric, adult, and elderly patients was significant (respectively, 39% (95% CI), 48% (95% CI), and 13% (95% CI) in rural areas, and 66% (95% CI), 30% (95% CI), and 4% (95% CI) in urban areas, with $p < 0.001$ for all three proportions). A significant difference was also observed in the proportion of unique patients using teledermatology, child telepsychiatry, and other specialties (respectively, 64%, 95% CI , 21%, 95% CI , and 3%, 95% CI , in rural areas, and 20%, 95% CI , 58%, 95% CI , and 5%, 95% CI , in urban areas, with $p < 0.001$ for teledermatology and child telepsychiatry and $p = 0.002$ for other specialties). **Figure 4**.

Analysis showed a significant difference between rural and urban areas in the proportion of total visits in teledermatology (44% of rural visits, 95% CI , and 13% of urban visits, 95% CI , with $p < 0.001$), child telepsychiatry (35% of rural visits, 95% CI , and 72% of urban visits, 95% CI , with $p < 0.001$), adult telepsychiatry (19% of rural visits, 95% CI , and 11% of urban visits, CI , with $p < 0.001$), and other specialties (2% of rural visits, 95% CI , and 4% of urban visits, 95% CI , with $p < 0.001$). Regressions of the number of visits or diagnoses per patient show a significant effect ($p < 0.001$) for specialty and location, but not for age or gender.

Predictors of Telemedicine use

The results of the multinomial logistic regression (**Table 3**) indicate that location, rural or urban area, is a significant predictor of the patient's use of a telemedicine specialty ($p < 0.001$). More specifically, the results of the binary logistic regressions, summarized in **Table 4**, and specifically the odds ratios, suggest that, all else being equal, i.e., for a patient of the same gender and age, the odds of an urban patient using teledermatology, as opposed to another specialty, are 84 percent lower than those of a rural patient (the 95% CI of the odds being , which does not include 1, with $p < 0.001$); the odds of an urban patient using child telepsychiatry, as opposed to another specialty, are 451 percent, or 5.5 times greater than for a rural patient (the 95% CI of the odds being , with $p < 0.001$); the odds of an urban patient using adult telepsychiatry, as opposed to another specialty, are 106 percent greater than for a rural patient (the 95% CI of the odds being , with $p < 0.001$); and the odds of an urban patient using telepsychiatry, child or adult, as opposed to another specialty, are 415 percent greater than for a rural patient (the 95% CI of the odds being , with $p < 0.001$). In summary, controlling for age and gender does not remove the effect of residency in an urban or rural area.

Although the proportion of males differed significantly between rural (55%) and urban (65%) patient populations, with $p < 0.001$, this was not reflected in the proportion of males for any individual specialty. (**Figure 5**) Throughout both urban and rural Missouri, males tend to outnumber females in the younger age groups, and females tend to outnumber males in the older age groups.[17] However, even as the observed rural patient population skews older and contains a higher proportion of females overall, the binary logistics regression indicated a significant (odds ratios of 0.448 for dermatology, with 95% CI , and 3.968 for child psychiatry, with 95% CI , and $p < 0.001$) effect of being male on the choice of specialty, even when controlling for age and location. This was not true in the case of adult psychiatry (odds ratio of 0.955, with 95% CI , which does contain 1, and $p = 0.743$).

The mean age of rural patients was 31 (95% CI); the mean age of urban patients was only 21 (95% CI), a statistically significant difference ($p < 0.001$). (**Figure 6**)

Rural patients are also less likely to be younger than 18 (39%, 95% CI , in rural and 66 percent, , in urban areas, with $p < 0.001$), more likely to be between 18 and 64 (48%, 95% CI , in rural, and 30 percent, 95 percent CI , in urban areas, with $p < 0.001$), and much more likely to be at least 65 (13%, 95% CI , in rural, and 4%, 95% CI , in urban areas, with $p < 0.001$).

In teledermatology, the difference in the proportions of rural and urban patients was significant only for pediatric (respectively 29% and 95% CI for rural patients, and 43% and 95% CI for urban patients, with $p < 0.001$) and elderly patients (respectively 19%, 95% CI , and 7%, 95% CI , with $p < 0.001$), but not for the proportion of adult patients (respectively 52%, 95% CI , and 50%, 95% CI , with $p = 0.38$). The mean age of patients also differed significantly for rural and urban teledermatology patients ($p < 0.001$), with a mean age of 40 (95% CI) for rural teledermatology patients and 25 (95% CI) for urban ones.

For child and adult telepsychiatry and other visits, there was no significant difference between the proportions of rural and urban patients in each age group, although the mean age of patients differed significantly between rural and urban areas for child telepsychiatry (respectively mean 13.0, 95% CI and mean 15.6, 95% CI , with $p < 0.001$).

The mean and maximum number of visits (Figure 7) and diagnoses were computed for each patient. While the number of visits ranged from a single one to 28, only a few patients, mostly rural, had a large number of visits, and the average number of visits ranged from 1.72 for teledermatology to 3.38 for child telepsychiatry. The mean number of visits per patient differed significantly between rural and urban populations only for adult telepsychiatry (3.87 rural mean visits, with 95% CI , and 1.56 urban mean visits, with 95% CI ; $p < 0.001$). Similarly, the number of diagnoses per patient ranged from a single diagnosis to twelve diagnoses, but is comparable for rural and urban patients, with the exception of adult psychiatry, where the maximum number of diagnoses was twelve for rural patients versus only four for urban. The average number of diagnoses ranged from 1.27 for specialties other than teledermatology or telepsychiatry to 1.97 for child telepsychiatry. The number of diagnoses per patient differed significantly between rural and urban populations only for adult telepsychiatry (1.94 rural mean diagnoses, with 95% CI , and 1.26 urban mean diagnoses, with 95% CI ; $p < 0.001$).

Discussion

This study investigated the differences in telemedicine use between rural and urban settings. More than 30 percent of the Missouri population, or about 1.8 million people out of nearly 6 million, live in rural areas.[18] This study found that a rural resident of Missouri is 4.2 times as likely to use telemedicine as an urban Missourian, which is consistent with the literature.[2]

Rural and urban populations were found to use telemedicine differently: at different rates (more than four times as much for rural populations) and for different specialties (for teledermatology and child telepsychiatry, the difference between rural and urban areas was significant in both unique patients and total visits; for adult psychiatry, the difference between rural and urban areas was significant in total visits but not in unique patients; in the “other” category, we observed no significant difference in either total number of visits or in number of unique patients). Overall, rural use involved older patients (13% of rural patients were older than 65, compared to 4% of urban patients) and was concentrated in teledermatology (64% of patients and 44% of visits), while urban use involved younger patients (66% of urban patients were younger than 18, compared to 39% of rural patients) and was concentrated in child telepsychiatry (58% of unique patients and 72% of visits). These findings concur with a recent study of telemedicine utilization by rural and urban veterans, which also found that rural veterans are more likely to access mental health care via telemedicine than their urban counterparts.[19]

Missouri's population is like most states: a sustained growth shows a 21 percent increase over the population in 2000.[20] In addition, older adults (45-64 age group) and the elderly (65 and older) populations have increased more significantly than other groups due to increasing longevity, which is transforming population demographics of the state.[21] Our findings, however, are consistent with the trends in population, with emphasis on older rural and younger urban telemedicine users.

Missouri is also sparsely populated state, with only three large cities with specialty medical centers.[20] Most of the specialists practice in major metropolitan areas, and a recent report indicates that only 10 percent of physicians practice in rural areas.[22] With this in mind, some of the observed trends in this report are expected, but the extent of child telepsychiatry use, especially in urban areas, was surprising. Anecdotal evidence suggests that parents rely on telepsychiatry to spare their children the stigma of being seen at a psychiatrist's office. There is no evidence in the literature on cultural norms and stigma around in-person versus child telepsychiatry services, and we suggest more studies focus on this challenging issue. The reason for rural telemedicine use, however, seems more directly linked to a dearth of specialty providers within a reasonable distance.

Our main finding was that an overwhelming majority (97%) of all telemedicine visits were for teledermatology and telepsychiatry. These specialties do lend themselves to telemedicine, since they rely on visual observation (dermatology) or conversation (psychiatry), with a reduced need for physical examination of the patient. This may also be due to the drive and dedication of the dermatology and psychiatry departments at UMHC, and enthusiasm for telemedicine by their respective professional associations.[23,24] In any case, telemedicine may offer help for the critical nationwide shortage of adolescent psychiatry providers in rural and urban areas.[25]

While the researchers were able to have access to the entirety of telemedicine visits with UMHC providers over ten years, this still amounted to only 5,411 visits; the system sees this many in-person ambulatory visits in two days. Note that Missouri has three urban areas with major hospitals: UMHC in Columbia, in the center of the state; and large hospital systems in Kansas City to the west, St. Louis to the east. The map in **Figure 2** shows telemedicine utilization from the Columbia academic hub.

We recommend that future studies compare these results with outreach efforts undertaken by the specialist clinics, to test whether different specialties targeted different originating sites. Other hypotheses that remain to be tested are whether different specialties' telemedicine use has waxed and waned over time, or whether there are other temporal trends in telemedicine use.

Conclusions

Urban patients access telemedicine significantly differently, with a much greater demand for child telepsychiatry. Telemedicine may offer help for the critical nationwide shortage of dermatologists and adolescent psychiatry providers in rural and urban areas. Health systems should consider adjusting resources to meet the different needs of these two populations. These specific findings may or may not generalize to other telemedicine programs, but it is clear that all telemedicine programs would be well advised to monitor the telemedicine usage of different populations in order to tailor resources.

Telemedicine helps robust health systems extend their reach to hard-to-reach populations. It helps to shift the paradigm for the "right care, at the right time, and at the right place." The Institute of Medicine (IOM) report on Crossing the Quality Chasm recommended redesigning care delivery and encouraging implementation of information technologies in order to improve workforce capabilities and quality of care.[26] This is the promise of telemedicine; it may save the lives of patients experiencing access issues. Rural farmers at high-risk for melanoma now have timely access to specialty dermatologic care via telemedicine right in their own communities. Similarly, child psychiatry telemedicine may help meet the needs of diverse populations at the community level, both rural and urban.

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Tables

Table 1 - Results of the multinomial logistics regression for which specialty a patient used (base is assumed to be teledermatology) with predictor variables the patient’s age, gender, and location.

Predictor variables	**Coefficient**	**Standard error of the coefficient**	**Z**	**P-value**	**Relative risk ratios**		
					Mean	**95% confidence Interval**	
						Lower bound	**Upper bound**
Child telepsychiatry							
Urban	2.165	0.136	15.89	< 0.001	8.714	6.672	11.381
Male	1.435	0.134	10.68	< 0.001	4.199	3.227	5.463

Age	-0.100	0.006	-16.04	< 0.001	0.905	0.894	0.916
Constant	0.120	0.153	0.79	0.431	1.128	0.836	1.521
Teledermatology: base outcome							
Adult telepsychiatry							
Urban	1.549	0.149	10.39	< 0.001	4.707	3.514	6.305
Male	0.334	0.136	2.47	0.014	1.397	1.071	1.822
Age	0.015	0.003	4.83	< 0.001	1.015	1.009	1.021
Constant	-2.419	0.178	-13.59	< 0.001	0.089	0.063	0.126
Other telemedicine specialty							
Urban	1.974	0.254	7.77	< 0.001	7.198	4.375	11.841
Male	-0.285	0.252	-1.13	0.259	0.752	0.459	1.233
Age	0.020	0.006	3.54	< 0.001	1.020	1.009	1.031
Constant	-3.948	0.335	-11.78	< 0.001	0.0198	0.010	0.037

Overall likelihood ratio $\chi^2 = 1313.28$ with $p < 0.001$

Table 2 - Number of unique female UMHC telemedicine by specialty, location, and age group, 2008-2017.

FEMALE PATIENTS

Specialty	**Pediatric Rural % (n)**	**Pediatric Urban % (n)**	**Adult Rural % (n)**	**Adult Urban % (n)**	**Elderly Rural % (n)**	**Elderly Urban % (n)**	***Total % (n)***
Child telepsychiatry	34.0% (69)	69.5% (89)	0.3% (1)	2.4% (3)	0	0	*17.7% (162)*
Adult telepsychiatry	0	0	24.1% (79)	42.5% (54)	4.4% (5)	27.8% (5)	*15.6% (143)*
Teledermatology	66.0% (134)	29.7% (38)	69.8% (229)	40.9% (52)	92.9% (105)	38.9% (7)	*61.6% (565)*
Other	0	0.8% (1)	5.8% (19)	14.2% (18)	2.7% (3)	33.3% (6)	*5.1% (47)*
Total	*100% (203)*	*100% (128)*	*100% (328)*	*100% (127)*	*100% (113)*	*100% (18)*	*100% (917)*

Table 3 - Results of the multinomial logistics regression for which specialty a patient used (base is assumed to be teledermatology) with predictor variables the patient's age, gender, and location.

Predictor variables	**Coefficient**	**Standard error of the coefficient**	**Z**	**P-value**	**Relative risk ratios**		
					Mean	**95% confidence Interval**	
						Lower bound	**Upper bound**
Child telepsychiatry							
Urban	2.165	0.136	15.89	< 0.001	8.714	6.672	11.381
Male	1.435	0.134	10.68	< 0.001	4.199	3.227	5.463

Age	-0.100	0.006	-16.04	< 0.001	0.905	0.894	0.916
Constant	0.120	0.153	0.79	0.431	1.128	0.836	1.521
Teledermatology: base outcome							
Adult telepsychiatry							
Urban	1.549	0.149	10.39	< 0.001	4.707	3.514	6.305
Male	0.334	0.136	2.47	0.014	1.397	1.071	1.822
Age	0.015	0.003	4.83	< 0.001	1.015	1.009	1.021
Constant	-2.419	0.178	-13.59	< 0.001	0.089	0.063	0.126
Other telemedicine specialty							
Urban	1.974	0.254	7.77	< 0.001	7.198	4.375	11.841
Male	-0.285	0.252	-1.13	0.259	0.752	0.459	1.233
Age	0.020	0.006	3.54	< 0.001	1.020	1.009	1.031
Constant	-3.948	0.335	-11.78	< 0.001	0.0198	0.010	0.037

Overall likelihood ratio χ^2 = 1313.28 with p < 0.001

Table 4 – Results of the logistics regressions for whether a patient used a specific specialty with predictor variables the patient's age, gender, and location.

Predictor variables	**Coefficient**	**Standard error of the coefficient**	**Z**	**P-value**	**Odds ratio**		
					Mean	**95% confidence Interval**	
						Lower bound	**Upper bound**
Binary outcome *"Did the patient use teledermatology?"*							
Likelihood ratio χ^2 = 583.87 with p < 0.001							
Urban	-1.824	0.110	-16.65	< 0.001	0.161	0.1310	0.200
Male	-0.801	0.100	-7.98	< 0.001	0.449	0.369	0.547
Age	0.021	0.002	9.11	< 0.001	1.022	1.017	1.026
Constant	0.351	0.113	3.10	0.002	1.420	1.137	1.772
Binary outcome *"Did the patient use child telepsychiatry?"*							
Likelihood ratio χ^2 = 1145.21 with p < 0.001							
Urban	1.706	0.125	13.67	< 0.001	5.505	4.311	7.030
Male	1.378	0.129	10.66	< 0.001	3.968	3.080	5.112
Age	-0.105	0.006	-16.95	< 0.001	0.901	0.890	0.912
Constant	0.074	0.148	0.50	0.616	1.077	0.805	1.441
Binary outcome *"Did the patient use adult telepsychiatry?"*							
Likelihood ratio χ^2 = 123.01 with p < 0.001							
Urban	0.722	0.138	5.24	< 0.001	2.059	1.572	2.697
Male	-0.046	0.131	-0.35	0.725	0.955	0.739	1.234
Age	0.030	0.003	10.43	< 0.001	1.030	1.025	1.036

Constant	-3.125	0.178	-17.53	< 0.001	0.044	0.031	0.062
Binary outcome *"Did the patient use telepsychiatry (child or adult)?"*							
Likelihood ratio χ^2 = 617.19 with $p < 0.001$							
Urban	1.640	0.107	15.39	< 0.001	5.153	4.182	6.350
Male	0.933	0.102	9.18	< 0.001	2.543	2.084	3.104
Age	-0.028	0.002	-11.31	< 0.001	0.972	0.968	0.977
Constant	-0.367	0.114	-3.21	0.001	0.693	0.554	0.867

Figures

Figure 1: Number of total 2008-2017 UMHC telemedicine visits and unique patients by specialty.

Figure 2: Map of unique 2008-2017 UMHC telemedicine patients by zip code.

Figure 3: Distribution of unique 2008-2017 UMHC telemedicine unique patients by age, specialty, and gender, where pediatric = 0-17 years, adult = 18-64 years, and elderly = 65 years and over.

(* indicates a significant difference (p < 0.001) between rural and urban populations)

Figure 4: Distribution of unique 2008-2017 UMHC telemedicine total visits by gender, and specialty, where pediatric = 0-17 years, adult = 18-64 years, and elderly = 65 years and over.

(* indicates a significant difference (p < 0.001) between rural and urban populations)

Figure 5: 2008-2017 UMHC telemedicine gender distribution by specialty.

Figure 6: 2008-2017 UMHC telemedicine age distribution by specialty.

Figure 7: Maximum and mean number of 2008-2017 UMHC telemedicine visits per patient by specialty and location.

There are no comments yet.

PROFESSIONAL NETWORKING FOR HEALTH INFORMATION MANAGEMENT/TECHNOLOGY STUDENTS AND NEW GRADUATES: A SURVEY OF HIM PROFESSIONALS IN MICHIGAN

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Professional Networking for Health Information Management/Technology Students and New Graduates: A Survey of HIM Professionals in Michigan

By Thomas (T.J.) Hunt, PhD, RHIA, CHDA, FAHIMA

Abstract

The purpose of this survey was to gather advice on professional networking to assist health information management/technology students and new graduates. An online survey was sent to members of the Michigan Health Information Management Association (MHIMA) through a series of e-mails with 119 responses. Open-ended questions were analyzed using qualitative summative content analysis. Overall trends identified from the advice were to be active in the health information management (HIM) community and engage in positive relationships while avoiding negative or self-centered behaviors. Online networking activities were also recommended to be included in the process although not as the only means of networking. Attending regional and state HIM association events and volunteering with regional associations were selected most often as effective networking activities.

Keywords: professional networking, health information management (HIM), career development, students, new graduates

Introduction

Many college students and new graduates have heard networking is important to their career development.[1] The challenge is determining what networking is and how to go about doing it. Michigan Health Information Management Association (MHIMA) members were asked to share their thoughts on professional networking to help guide students and new graduates. In reviewing literature regarding networking, there are many different definitions and proposed outcomes.

Addams[2] suggests identifying and communicating what successful networking looks like is relatable to answering the question "what does salt taste like?" A person who has tasted salt knows the taste yet may find it difficult to explain without simply responding "salty". Similarly, a person who has successfully established relationships with a network of colleagues knows what it looks and feels like, yet those who haven't may have difficulty understanding how to network. There are many opinions regarding networking, types of networking, antecedents to and outcomes of networking although relatively little regarding the topic of advice or instructing those new to the workforce how to do it. This is the intent of this study – to ask current Health Information Management (HIM) professionals and future HIM colleagues open ended questions regarding the advice they would give to students and new graduates regarding networking. It is hoped the overall trends identified from responses can provide insight to students and new graduates who are seeking to grow their professional network.

Background

Health Information Management

Health information management (HIM) is "the practice of acquiring, analyzing, and protecting digital and traditional medical information vital to providing quality patient care. It is a combination of business, science, and information technology."[3] The state of Michigan has one graduate degree program, four bachelor degree programs, and six associate degree programs accredited by the Commission on Accreditation for Health Informatics and Information Management Education (CAHIIM).[4] The programs qualify graduates to sit for the Registered Health Information Administrator (RHIA) and Registered Health Information Technician (RHIT) exams through the American Health Information Management Association (AHIMA). "Founded in 1928, AHIMA is the premier association of health information management (HIM) professionals worldwide. Serving 52 affiliated component state associations and more than 103,000 health information professionals, AHIMA is the leading authority for "HIM knowledge" and widely respected for its esteemed credentials and rigorous professional education and training."[5] The Michigan Health Information Management Association is a Component State Association of AHIMA. There are also local/regional associations which are formed within an area of a state and work in partnership with the state association. Michigan has four regional associations: Southeast Michigan, West Michigan, Lake Huron, and Upper Peninsula.[6]

Professional Networking

A review of literature was conducted using online databases seeking articles related to professional networking. There were many results investigating social networking which were not considered for this review. Certainly, the image a person projects online even on social networking sites may have career implications,[7] although the focus of this study is advice for students pursuing professional networking skills. Most of the research found related to defining networking, antecedents to networking, or the outcomes/benefits of networking relationships. Literature is spread through many disciplines and no consensus of the many aspects has been reached – including definition or best way to measure in a study.[8] Recommended steps of what to actually do while networking was not addressed in most of the studies.

There are multiple definitions of professional networking. Gibson, Hardy, and Buckley[9] seem to have crafted an inclusive definition of networking "goal-directed behavior which occurs both inside and outside of an organization, focusing on creating, cultivating, and utilizing interpersonal relationships."[9(p146)] Most definitions include relationships to exchange information, benefits, influence, opportunities, and access to resources for mutual benefit. These relationships have been found to help in obtaining new roles,[10] career success,[11] salary progression, and access to information for job performance.[12] The benefits and definitions found in the literature encompass more than seeking and obtaining employment. Students and new graduates may want to keep this in mind when thinking about their professional network.

Even within activities considered to be professional networking, different types were identified in the literature. Networking can be individual, job level, organizational, ethical, unethical, face-to-face, and online through networking websites. Networking is related to, although different from topics such as mentoring, social networks (due to different goals and intents), political skill, or impression management.[13]

Most recommendations gained from current peer-reviewed literature comes from advice or metareview articles. Also, there are advice books and articles in non-scholarly magazines although research has lagged behind.[14] Advice for positive, ethical networking for the mutual benefit of all parties found in the literature includes:

- Say thank you, connect with people even when there is nothing needed or no current issue to solve[15]
- Join clubs, fraternities/sororities, student associations to practice communication and relationship building[16]
- Work every day to expand your network (it does take work)[17]
- Help others when you see a need arise[18]
- "Don't wait until you need a job to start being outgoing. It takes years to build a network of friends in the business, and one must maintain those relationships with phone call, e-mails, or chit-chat. Networking is fun, rewarding, and good insurance for the security of your career in your lifetime"[19(p218)]
- "Talk about your professional interests with others, and emphasize what you can do for them"[20(p217)]
- Attend professional conferences for opportunities to meet like-minded people[21,22,23]
- Prepare beforehand what you are going to do to interact with people at the conference[24]
- While attending conferences, spend time engaging new ideas and people instead of collecting marketing materials and business cards from booths[25]

Mele recommends following ethical professional networking practices when building a professional network. When engaging in the examples listed above some ethical networking guidelines include:[26]

- Acting in good faith, sharing honest goals, participating in lawful activities
- Sharing information, knowledge, and resources with reciprocity and gratitude
- Serving with justice in asymmetric power relationships
- Exercising positive ethical influence with the network

Acting in bad faith, abusing or misusing power, or abusing the trust of a colleague are unethical actions to be avoided. Cronyism, bribery, and predatory opportunism are also unethical actions which are not to be mistaken or construed to be networking.[27]

The ideas identified in previous studies and reviews do give some advice regarding professional networking which seems to be generalizable to many professions and career-levels. Hopefully this review of literature and responses of the study will also result in useful advice specifically for health information management students and new graduates.

Barriers

There are multiple barriers reported in the literature which can be stumbling blocks for students and new graduates. Many people find both in-person and online networking intimidating,[28] especially students who may not have the confidence to contact or follow-up with potential employers.[29] After meeting new people at a conference it is easy to lose momentum in following up.[30] When looking to connect online, one study of health administration students and found 72 percent had engaged in social networking online, yet only 27 percent had used a professional networking website. Whether it be a social or professional networking, students have reported they are unsure of online "rules"[31] and would like to hear more advice regarding networking online. In another study, students felt employers had perceptions of what a college graduate "should be," which in reality didn't match the diverse pool of students and graduates. Students felt as though they did not fit what idea employers had in mind.[32]

Advice to overcome these barriers for students and new graduates includes early involvement in networking while still in college. Alumni in one study advised students and faculty regarding the necessity of networking with employers before graduation. "Linking current students to those in the field, primarily though internships, was viewed by alumni as essential to developing ongoing opportunities for students to network and gain access to a challenging job market."[33(p63)] Students like to hear specific real-life scenarios of networking to learn from whether it be from alumni, current practitioners in the field, or faculty. Practicing developing relationships—personal and professional—is recommended to overcome some of these barriers.[34] As far as developing online professional relationships, students reported a desire to learn about professionally appropriate online activities.[35]

Gaps

Gibson's metareview suggested more open-ended/qualitative research to better understand nuances and distinguish networking behaviors. Currently, most attention in research has been to antecedents and outcomes. In order to move forward more should be on the mechanisms which drive success, and what behaviors translate to success.[36]

Methods

An online survey with open-ended questions was selected to gather this data in order to reach more people than could be accomplished with individual interviews. Data was gathered using an online survey link. The link was distributed by MHIMA to all state association members via a series of e-mails and announced in their quarterly FOCUS newsletter. It was also posted online in the AHIMA Engage communities of practice Michigan CSA forum. The total population that could have been reached at the time with the internet survey link included the total MHIMA membership of 3,291 HIM professionals and students.[37]

The survey was intended to be short to encourage completion by potential participants. It included two demographic questions, three open-ended questions regarding professional networking, and one multiple-selection question. Potential respondents consented to participating by continuing with the survey after reading the informed consent information. Participants could discontinue the survey at any time and were free to decline to answer any question. The survey and methods were reviewed and approved by a university Institutional Review Board.

The two demographic questions asked participants what their HIM role was and where they were located. Options for role included current student or those who graduated within the previous year, faculty, or HIM professional (not faculty/student/new graduate). Students and recent graduates were included because they could have successful strategies to share with others. Locations were categorized as urban or rural using State of Michigan and U.S. Census guidelines.[38]

Open-ended responses were categorized into groups based on the emerging trends of responses. The categories were not pre-selected; however, through the review of literature some ideas of potential trends, and terms such as relating to relationship-building and involvement in professional groups were identified. The final trends were formed based on responses from the participants. This followed the qualitative coding procedure of summative content analysis outlined by Hsieh and Shannon.[39] Each response was assigned a grouping based on what trend it most closely aligned with. An individual's open-ended response could result in multiple pieces of advice which may have been recorded in more than one category. For example, if one response included three suggestions, then each suggestion was categorized.

The final question asked participants to select what they felt were the best five networking activities out of 17 suggestions. There was also an option for entering a suggestion not listed. The question did not seek a 1-5 ranking, only selecting what group of five suggestions the respondent felt were most effective. A strict ranking was not pursued because the goal was to gather information on successful strategies, not stratify or grade them individually. The results then communicate which suggestions were most often selected as an effective networking activity. For example, the activity gaining the most responses indicates it was included the most in top five suggestions, yet not necessarily ranked number one by the most respondents.

Results

A total of 119 current HIM professionals, faculty, college students, and new graduates responded to the survey. Of the 119 responses, 21 were students or had graduated within the last year, 18 were educators in college or university health information degree programs, and 79 were working in the healthcare industry. One person chose not to identify their role.   Of the 119 respondents, 97 (82 percent) were located in an urban area, and 22 (18 percent) were located in a rural area.

The first open-ended question asked what professional networking advice you have for students and new graduates. Most suggestions followed the trends of participating or volunteering in activities, seeking to build relationships, leveraging internships or work experiences, and utilizing online networking strategies. The totals are listed below.

- Participating/Volunteering – 65
- Relationship Building – 28
- Internships/Experiences – 12
- Online Strategies – 4
- Other - 11

The second open-ended question asked participants to share what specific networking examples they recommend. In grouping the activities suggested, they formed the following trends:

- Involvement in Professional Associations – 67
- Utilizing Online Networking Websites – 23
- Initiate Personal Relationships – 21
- Involvement in School Events/Groups – 19
- Being Open-Minded to New Experiences & Opportunities – 15
- Job Shadowing – 8
- Display Professional Behavior – 3
- Other – 4

The third open-ended question asked what participants would recommend students and new graduates avoid when professional networking. The responses trended into the following groups of behaviors to avoid:

- Aggressive or Nagging – 18
- Unprofessional Behavior or Attire – 17
- Gossip or "Burning Bridges" – 16
- Being Closed-Minded – 14
- Self-Centered Discussions or Behavior – 8
- Shyness – 8
- Using Only Technology/Online Strategies – 6
- Neglecting Relationships – 5
- Other – 11

The final question of the survey asked participants about specific networking activities. Seventeen activities were suggested with an option to also write-in activities not listed. Participants were asked to select five of the networking activities they believed were most effective for HIM students and new graduates. The activities suggested are listed in **Table 1** and the five activities selected most are detailed below.

- Attending local/regional HIM association continuing education conference/seminars – 99 (83 percent)
- Attending state HIM association (Component State Association - CSA) continuing education conferences/seminars – 69 (58 percent)
- Volunteering with the local/regional HIM association – 58 (49 percent)
- Seeking job shadowing opportunities – 55 (46 percent)
- Online networking with LinkedIn or similar websites – 49 (41 percent)

Discussion

Response to the survey was 3.6 percent of the estimated population of AHIMA certified or affiliated HIM professionals in Michigan. This is a low percent of the estimated pool of possible participants; however, the goal of the study was to gather as much helpful information as possible for new and future professionals. It is felt the advice gathered is useful to students and new graduates regardless of the response rate to the survey.

Conducting interviews with a smaller number of people would have also been an option to collect information regarding professional networking. Most responses to the open-ended questions on the survey were a few sentences or less, while interviews could have possibly collected more information from each participant. It would have allowed for a deeper qualitative examination of suggestions and been easier to share specific examples from each person. In this case, gathering advice from over 100 colleagues does provide a broad overview of activities to pursue and could lead to valuable guidance. Attempting to share every specific example from each person in a publication would result in a very long list. Even though each individual suggestion is not included here, it is felt the overall trends can be useful information for students and new graduates to know when networking.

The trends from each open-ended question seem to align with professional networking suggestions in the literature review. Most responses valued being active in the HIM community and engaging in positive relationships while avoiding negative or self-centered behaviors. Online networking activities were also recommended to be included in the process although not as the only means of networking. This is encouraging to know in cases where physical attendance at events may be limited due to funds, distance, or health and safety factors. Respondents to the survey felt the regional and state health information management associations were valuable assets to networking. Attending events and volunteering in the associations were some of the most popular options when recommending effective networking activities.

Conclusion

The intent of this study was to provide support and advice to health information management and health information technology students as they begin their careers. The results may also help faculty and current HIM professionals to advise and encourage new and future colleagues. The literature review and survey responses recommend being involved in activities of regional and state HIM associations. Pursuing positive relationship-building, avoiding being overly aggressive regarding jobs, and refraining from unprofessional behavior and conversation were also recommended. Additional recommendations included incorporating online methods into professional networking activity. Even though professional networking has been found to have many benefits, employment opportunities seem to be the reason most people think of first. People are hired for job expertise not who knows who – yet sincere relationships help communicate your skills and character.[40] The recommendations of over 100 HIM professionals will hopefully help those new in their HIM career to meet colleagues and establish meaningful relationships.

The author would like to acknowledge and thank the Michigan Health Information Management Association for communicating the opportunity to participate and distributing the web survey link to members.

Author

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There are no comments yet.

POPULATION HEALTH: IDENTIFYING SKILL SETS AND EDUCATION ALIGNMENT FOR HIM PROFESSIONALS

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Population Health: Identifying Skill Sets and Education Alignment for HIM Professionals

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Abstract

The COVID-19 pandemic has increased the emphasis on population health, therefore potentially amplifying demand for healthcare workforce professionals in this area. There is an urgent need to explore and define the roles of health information management (HIM) professionals in the population health workforce. This study sought to identify the skill sets and qualifications needed, and HIM education alignment with skills necessary for HIM professionals entering the population health workforce. An intentionally broad internet search of job postings was conducted to determine skills in population health. Population health-related job descriptions and qualification requirements were abstracted and analyzed using ATLAS.ti. Three common job categories were identified: management, analytics, and coding. Skill set requirements included soft skills, problem solving, project management, research, and data analysis. The study results identified HIM educational alignment and found that HIM professionals are generally a good fit to meet the increased need in the population health workforce.

Keywords: Workforce, population health, skill set, health information management, qualitative content analysis, COVID-19 pandemic

Introduction

The 2020 COVID-19 pandemic has impacted all aspects of society, most notably healthcare, the economy, social and cultural issues, and politics. One area that has become integral to fighting the pandemic is population health. Testing, tracing, research, data analysis, and public education have become keys to our society's response to the pandemic. This has demonstrated a need for a strong population health workforce. Based on the emerging need for additional population health employees, there is a role for health information management (HIM) professionals to examine current education and skill set preparation in population health, and to the population health workforce.

Population health focuses on the well-being of both sick and healthy people within a specific group. The term "population health" originated in Canada in 1997 and was defined as "the health of a population as measured by health status indicators and as influenced by social, economic, and physical environments, personal health practices, individual capacity and coping skills, human biology, early childhood development, and health services."[1] These overlapping conditions and elements shape the health of a population, and population health management identifies the trends and patterns resulting in outcomes that are used to formulate and adopt policies advocating for the improvement in the welfare of those populations.[2] The conceptual framework for population health definitions include the following terms: public health, population health improvement, population health management (PHM),[3] and population health equity.[4] Researchers note that for population health initiatives to be successful, consideration must be given to social, environmental, and medical factors, including determinants of health.[5]

Population health, especially those functions related to information management, presents potential new opportunities for HIM professionals in the population health workforce.[6] While HIM professionals have not played a large role in population health to date, now is the ideal time for them to step into roles such as creating business intelligence (BI) reports for healthcare entities, analyzing big healthcare data, and leading health information exchange (HIE) implementations. Population health has evolved and become data-driven with increased data collection of health information brought about by the effective use of electronic health records (EHRs). Claims data produced by health information professionals through the abstracting of information and application of medical codes to patient encounters is a valuable tool used in PHM. In addition to the claims data, clinical data along with patient satisfaction survey data provides a more comprehensive picture of the care delivered, and provides useful information for quality improvement and cost control initiatives. With payment reform and the shift from reimbursement for volume to value, the use of PHM is essential for success in the value-based payment model. A focus on healthcare and community needs in association with data analytics is central to a population health approach. A deep understanding of a patient population impacts the types of healthcare services provided for disease prevention and disease management with a focus on disease reduction. This entails the capture and analysis of patient data as well as community information that together supports evidence-based care.[7]

Population health, as well as the entire healthcare system, is facing continuous challenges in improving health outcomes for all. The COVID-19 pandemic has pointed to many issues that exist today, including, the lack of automated software to alert patients to diagnoses, the ability to test and trace mass numbers of individuals, complex healthcare policies and laws, and the implementation of sustainable initiatives to manage population health. However, HIM professionals have a skill set to help improve population health. HIM academic programs are preparing students to become professionals in all areas of health care and health information, including population health.[8]

The AHIMA Council for Excellence in Education (CEE) is responsible for the continued development and updating of required curricular competencies based on the needs of and input from industry stakeholders. Educational HIM programs ensure graduates are competent in the recommended knowledge and skill sets outlined by the curricula competencies. In response to the AHIMA's HIM

Reimagined (HIMR) initiative, updated 2018 HIM Curricula Competencies along with revised and required Bloom's Taxonomy levels were introduced and approved for implementation by the AHIMA Council for Excellence in Education. All AHIMA accredited HIM education programs must be compliant with the 2018 AHIMA/CEE curriculum per the designated date in 2021.[9]

The 2018 HIM Curricula Competencies consist of six common domains representing the academic framework for the areas of mastery vital for all health information professionals regardless of academic level. With the 2018 HIM Curricula Competencies, previous subdomains were removed, and the competencies were revised in a broader context that allows for more flexibility allowing educators and academic programs to adjust to changes in educational demands. Specific curricula competencies are addressed in the following six common domains:[9]

- Domain I. Data Structure, Content, and Information Governance
- Domain II. Information Protection: Access, Use, Disclosure, Privacy, and Security
- Domain III. Informatics, Analytics, and Data Uses
- Domain VI. Revenue Cycle Management
- Domain V. Health Law and Compliance
- Domain VI. Organizational Management and Leadership

Methods

Study Design

This is a cross-sectional qualitative study in which data were collected from an intentionally broad internet search of job postings related to population health over a three-month period from December 2019 to February 2020. Using a search key word of "population health," ten HIM professionals from the AHIMA Foundation Research Network Population Health Workgroup conducted independent random searches for advertised population health positions posted to websites by United States employers. Each professional submitted five search results with the job titles, responsibilities and qualifications. Due to the fact that the data were drawn from public domain, institutional review board (IRB) approval was not needed.

Data Collection

A total of 50 job postings were collected, abstracted, and assembled into one data file, with three key data components of 1.) job title, 2.) job description, and 3.) job qualifications for each posting. One duplicate position was eliminated, resulting in 49 unique job postings.

All collected job titles were categorized into four groups: 1.) management positions, including different managerial level positions, such as director, manager, supervisor, and lead; 2.) analytical positions, including any job titles with analytical and technical aspects, such as analyst, health scientist; 3.) coding positions; and 4.) other positions, defined as all positions that were not included in the previous three groups, such as consultant or faculty.   Job descriptions included postings that described the responsibilities of the job. Qualifications included education level requirements, specific skills and technical specialty area requirements, and prior experience.

HIM Domains

2018 Health Information Management (HIM) Curricula Competencies were used for comparative analysis. Data related to job responsibilities were matched with each of six domains from the Competencies. The six domains included in the analysis consist of:

- Domain I. Data Structure, Content, and Information Governance
- Domain II. Information Protection: Access, Disclosure, Archival, Privacy and Security
- Domain III. Informatics, Analytics, and Data Use
- Domain IV. Revenue Cycle Management
- Domain V. Health Law and Compliance
- Domain VI. Organizational Management and Leadership

Data Analysis

Data coding was conducted for job titles based on the functions of the posted positions. After data coding, classification, and categorization, the master data were formatted in Excel and imported into ATLAS.ti scientific software for qualitative data analysis. Thematic content analysis was used to identify themes, and descriptive statistics were computed and summarized.

A total of four themes emerged from the search results, which included 1) job titles and job categories; 2) job responsibilities; 3) job requirements for education level and special skill sets; and 4) alignment between job responsibilities and HIM education domains/competencies. Thematic content analysis was conducted both manually and with the use of ATLAS.ti software.

For the purposes of the study, data were analyzed for job category, job responsibility, education and skill requirements, and alignment between responsibilities and HIM education domains and competences.

Results

Job Titles and Categories

A sample of fifty population health-related job postings were reviewed. One was a duplicate resulting in 49 postings to be analyzed. The results are summarized in **Table 1**. Of the postings analyzed, 33 (67 percent) of the job titles fell into a category entitled Management. This included roles such as coordinator, specialist, liaison, lead, or any title involved in the day-to-day managing process. The second category of job titles was Analyst & Technical, with 10 (18 percent) roles. All the job titles in this sample group were analysts. Medical Coding had two (4 percent) job titles from the postings, and four (8 percent) other titles including consultant, advisor, or educator were grouped into a category labeled Other.

Education Requirements

The education requirements for the job postings were also analyzed and grouped by requirement. There were 55 instances of educational requirements included in the population health jobs in this sample. **Table 2** displays the educational requirements found in the postings, while **Table 3** displays the requirements divided by job category. Two of the jobs required a high school diploma or equivalent. Two required an associate degree. Two indicated a bachelor's degree was preferred, while 30 required a bachelor's degree. Sixteen postings indicated a master's or doctoral degree was preferred and three required a master's degree. Overall, of the 59 times education was mentioned in the population health job postings, 55 (93 percent) were looking for a bachelor's degree or higher, and 19 (35 percent) were seeking candidates with graduate education.

Skill-Set Requirements

The sample was also reviewed to identify the skills most cited in the job postings. One hundred seventy skills were mentioned in the postings. The most commonly occurring, related to social and communication skills, were grouped together and labeled soft skills. These were found in 40 (82 percent) of the 49 job postings. The skill sets, descriptions, and respective job categories are displayed in **Table 4** and **Table 5**. The second most common skill set, including problem solving, reporting, and spreadsheet skills were included in 17 postings (35 percent). Skills relating to workflow appeared in 16 (33 percent) of the postings. Project management (13), research (13), data analysis/visualization (12), electronic medical record (11), database (8), and classification systems (6) rounded out the list. Table 4 also includes the AHIMA 2018 Health Information Management Curriculum Competency Domains most closely associated with the skill sets. The domain occurring most frequently was Domain III Informatics, Analytics, and Data Use, which was most closely related to six of the identified categories of skills. Domain VI Organizational Management & Leadership matched most closely with the two categories of skills appearing in the most job postings, Soft Skills (40) and Problem Solving (17).

AHIMA Competencies

A total of 166 skills were identified in the sample of 49 population health job postings. The skills from the population health job posting were paired with the AHIMA 2018 Health Information Management Curriculum Competency Domains that best matched the description. In the sample of 49 job postings, 18 items were mentioned that matched with Domain I. Data Structure, Content, and Information Governance. Six matched with Domain II. Information Protection: Access, Use, Disclosure, Privacy, and Security. Domain III. Informatics, Analytics, and Data Use, matched with 44 skills mentioned in the postings. Domain IV. Revenue Cycle Management, had two job responsibilities and/or qualifications that matched, and Domain V. Health Law & Compliance, was mentioned 10 times. Domain VI. Organizational Management & Leadership, matched the most skills,

86. **Table 6** shows these results matched with examples of the job titles in which the domains were found and the categories of skills identified. **Table 7** includes the job categories in which the domains were included.

Discussion

This study assessed skill set and education requirements for positions in population health using data extracted from random population health job postings. The skills and requirements were mapped back to the AHIMA curriculum domains for the purpose of evaluating the knowledge skills and abilities required by CAHIIM accredited programs. We also examined whether HIM professionals and graduates would satisfy common minimum job requirements in the population health related field of practice. The results of this study suggested that HIM graduates and professionals generally possess the skills listed as required in population health related job postings. This study identified HIM graduates and professionals as viable candidates capable of successful performance in population health management positions.

Skills for population health positions identified from our study matched previous literature.[10] No major gaps between HIM education and population health skill sets were observed. All skills required in the job postings mapped directly back to one of the six AHIMA domains. The majority of the skills such as data analysis, EHR, problem solving, and soft skills, fell within Domain III. Informatics, Analytics, and Data Use or Domain VI. Organizational Management & Leadership. HIM students and practicing professionals receive extensive education and training within these domains. Additionally, HIM professionals receive training in coding systems, electronic medical records systems, and anatomy and physiology that provide a broad foundational skill set that can be readily applied to population health. While all skills listed in the population health job postings map back to the AHIMA curricular domains, there may be opportunities to expand or strengthen some domains and skills related to population health. The results from this study highlight the importance of skills and competencies taught in the leadership and data analytics related domains in HIM education.

The limitations of the study should be noted. First, this study did not identify the level of skill or depth of knowledge required to be successful in the population health jobs. An additional study using job descriptions, position analysis, or manager survey would be required to obtain data at this level of detail. Second, the results from this study have limited generalizability as the job postings were selected at random and not obtained using purposeful or systematic sampling techniques. The small sample size could be another drawback of the study that limited our data collection and analysis at a broader content perspective.

While further study is needed, this study opens the door for HIM professionals in the population health realm. Additional study can lead to analysis of areas in which HIM education and training can be strengthened in the areas of population health to best prepare HIM professionals to fill these roles. Further in-depth analysis would be required to identify and understand any knowledge gaps among HIM professionals or to identify areas for improvement in the AHIMA curriculum to strengthen the job opportunities of HIM graduates seeking employment in the population health field.

Conclusion

The results of this study showed a potential opportunity for HIM professionals in the population health field. The skills required as found in the population health job postings align with the curriculum competencies required for HIM education. With the projected increased demand for population health professionals due to the COVID-19 pandemic, HIM professionals provide an additional source of skilled employees. HIM professionals are well versed in the skills needed in population health, including data analytics, project management, community health assessment, EHRs, and systems thinking. Future study should attempt to develop strategy for continuous improvement of HIM skill sets in population health workforce and education.

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There are no comments yet.

PHYSICAL THERAPY AND HEALTH INFORMATION MANAGEMENT STUDENTS: PERCEPTIONS OF AN ONLINE INTERPROFESSIONAL EDUCATION EXPERIENCE

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Physical Therapy and Health Information Management Students: Perceptions of an Online Interprofessional Education Experience

By Lois Stickley, PT, PhD and David Gibbs, PhD, CPHIMS, CPHI, CHPS, CISSP, FHIMSS

Abstract

This study described the results of online interprofessional education (IPE) between physical therapy and health information management students. Using the published *Student Perceptions of Interprofessional Clinical Education – Revised, version 2* (SPICE-R2) survey, this study measured changes in perception about IPE before and after three online interactions. Survey results included an overall score and three factors: Interprofessional Teamwork and Team-Based Practice (T), Roles/Responsibilities for Collaborative Practice (R), and Patient Outcomes from Collaborative Practice (O). Data were analyzed using two-way analysis of variance tests using time and program as factors. The overall scores improved significantly for time (ρ=.019). The T factor demonstrated a significant change for program (ρ=.006) and the R factor improved significantly over time (ρ=.005) and by program (ρ=.022). Narrative student comments focused on role and responsibility clarification, communication and coordination, and participation in a realistic experience involving multiple professions. The students believed that the experience was beneficial and important.

Keywords: Interprofessional education, electronic health records, physical therapy, health information management, SPICE-R2, online education, distance learning

Introduction

This study described interprofessional education (IPE) activities between Doctor of Physical Therapy (DPT) students and Master of Health Information Management (MHIM) students at one large public university in Texas. Using online collaboration tools, students learned about each other's roles and responsibilities in health care, provided and received feedback about a medical documentation assignment, and discussed electronic health record (EHR) systems. The objectives of this study were to 1) determine student perceptions of interprofessional core competencies, and 2) measure the effectiveness of a planned online interprofessional learning experience. IPE is encouraged for all healthcare professions as important for addressing patient safety issues including medical errors.[1] We found no existing literature describing a study of IPE targeting physical therapist (PT) and health information management (HIM) students, which necessitated this study, with the hypothesis that there would be a significant change between pre- and post-experience perceptions of PT and HIM students.

Participation in IPE activities is appropriate and timely for HIM students and practitioners. The HIM profession has evolved rapidly in recent years with increased involvement with EHR systems, data integrity, informatics, data analytics, cybersecurity, and other relevant areas. IPE activities provide opportunities to raise awareness among other healthcare related professions about the expanding roles of HIM professionals.

Background

IPE is defined by the World Health Organization as activities in which "students from two or more professions learn with, from, and about each other to enable effective collaboration and improve health outcomes." [1] The explicit goal of IPE is to transform professional identities, practices, and relationships within and across health professions through the development of interprofessional practice.[2]

The Interprofessional Education Collaborative (IPEC) was formed in 2009 by six national associations of schools of health professionals to promote and encourage interprofessional learning.[3] By 2016-2017, IPEC had grown to include over 20 institutional members committed to addressing "the urgent need for health professionals to work together." [4] The urgency was driven by continuing concern about patient safety with medical errors persisting as the third leading cause of death in the United States.[5] IPEC has identified four core competencies for IPE which guided this study.

1. Values/Ethics: Work with individuals of other professions to maintain a climate of mutual respect and shared values.
2. Roles/Responsibilities: Use the knowledge of one's own role and those of other professions to appropriately assess and address the healthcare needs of patients and promote and advance the health of populations.
3. Interprofessional Communication: Communicate with patients, families, communities, and professionals in healthcare and other fields in a responsive and responsible manner that supports a team approach to the promotion and maintenance of health, and the prevention and treatment of disease.
4. Teams and Teamwork: Apply relationship-building values and the principles of team dynamics to perform effectively in different team roles to plan, deliver, and evaluate patient/populations-centered care and population health programs and policies that are safe, timely, efficient, effective, and equitable.[3]

The importance of IPE has been recognized by Health Professions Accreditors Collaborative (HPAC) members including the Commission on Accreditation in Physical Therapy Education (CAPTE) and the Commission on Accreditation for Health Informatics and Information Management Education (CAHIIM). The HPAC members "recognize that accreditation must play an important role promoting quality IPE that leads to effective health outcomes."[4] Current standards for accreditation in physical therapy include: "6F. The didactic and clinical curriculum includes interprofessional education; learning activities are directed toward the development of interprofessional competencies including, but not limited to, values/ethics, communication, professional roles and responsibilities, and teamwork," [6] which aligns closely with the IPEC core competencies. Curriculum requirements for accredited health informatics programs include a domain of knowledge, skills, and attitudes for interprofessional collaborative practice.[7] Curriculum guidance for health information management includes competencies to "design effective teams … that are interprofessional and interdisciplinary" to address "development of interprofessional relationships" and to promote "diversity in interprofessional relationships." [8]

Although health informatics and information management professionals are often not direct patient care providers, they do have an impact on patient outcomes through management of clinical data, information, and systems used by clinicians to make clinical decisions and to coordinate and communicate about patient care.[9] With electronic health records and health information technology used by practitioners across all health professions, the collective field of health informatics and information management is inherently interprofessional.[10]

IPE approaches vary from dedicated programs to shared course offerings[11] and short-term small group activities. A systematic review and meta-analysis by Guraya and Barr reported significant improvements in knowledge, skills, and attitudes after IPE activities in 11 of 12 articles reviewed.[12]

The tool used in this study to measure changes in perception about interprofessional education was the Student Perceptions of Interprofessional Clinical Education – Revised, version 2 (SPICE-R2) instrument. It contained ten Likert items which represented three factors: Interprofessional Teamwork and Team-Based Practice (Teamwork), Roles/Responsibilities for Collaborative Practice (Roles/Responsibilities), and Patient Outcomes from Collaborative Practice (Outcomes). Two of these factors were based on the IPEC core competencies (2) Roles/Responsibilities and (4) Teams and Teamwork. Although "clinical education" is in the name of the survey, this is not a clinical education outcome tool and has been used in many settings besides clinical education.

The SPICE-R2, used in the current study, was "designed for all health professions students"[13] and was validated in a study of 1,708 multi-disciplinary students across five institutions, including 157 PT students. Another multi-institutional study presented in 2017 by Zorek, Lockeman, Eickhoff, and Gunaldo involving 810 medical, nursing, and PT students at three large public academic institutions confirmed the model structure of the SPICE-R2.[14] The SPICE-R2 has good reliability (0.83) and acceptable-to-good reliability across factor subscales Teamwork (0.74), Roles/Responsibilities (0.72), and Outcomes (0.83). Profession-specific reliability for physical therapy is excellent (0.83).[13] Reliability for health information management has not been established.

Methods

The design of this study was a two-group pre- and post-test survey. The SPICE-R2 survey as previously published[15] was used with permission from one of the authors. In the survey, students rated their level of agreement with 10 statements. A five-point Likert scale was used with one (1) as strongly disagree and five (5) as strongly agree. The survey measured three of the four IPEC competency factors focusing on Teams and Teamwork (T), items 1, 4, 7, & 10; Roles/Responsibilities (R), items 2, 5, & 8; and Outcomes (O), items 3, 6, & 9. The maximum score for the survey was 50, with the T maximum score of 20, the R maximum of 15, and for O the maximum score was 15.[15] Four additional administrative and demographic items were included in the survey: consent to use responses in this research project, student age and gender, and the course in which the student was enrolled. The post-survey instrument also included three open-ended questions eliciting comments from students about their perception of IPE experience. Those questions were: 1) Briefly describe what elements of the IPE activity you thought were MOST beneficial to you, 2) Briefly describe what elements of the IPE activity you thought were LEAST beneficial to you, and 3) What changes would make the IPE activity even more beneficial to future students?

Subjects

A convenience sample was used targeting students enrolled in specific courses. Thirty-eight PT students and seven HIM students participated in an IPE activity from February through April 2019. One PT student did not consent to participate in the research portion of the activities, resulting in 37 PT student responses. The PT students were enrolled in a face-to-face doctoral professional (entry-level) program and were in the sixth semester of a nine-semester program. This was the final semester of full-time academic coursework prior to the PT students completing 36 weeks of full-time clinical education. The seven HIM students were enrolled in a master's degree program delivered entirely online to geographically distributed students in US. Some of the HIM students had recently completed undergraduate HIM degrees and were continuing immediately to graduate school while others were HIM professionals with many years of experience. The HIM course was an elective, not required, and therefore had relatively low enrollment. These courses were selected by the coordinating faculty members because they involved subject matter and assignments that invited interdisciplinary engagement and were offered during the same semester.

The inclusion criteria were enrollment in either PT 7165, Clinical Decision-Making IV, or HIM 5340, Healthcare Informatics, and being over 18 years of age. There were no exclusion criteria. The study was approved by the Texas State University Institutional Review Board (IRB) (IRB #6240).

Procedures

The researchers met in person and online to develop the IPE experience for approximately six hours. They developed the learning objectives, activities, and assessments prior to beginning the semester. The PT faculty developed a patient case study and an associated assignment in which the PT students used an electronic documentation format. The HIM faculty developed a corresponding assignment for the HIM students to audit the PT students' documentation and provide feedback.

Once the semester began, students were randomly assigned to one of the seven groups, with each group consisting of five to six PT students and one HIM student. Students interacted together three times during the term. **Figure 1** provides a flowchart of the sequence of activities used in the study. *Pre-Meeting Work by Students:* All participants submitted the pre-IPE survey (SPICE-R2 and demographic questions) through the university's online learning management system in their respective courses.

Online Workgroup Meeting 1: Students in assigned workgroups introduced themselves and discussed their professional educational backgrounds and roles via an online meeting tool such as Zoom, Teams, Facetime, or similar tools chosen by the students. Although the PT students were together on campus, the online HIM students were in different geographical areas, so no in-person meetings took place involving all students in the workgroups. After the meeting, each student wrote a reflection paper summarizing what they learned about themselves and the other professional discipline.

Between-Meetings 1 and 2: The PT students completed an initial evaluation of a patient case study and submitted the resulting documentation. The documentation was distributed for auditing by the HIM student in the group. The HIM students also received a copy of the case and a rubric identifying important information.

Online Workgroup Meeting 2: After the HIM students completed the audit of the PT students' documentation, the students met in their assigned workgroups via the online meeting platform to discuss the findings of the audit. Students provided rationales for decisions made while producing and auditing the documentation. Afterward, students wrote a paper reflecting on their interpersonal skills and communication as well as their experience of being part of an interprofessional team.

Online Workgroup Meeting 3: The workgroups met via the online meeting platform a final time to discuss the pros and cons of electronic versus paper medical records and of specific electronic health record (EHR) systems. Since EHR systems are used by both PT and HIM practitioners, this topic of common interest was specified in the assignment to motivate engagement. This approach was based on earlier studies that demonstrated the value of using EHR systems to link student assignments[16] and studies to motivate students to learn about EHRs.[17, 18] Students wrote a final paper reflecting what they learned about themselves from the IPE experience. After all student meetings concluded, the students completed the post-IPE survey (SPICE-R2 and additional questions).

Data Analysis

Demographic information was analyzed using descriptive statistics. The t-test for unequal variances was used to identify any difference in the ages between the PT and HIM students. The results of the survey were analyzed using four Two-Way ANOVAs (program x time) for the overall SPICE-R2 and the R, T, and O factors. Data analysis was conducted using SPSS.

Results

Thirty-seven of 38 (97.37%) PT students completed the pre-test and 31 (81.58%) completed the post-test. All seven HIM students (100%) completed both the pre- and post-test.

Of the 37 PT students who participated in the study, 24 were female and 13 were male with the mean age of 27.10 and a range of 23-40 years. The mean age of the seven HIM students was 27.14 with a range of 23-36 and all were females. There were no statistical differences in age between the two groups ($t = -.237$, $\rho = .814$).

Means and standard deviations (SD) for the overall SPICE-R2 pretest scores for the PT students were 38.36 (SD=3.58) and 40.14 (SD=3.18) for the HIM students. The post-test mean scores and standard deviations were 40.77 (SD=4.51) for the PT students and 43.43 (SD=4.65) for the HIM students, as seen in **Table 1**.

The differences in the overall SPICE-R2 scores by program (PT, HIM) and time (pre- and post-test) was significant for the main effect of time ($F=5.784$, $\rho=.019$), but not for program ($\rho= .065$) or the interaction of program and time ($\rho= .714$). Examining the individual factors, there was a significant difference in the main effect of program ($F= 8.121$, $\rho= .006$) for the T factor and no significant difference for time ($\rho= .214$) or for the interaction of program and time ($\rho=.808$). The R factor had significant differences for both main effects, program ($\rho=.022$) and time ($\rho=.005$), but not for the interaction of program and time ($\rho =.625$). There were no significant differences for the main effects of program ($\rho=.196$) or time ($\rho=.292$) or the interaction of program and time ($\rho=.563$) for the O factor scores, as seen in **Table 2**.

Discussion

The IPE activities promoted a positive perception of PT and HIM students working in a collaborative interprofessional manner, confirming the hypothesis. The overall SPICE-R2 and the R factor scores for PT and HIM students combined improved from the pre- to the post-test survey. The T and R factor scores showed significant differences in pre- and post-test scores between the PT and HIM students.

Qualitative results from this study will be reported separately, but briefly the narrative responses to open-ended survey questions and reflection paper assignments demonstrated that most PT and HIM students found the IPE experience valuable. Three themes emerged from the narrative data: roles and responsibilities, communication and coordination, and participating in an activity that simulates realistic engagement between healthcare professionals.

Another important point demonstrated by this study was that benefits from IPE can be achieved when students are geographically distributed by using widely available online collaboration tools. As other studies have shown, the same strategies and tools that are increasingly used to facilitate online teaching and learning within disciplines can also be used across disciplines.[19] In our study, synchronous online collaboration platforms were effectively used to facilitate IPE among students distributed across geographically separate locations. While students reported challenges of scheduling meetings with multiple attendees, the logistical challenges would have been even more significant if travel time and physical presence were required.

This study demonstrated that students may realize benefits from IPE without substantial time commitments from faculty. The two instructors involved in this study spent no more than six hours throughout the semester on IPE activities, including planning, delivery, and assessment. Following a strategy of awareness and integration before creation, the instructors recognized the opportunity to make slight adjustments to existing courses and assignments rather than creating entirely new IPE activities.[20] This approach also avoided issues related to managing the total number of hours allowed for accredited programs and was consistent with the HPAC recommendation to integrate IPE activities into existing professional curriculum.[4]

Limitations

This study was limited by several factors. A potential limitation is that the SPICE-R2 has not yet been validated for HIM students and that in the 2017 study by Zorek et al., there was suboptimal fit and questions about reliability for PT students in the roles/responsibilities (0.61) and patient outcomes (0.69) even though the overall profession-specific reliabilities were good for physical therapy (0.86).[14] Although the SPICE-R2 has good psychometric properties, a correlation between its scores and acquisition of interprofessional skills has not been established.[15] Despite these limitations, the authors of the current study believe that it was an appropriate instrument to use. The SPICE-R2 provided information about perceptions of IPE, but without a focus on any particular profession. The survey was relevant to all participants in this study because the questions focused on interprofessional collaboration rather than direct patient care. It is an appropriate instrument to measure differences between health professions, to measure differences between students with and without healthcare experience, and differences before and after an IPE.[21]

Another limitation was the scope of the study being focused on one university and two disciplines. Future research could expand this approach to include more institutions and more disciplines to increase the generalizability of the results.

As the first attempt at this type of IPE between PT and HIM at our university, the participants were limited to students enrolled in courses taught by the collaborating researchers during the study period. The course in which the HIM students were enrolled was an elective and therefore participants' number was small compared to the PT students who were enrolled in a required course. Expanding the scope to additional courses and across additional healthcare disciplines would improve future studies of this type. The study was also limited by the time of being a single academic semester. Future research monitoring the benefits of IPE from matriculation to graduation from an academic program would be beneficial.

Conclusion

This study described interprofessional learning activities between PT and HIM students that consisted of homework assignments and three synchronous online workgroup meetings which provided a unique learning experience for both sets of students. Students met online to learn about their roles and responsibilities in health care, to provide and receive feedback about a documentation assignment, and to discuss different types of electronic health record systems. Students' scores on the overall survey improved significantly as did the T and R factors. Students' reflections focused on role clarification, communication and coordination, and participating in a realistic experience. The students believed that the experience was beneficial and important to them.

Authors

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Convenience Sample (n=45)

38 PT, 7 HIM students

1 PT student did not provide consent for research, participated in IPE

Administration of survey (n=44)

Random assignment of students into 7 workgroups

1 HIM:5-6 PT student per workgroup

Online Workgroup Meeting 1:

Introductions

Reflection Paper 1

PT students submit documentation of patient case to HIM student

HIM student audits PT documentation

Online Workgroup Meeting 2:

Review of audits

Reflection Paper 2

Online Workgroup Meeting 3:

Discussion of electronic health records

Reflection Paper 3

Administration of survey (n=38)

31 PT students, 7 HIM students

Legend

PT = Physical Therapist

HIM = Health Information Management

Figure 1. Flowchart of methods

Table 1. Descriptive Statistics

	Physical Therapist Student	**Health Information Management Student**
	Mean (Standard Deviation)	Mean (Standard Deviation)
Overall		
Pre-test	38.36 (3.58)	40.14 (3.18)
Post-test	40.77 (4.51)	43.43 (4.65)
Team/Teamwork (T)		
Pre-test	16.25 (2.23)	18 (1.29)
Post-test	17.097 (1.68)	18.57 (1.62)
Roles/ Responsibilities (R)		
Pre-test	9.56 (1.52)	10.57 (2.44)
Post-test	10.87 (2.17)	12.43 (1.51)
Patient Outcomes (O)		
Pre-test	12.56 (1.80)	11.57 (1.27)
Post-test	12.81 (1.82)	12.43 (1.90)

Table 2. Results of Two-Way ANOVA

Comparison	**Program Main Effect**	**Time Main Effect**	**Interaction Program x Time**
Overall	ρ=.065	ρ=.019*	ρ=.714
Teams/Teamwork	ρ=.006*	ρ=.214	ρ=.808
Roles/Responsibility	ρ=.022*	ρ=.005*	ρ =.625
Patient Outcomes	ρ=.196	ρ=.292	ρ=.563

Key: * indicates significant finding, with alpha = .05.

There are no comments yet.

OVERCOMING CHALLENGES OF MERGING MULTIPLE PATIENT IDENTIFICATION AND MATCHING SYSTEMS: A CASE STUDY

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Overcoming Challenges of Merging Multiple Patient Identification and Matching Systems: A Case Study

By Donna Crew, RHIA, Pete Furlow, and Shannon H. Houser, PhD, MPH, RHIA, FAHIMA

Abstract

Northeast Alabama Regional Medical Center (RMC) in Anniston, Alabama purchased a smaller hospital in 2017. Staff at the two hospitals were tasked with merging the two Electronic Medical Record (EMR) systems into one unified system. From the outset, there were two systems with different medical record number specifications and patient identification systems as well as two different patient name parameters. The merging of these records and systems meant dealing with different vendor EMR systems and ancillary systems to produce a single unified record within RMC's EMR and the document imaging system that housed the legal medical record for each patient.

This case study describes the process and procedures of merging the patient records from both hospitals to create one Enterprise Master Patient Index (EMPI); and the collaboration between the Health Information Management and Information Technology departments to accomplish this goal. It also reviews the impact and challenges related to the system's development, as well as lessons learned while completing the project.

Keywords: medical records systems, computerized/organization & administration, patient identification systems/standards, duplicated medical records

Introduction

Healthcare delivery has changed and increased in pace especially in the past three decades to include merging and acquisition of other healthcare organizations.[1] Mergers and acquisitions benefits integration of care, decreases duplication of clinical services, fosters clinical standardization to reduce cost for operating expenses and improves overall quality.[2, 3] As more hospital systems purchase external clinics, physician practices and hospitals, the goal should be to have all operations using one medical record system to ensure quality of care is consistent among all providers and information is accessible by all entities within the system serving the patient. Patient identification and duplicated medical records are always challenges and are major issues to be resolved when merging medical record systems.

The challenges in hospital mergers and acquisitions involve multiple functions of the facilities, health information technology being one of the most challenging components.[4] Other impacted areas, such as financial and accounting systems, purchasing and supply systems, pharmacy, radiology, laboratory and human resources systems require active reconciliation.[4,5] Healthcare informatics is the field of information science concerned with the management of all traits of health data and information through the application of computers and computer technologies. Increased technology, such as advanced Enterprise Master Patient Index (EMPI), algorithms, radio frequency identification and smart cards, are major tools in solving duplicate medical records and patient identification matching issues.[6, 7] Because of the current culture of mergers in the overall health care system, it is highly likely that a Health Information Management (HIM) Director or Manager, will be required to be responsible for making decisions on how to accomplish a unified medical record and an EMPI.[6] A strong, collaborative and capable leadership team is the key for a project to be successful in merging and implementation of a new system within healthcare organizations.[8]

This case study describes the collaborative efforts between HIM and Information Technology (IT) as a very specialized team, their accomplishment of creating an Enterprise Medical Record System, the processes of the system's development and steps involved in the merging process. It also reviews the impact and challenges related to the system's development. Lastly, several lessons learned and recommendations for merging medical record systems and the alliance of HIM and IT collaboration works are discussed.

Methods

Project Scope

The purchasing hospital, Northeast Alabama Regional Medical Center (RMC)[9] serves a five-county area as the region's leading healthcare provider in northeast Alabama. The hospital that was purchased (Purchased Hospital) is in the same city as RMC. Statistically about 90% of the local physicians are on staff at both hospitals. The purchase was intended to align the delivery of healthcare in the region and reduce waste and duplication of limited healthcare resources.

As part of the acquisition, RMC was required to disconnect the Purchased Hospital from its legacy Electronic Medical Record (EMR) within 14 months of the purchase date. Dozens of systems had to be migrated in the 14-month timeframe, with the largest and most complex of these being the EMR and storage system for the legal medical record. RMC's EMR is Allscripts Paragon, a single integrated system that allows both physicians and clinical staff to document, order and review patient information. The EMR transfers the data into OneContent, a Hyland Product, which is the document imaging storage system where the legal medical record is located. The Purchased Hospital's EMR was a group of systems proprietary to the previous owner that provided the EMR functions for physicians and nurses. The Purchased Hospital used McKesson's Horizon Patient Folder (HPF), an earlier software version of OneContent, for the document imaging storage system. RMC's challenge was to convert and implement Paragon (and other key systems) at the Purchased Hospital for all EMR activities such as clinical functions, billing, General Ledger (GL)/Accounts Payable (AP), charge master and materials management.

RMC had decreased the clinical paper documentation to 30% since implementation in 2013 and only uses paper documentation in some outpatient areas. One goal would be to standardize the documents and continue decreasing paper at both hospitals. This was a large adjustment to the Purchased Hospital's processes which would require RMC to educate and train all clinical disciplines how to document in Paragon. Since 90% of the physicians were using Paragon at RMC, the responsibility for physicians only included training 10% of the medical staff.

There was a total of 709,528 medical records in both systems with a potential 50% to 60% overlap which meant the patient had been at both facilities. This data was provided by an algorithm report that RMC contracted a vendor to provide RMC. The first algorithm report showed that we would need to create an estimated 60,000 new medical record numbers for patients that were not in the RMC's Master Patient Index (MPI). The goal was to decrease that by matching more of the patients by investigating each case to ensure the patient truly was not in RMC's MPI. RMC's Paragon had a total 482,528 medical records with a potential duplication rate of less than 2%. The medical record numbers were 6-digits (123456) and the account numbers were 10-digits (1234567890). The Purchased Hospital had 227,000 medical records with an 8% potential duplication rate. The medical record number was a 10-digits number which had 4 leading zeros (0000123456) and the account numbers had 7-digits (1234567). **Table 1** illustrates the basic comparison of characteristics of medical record systems from RMC and the Purchased Hospital.

Project Goals

The primary goals of the project include:

1. Assess the feasibility, compatibility of the systems, and determine the scope of the project.

2. Design an electronic system that would merge and store all the medical records and administrative data from both hospitals.

3. Identify all potential duplicates in medical records, and upon verification, merge in the hospital information system.

4. Develop a team to ensure that any downstream systems that operate using a medical record as identification are updated or changed at the same time.

5. To create a new medical record number with all the patient's visits from the Purchased Hospital's system into RMC Paragon and OneContent. An example would include radiology films must match your EMPI.

6. Migrate all patient medical record documents stored in HPF into OneContent under the correct patient medical record number.

Definitions

- **Person**: Any individual contained within the Paragon database. A person can be a patient, physician, employee, guarantor, etc.

- **Patient**: A person within the Paragon database who has been registered for at least one visit. All patients are persons within Paragon, but not all persons are patients.
- **Potential Duplicate**: A patient identified as having two or more medical record numbers.

Project Phases and Timelines

This project consisted of three phases. It started from Phase I Analysis and Design in May 2017 and ended in Phase III Go Live in July 2018 (see **Table 2**).

Results

Project Procedures

In order to carry on the merging of duplicated records, a three-step process should be followed: identification, verification, and merging.

Step 1: Identification

1. Identification of potential duplicates is ascertained through daily monitoring of the *Possible Duplicate Persons* report housed in the Paragon Medical Records Reports Module and communication from hospital personnel who identify potential duplicates through the course of their job duties.

2. Printing the *Possible Duplicate Persons* report. Research the entries to confirm whether valid duplicate medical record numbers exist (see **Figure 1**).

3. Notifications regarding potential duplicates that are received via the Medical Record Number Correction form, e-mail, telephone call, etc. will be processed according to this policy and procedure.

Step 2: Verification

1. In order for the potential duplicates to be considered a 100% match all the following criteria MUST match:

a.) Date of Birth

b.) Social Security Number

c.) First Name

d.) Last Name

2. Access **Abstract Maintenance** in **Paragon Medical Records** to verify the information. Compare the print outs. If all items listed in #1 match for both persons, the merge process can begin. Otherwise, continue verification process.

3. Verify Social Security Number at OneSource. If social security verification determines person is not

a duplicate, stop here and do not merge (see **Figure 2**).

4. Verify insurance using Paragon Patient Management and OneSource. Determine patient's insurance type through Paragon Patient Management. Use OneContent to compare information such as insurance cards, signatures. Global documents will include information such as insurance cards, and driver's license which can be used to verify patient's identity (see **Figure 3**).

Step 3: Merging

Merging has two conditions:

a.) Merging when all medical record numbers are attached to a visit;

b.) Merging when one or more medical record numbers are not attached to a visit.

1. When determining which medical record number to retain, check to see if **any** of the medical record numbers have an active account. The merge cannot be completed until the account(s) have been discharged and are no longer active. Typically, the medical record number with the most visits will be retained. If the medical record numbers being merged have an equal number of visits, retain the medical record number with the most recent account.

2. After determining which medical number will be retained, review the demographic sheet print out and ensure the following data elements match the medical record number with the **most current visit**. The elements in **bold** must match for Paragon to allow the merge.

a.) **Date of birth**

b.) **Sex**

c.) **Race**

d.) Social Security number (enter 9 zeros for all medical records **not** being retained)

e.) Ethnicity

f.) Marital status

g.) Religion

h.) Preferred language

i.) Privacy note date

j.) Advance directive

The Key Tasks and Accomplishments in Each Phase

Phase I. Analysis and Design (May 2017-September 2017)

1. Assigned leadership responsibilities to the Director of Health Information Services (HIS) from RMC (with 33 years' experience in HIM) to work with Chief Information Officer (CIO) (with 25 years hospital IT experience and system implementation) to have oversight for the project. Due to the nature of the project, it required both HIM and IT skill sets to accomplish this major project.

2. After assessing the systems at both hospitals, the team decided on the best approach to combine the disparate data sets. EMPI teams were formed to compare and review the data for accuracy for the overlay patients, duplicate patients and the patients that had not been to RMC. This team would determine which patients would need to be assigned a new medical record number. To correct each duplicate record, it was estimated that the length of time to take 38 minutes per record. Each person on the team could potentially fix 10 to 15 records per day.

3. Conducted an investigation to determine if new medical records would need to be created for all 60,000 patients. The investigation was needed due to discrepancies in the data fields such as different last names, dates of birth, unknown sex and social security numbers being off by one digit. It was estimated to take approximately 1 to 2 hours to complete the needed investigation work per patient record. This estimate included the time it took to switch and compare data between two systems. This goal was critical to patient safety to ensure a complete medical record was being implemented. Contracted with one HIM vendor to assist in doing the investigations for three months due to of the amount of time it would take to investigate each case.

4. Analyzed how the mapping would occur for the documents, bar codes and images from the Purchased Hospital's HPF system into RMC's OneContent system. The team made the decision to use RMC's naming convention since RMC was the larger database and was built with more complicated workflows. An example of naming conventions would include a document name in the Legacy System such as Consent for Treatment and in OneContent that document name would be listed as Adm Consent Treatment. The team had to ensure that all documents would be stored properly for the legal medical record. **Table 3** illustrates examples of documentation names.

5. Created an EMPI in Paragon and OneContent. Both hospitals would require training on how to locate the patient and medical record. Screen shots were developed for purpose of training the staff.

6. Set-up a messaging system to alert when there is a change in medical record numbers to downstream systems, such as laboratory radiology, cardiology, Tumor Registry and the patient portal, where the EMPI in the systems could be updated immediately.

7. Mapped financial data, such as patient types, payer codes, insurance, financial class and account types.

8. Developed training manuals and procedures by both HIM and IT teams. For protection of patient safety and data integrity, every staff member is responsible in following the procedures.

Phase Two: Action Steps (October 2017-July 2018)

1. Established a subset of EMPI data including medical record number, Social Security number, last name, first name, middle name, DOB, address, age and sometimes maiden name from both hospital systems. Determined which data subset contained the latest demographic data for each patient. These data subsets were used with a scripting tool to verify the data comparisons to the first algorithm report.

2. Merged all confirmed duplicate medical records in the live systems. The goal was to decrease the number of duplicate medical records before the systems Go Live.

3. Identified if a patient needed a new medical record number in RMC's EMPI or if we needed to merge the patient's medical records between the two hospitals. These reports were worked and saved weekly.

4. Weekly reports were run by Paragon and OneContent representatives to measure how many patients were left to match. The patients' data were updated in the test system weekly and would be pulled from test into the live system on July 30, 2018.

5. Created a medical record process for new patients being registered in the hospital to allow automatically and systematically assigned medical record numbers.

6. Tested the amount of time it would take to move the medical records numbers, account numbers and documents with the images from the Purchased Hospital into Paragon and OneContent. These tests assisted with estimation of the required downtime during the Go Live conversion.

7. Determined how incorporating the Purchased Hospital into one system would affect the patient portals with an immediate HL7 feed at both facilities.

8. Consolidated statistical data or reports for financial, quality, state or federal reporting by multiple teams including Administration, IT and HIM. Formatted documentation forms with barcodes. Tested the amount of time that it took to move the actual document images. Mapped patient index files that required by Centers for Medicare and Medicaid Services (CMS) and The Joint Commission (TJC) to be permanent from both hospitals.

9. Provided screen shots to identify and teach all the staff on both campuses on the EMPI and how the new set-up will look.

10. Evaluated medical records from both hospitals for matching the Purchased Hospital's 10-digit registration system. Many tests were required as this feature caused the hospital to have false data on the patient algorithm reports. Many of the 60,000 were actual one to one matches once the data was reviewed for 11-character names such as Christopher.

11. Matched EMPI number and medical record number in Paragon and OneContent. The team verified admission and discharge dates and times were correct for RMC and the Purchased Hospital.

12. Set-up Go Live date and time as July 30, 2018, at 7:00 am. All systems at Purchased Hospital were

taken offline on July 27, 2018 at 5:00 a.m. and would begin manual downtime processes. Registration tracked all patients that were in-house at downtime and any other patients that were treated at the hospitals.

13. Uploaded verified data into the live system starting around 11:00 p.m. on July 29, 2018. During this time, IT pulled new reports and sent this to the team to analyze the data to ensure the data was uploaded correctly in the live system.

Phase III. Go Live (July 30, 2018)

1. Activated entire hospital system. All systems were brought on-line at 7:00 a.m. The EMPI team continued to verify the data and documents had uploaded correctly in the live systems. The Business office registered all the patients that had presented to the Purchased Hospital from July 27, 2018, 7:00 a.m. until Go Live on July 30, 2018 at 7:00 a.m.

2. A swat team of IT and clinical staff was maintained at the Purchased Hospital to support all hospital staff after Go Live. This team was stationed there for several weeks to ensure quick assistance and issue resolution.

3. Monitored all patient census coming into the system during the downtime.

4. Monitored and tested for any type of errors that may have been loaded in all systems for one month after Go Live. For example, patient portal reports were built to ensure that the correct patient's information was automatically being sent to the portal.

5. Assigned one employee to report the census and another to work on any new duplicate medical records created after Go Live for both facilities from Paragon.

Discussion

When approaching a project such as this one it is essential to have an effective leadership team from both HIM and IT for a successful project. The MPI is the foundation base for all EMRs and it is critical that the information is accurate. Our key points on lessons learned and recommendations during the conversion include involve the right staff, clean up MPI, know the workflows, consolidate systems, interface to automate, and source of truth.

Involve the Right Staff

Involve all the key players from both facilities. It is very important to ensure all key areas are represented while planning and working through the conversion process. This should include not only HIM and IT but areas such as registration, scheduling and the business office. These areas work with the patient accounts daily with very different functions that involve data being represented in the EMPI and patient accounts. Be prepared to commit to weekly or bi-weekly communication either by conference calls or video between all members. It is believed that this communication saved the hospital from many issues on the constant updating of data and meeting the goals.

Clean Up that EMPI

If your IT system has the ability to run an analytical report on both the current and the newly purchased systems this must be your first step. If not, we suggest purchasing an algorithm report. That will be your base to determine the amount of time needed and what type of work will need to be performed. Do as much cleanup work on the EMPI as possible before you begin to merge any data. The more time spent identifying duplicate persons, missing data elements and cleansing data the better. In our situation we had a large percentage of overlapping patients that had accounts at both hospitals. This proved to be very challenging and required a lot of manual data verification to ensure the right accounts would be merged, and new accounts created when necessary.

Know the Workflows

It is critical to understand the workflows and the culture of the other organization. This is a lesson we learned quickly. While a workflow may work fine at one facility it may need to be tweaked to work just a little differently at the other facility. Standardizing workflows and processes should be a goal but be flexible when needed. Look at all options and possibilities. Keeping in mind the way you are currently performing a process may not actually be the most efficient way to start with. Just because it's always been done that way does not mean it's the right or best way.

Consolidate Systems

Consolidate systems when possible, as it is much easier to manage and support. This holds true for not just clinical applications but any system being used at both facilities. During our conversion the goal was to ensure both hospitals were using the same systems both clinical and non-clinical across the board. This helps with staff orientation, training and when staff may float between hospitals. A good example of this is the policies and procedures that are attached to your workflows or documentation.

Interface to Automate

Interface to eliminate manual processes. Interfaces are the backbone of healthcare applications allowing different systems to pass information back and forth. Interfaces can save hundreds of man hours and ensure data is available in real-time. Ensure you have a robust Interface Engine in place that can handle the multiple interface loads as well as being able to customize interfaces as needed. And always remember a standard admission, discharge, transfer (ADT) interface is never "standard".

Source of Truth

With so many different computer systems sharing data within a healthcare environment, it is critical that there be a single source of truth (SSOT) for EMPI data. This SSOT is the master key to all EMPI related data. All downstream systems will receive data from the SSOT provider, and that data should be considered golden. Any and all changes to EMPI data should be made at the SSOT point.

Conclusion

Patient matching continues to be a challenge for hospitals and health information exchanges. This situation increases the hospital expenses and endangers the integrity of the patient medical records. A solution to ensure that patient data can be matched correctly is needed whether that is a national unique patient identification or allowing the private sector to help solve the problem. With increased technology and informatics, patient identification and matching issues can be resolved effectively and efficiently. This must be one of our nation's priorities. A collaborative team between HIM and IT and a strong leadership are the key for a successful project in merging medical record systems.

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There are no comments yet.

HEALTH INFORMATION PRIVACY LAWS IN THE DIGITAL AGE: HIPAA DOESN'T APPLY

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Health Information Privacy Laws in the Digital Age: HIPAA Doesn't Apply

By Kim Theodos, JD, MS, RHIA, and Scott Sittig, PhD, MHI, RHIA

Abstract

The notion of health information privacy has evolved over time as the healthcare industry has embraced technology. Where once individuals were concerned about the privacy of their conversations and financial information, the digitization of health data has created new challenges for those responsible for ensuring that patient information remains secure and private. Coupled with the lack of updated, overarching legislation, a critical gap exists between advancements in technology, consumer informatics tools and privacy regulations.

Almost twenty years after the HIPAA (Health Insurance Portability and Accountability Act) compliance date, the healthcare industry continues to seek solutions to privacy challenges absent formal contemporary law. Since HIPAA, a few attempts have been made to control specific aspects of health information including genetic information and use of technology however none were visionary enough to address issues seen in today's digital data focused healthcare environment. The proliferation of digital health data, trends in data use, increased use of telehealth applications due to COVID-19 pandemic and the consumer's participatory role in healthcare all create new challenges not covered by the existing legal framework. Modern efforts to address this dilemma have emerged in state and international law though the United States healthcare industry continues to operate under a law written two decades ago. As technology continues to advance at a rapid pace along with consumers playing a greater role in the management of their healthcare through digital health the privacy guidance provided by federal law must also shift to reflect the new reality.

Keywords: HIPAA, digital health, privacy, health data, consumer informatics

Introduction

Throughout history, ethics rather than regulation governed the privacy of patient information. Originally, individuals were concerned primarily with invasion of their homes, financial records and personal conversations yet with the proliferation of digital health tools individuals are becoming more aware of the vulnerability of their health data.[1] The digitization of healthcare coupled with consumers taking a more active role in their healthcare management has created an abundance of health data that falls between the cracks of current privacy regulations.[2] Current regulations have emerged over time; initially rooted in ethical principles and often loosely interpreted and applied to health information.

One of the first attempts to regulate privacy of health information was the Privacy Act of 1974. It focused on protection of health records collected and maintained by the Federal Government. Most notably, only federal agencies were required to comply, although it did give best practices for use and disclosure of patient information. Healthcare providers were predominantly unaffected and continued to practice privacy based on ethics until more comprehensive legislation was passed.[3]

Previous attempts at privacy regulations were insufficient; therefore, the Health Insurance Portability and Accountability Act of 1996 was written and included the privacy and security rules creating comprehensive yet general restrictions for health information privacy. HIPAA remains the most critical law related to healthcare privacy because it provided a direct and unavoidable right to privacy for all patients.[4–6]

Compliance with the original HIPAA regulations took significant time and effort by healthcare facilities, and more changes were on the horizon as the focus on patient rights grew. As the challenges and risks of healthcare privacy took center stage, legislators became increasingly eager to draft privacy legislation with a narrower scope.

In the late 1990s, discrimination based on genetic information became a major concern for patients and physicians. Genetic data is more sensitive than clinical patient data as it involves identification of not only the individual patient but also his/her family members. Modern courts recognized the sensitive nature of genetic information, and their decisions reflected a perceived need for additional protection of this type of information beyond what HIPAA offered.[7,8] Congress passed the Genetic Information Nondiscrimination Act (GINA) in May of 2008. GINA became the legal standard for the collection, use, and disclosure of genetic information.[7,8] Although only focused on genetic information, GINA served as a further step in the evolution of health information privacy laws.

The American Recovery and Reinvestment Act (ARRA) passed in 2009 intended to provide economic stimulus to the sluggish American economy.[9] The healthcare industry was front and center in many parts of the Act, but mostly in the Heath Information Technology for Clinical Health Act (HITECH) portion.[9] While spotlighting and investing in electronic health records and healthcare information technology, HITECH also amended some privacy provisions of HIPAA. It redefined some key terms found in HIPAA as well as creating an official structure for governance of policy and standards relating to healthcare privacy and security.

HITECH's Meaningful Use program successfully incentivized adoption of Electronic Health Records with substantial increases in use of IT throughout the healthcare industry.[10,11] This moved much of the traditional patient data from a paper record to a digitized format which was encouraged by HITECH. Meaningful Use created new channels of health data access (i.e., patient portals) for patients to access their health information, but it also introduced new concerns for health data privacy.[12] Although HITECH made great advancements in health information technology, it failed to address the new privacy and security challenges presented by the digitization of health information.[13]

Up to this point, the aforementioned privacy and security laws did not address the transition of healthcare into the digital age. With the implementation of digital heath tools such as patient portals, health information exchanges, genomic registries, wearables, and mobile health (mHealth) applications, a void in the protection of health data emerged.

Modern Privacy Laws

Recent attempts have been made at the federal and state level to acknowledge digital health data however privacy and security guidance has been limited. For instance, the 21st Century Cures Act was signed into law (2016) reflecting a major push in the pharmaceutical industry to modernize drug development and create innovative pathways and clinical trials.[14] This legislation did address interoperability issues associated with data exchange and emphasized a patient's right to access their own information, yet it did not go far enough to change or reclassify patient privacy or further define the data that is covered by privacy regulations.[15,16]

Where no federal law or less restrictive federal law exists, states are allowed to pass legislation at their discretion. Given the lack of comprehensive privacy law updates as well as modern advancements in how healthcare data is managed, stored and transmitted, many states have individually passed privacy laws that are stricter than HIPAA, GINA and ARRA. Many of these state laws also deal with digital health data as well as reinforcing patient rights.

For instance, the state of California recently passed a unique privacy law focused on protecting residents' data privacy rights.[17] The California Consumer Privacy Act was signed into law in 2018 with a 2020 compliance date. This legislation addresses modern challenges associated with consumer privacy such as opt-out options for consumers who do not wish for their information to be sold to third parties as well as more detailed disclosure of how consumer data is used to promote transparency and understanding by consumers. The main limitation of CCPA is the narrow scope of businesses that must comply. Primarily this law focuses on large corporations with substantial revenues and/or customer volume.[17]

In 2018, Colorado passed an innovative law requiring the most stringent measures in the United States to protect consumer data privacy. The Colorado Consumer Privacy Act defines a covered entity as any organization or person who "maintains, owns, or licenses personal identifying information of an individual residing in Colorado."[18] This is a much broader definition than HIPAA provided and includes many of the corporations not covered by the HIPAA definition of a covered entity. The Colorado law's breach notification terms include a more stringent timeframe (30 days compared to 60 days in ARRA) as well as requiring notification of Colorado government officials of any breach affecting more than 500 residents.[18] Finally, the data included in this law includes both healthcare as well as financial data.[18]

Similar to the Colorado Consumer Privacy Act, the European Union (EU) implemented new regulations of digital data privacy to include healthcare data. The EU General Data Protection Regulation passed in 2016 with a compliance date of May 2018, is a notable international law aimed at protecting privacy of individuals in the European Union.[19,20] The legislation mimics HIPAA in some areas with breach notification rules, penalties, and patient rights however it focuses on data, technology, cloud-based applications and third-party access to data.[19,20] Many see this law as an upgrade to the outdated version of HIPAA still used in the United States.[19,20]

Even with these notable changes there are still health data privacy concerns as many digital health tools are not covered by current HIPAA privacy laws. For instance, recent research has shown that some mobile health (mHealth) applications leave residual protected health information data on the hardware of the device utilized.[21,22] This leaves the consumer's health data vulnerable to be utilized or accessed for purposes other than which the consumer agreed upon.[23,24]

Current Challenges with Digital Data and Privacy

Emerging technologies such as genealogical databases (i.e. 23andme and Ancestry) as well as wearable devices and mHealth apps have created a new risk for data privacy that is not covered by HIPAA. These digital health tools are not covered entities therefore they are not required to protect the data they collect under HIPAA. The Department of Health and Human Services nor the Office of Civil Rights have purview over this data or any breach of the consumer's information. Any complaint regarding a breach of consumer's health data is rejected, as there is no controlling law currently for this type of data. Complaints of this type go to the Federal Trade Commission; however, many consumers are never aware that their information is breached, shared or sold to a third party because there is no breach notification requirement in place.

The novel Coronavirus (COVID-19) pandemic has further highlighted the need for the modernization of HIPAA. Although HIPAA disclosure laws found in the Privacy Rule remained applicable for sharing of patient data for patient care and public health purposes, the considerable increase in use of telehealth as a result of COVID-19 poses challenges for HHS. In March 2020, HHS released a notification of enforcement discretion surrounding use of remote communication applications, software and technology such that the use of those technologies is in good faith.[25] This included use of video chat and communication platforms supporting telehealth visits which did not require Business Associate Agreements for these third-party vendors as normally required under HIPAA. The mechanisms of delivery of healthcare have been completely altered, use of technology is now undeniable and applicable laws such as HIPAA must be revised.

Consumer Health Informatics

The field of consumer informatics continues to grow rapidly as consumers (i.e. patients) take a more active role in their healthcare utilizing technology such as: patient portals, online forums, personal health records, wearables, medical Internet of Things (IoT) and mobile health applications (mHealth).

Medical internet of things (mIoT) is a system that connects devices such sensors, smartphones (mobile health apps), wearables, smart TVs and intelligent virtual assistants (i.e. Amazon Echo, Google Home) to facilitate the healthcare delivery process.[26] The assimilation of mIoT and mobile health apps into the healthcare ecosystem has vastly changed the manner in which healthcare is delivered and has the potential to improve the quality, safety and efficiency of healthcare services.[27–29] Medical internet of things (mIoT) is driven by the monitoring of personal health information by sensors and the analyzation of the data received from these sensors. mIoT and mobile health applications have emerged as revolutionizing technologies that are redefining the way patient data is accessed, stored and delivered.

While accessing and utilizing these consumer informatics tools helps consumers make more informed health decisions it also presents a privacy challenge since most of the consumer health informatics tools are not governed under the HIPAA Privacy Rule.[30] This is especially true in the wearables and mHealth app markets where these tools/applications seem to fall between FDA regulation and the HIPAA Privacy Rule.[31] Many wearables and mHealth solutions store consumer health data on the cloud of which the consumer may be unaware.[30] As long as the consumer health informatics tool is not integrated as part of a healthcare system then the consumer health informatics tool vendor does not have to meet HIPAA or HITECH guidelines.[30,32] This leads to a critical gap in privacy protection where consumers have very little understanding and control of how their health data is stored, accessed and utilized.

Genomic Data

With reductions in the cost of genomic sequencing there has been an increase in the utilization of genomic data for clinical research and healthcare delivery.[33] In addition, there are new options such as direct-to-consumer genetic testing which allows consumers to initiate genetic testing for specific mutation risks. For instance, the FDA allowed 23andMe a direct-to-consumer *BRCA1* or *BRCA2* mutations testing for women to help identify breast cancer risks.[34] Due to the gaps in health data privacy across the digital health ecosystem there has been an increase in the sophistication of attacks on stored genomic data.[33] These sophisticated attacks utilize public information (e.g. demographic data and genealogical data), genomic-sharing websites (e.g. PatientsLikeMe), online forums and online social networks to triangulate the data in an effort to identify the consumer (i.e.

patient).[33] Genomic data is another segment of digital health data that that lacks appropriate protection under GINA and HIPAA.

Conclusion

In 1963, Justice Earl Warren was quoted as saying "The fantastic advances in the field of electronic communication constitute a greater danger to the privacy of the individual."[35] This prophetic statement speaks to the challenges faced in health information privacy today.

With no major updates in the last 20 years, HIPAA remains the preeminent comprehensive health information privacy law. HIPAA was written and passed in the late 20th century when the health information environment was primarily paper based and before the explosion of digital health tools. Two decades later, the health information industry has transformed leaving substantial gaps between advancements in digital health and privacy laws. Individual states as well as the European Union have taken more modern approaches to creating privacy laws reflecting contemporary practices thus demonstrating an awareness of the challenges that exist in management of digital data. These modern approaches to legislation could serve as guides for necessary changes to federal law. Although the benefits of digital data and the opportunities associated with electronic data are "fantastic" as proclaimed by Warren, he was also accurate in his prediction of the dangers now challenging the patient's right to privacy.[35] In order to protect consumer health data so that consumers and health professionals can leverage the power of data in the digital age, revisions to the current privacy laws are vital.

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HEALTH INFORMATION MANAGEMENT REIMAGINED: ASSESSING CURRENT PROFESSIONAL SKILLS AND INDUSTRY DEMAND

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Health Information Management Reimagined: Assessing Current Professional Skills and Industry Demand

By Kim Beesley, MHIM, RHIA; Alexander McLeod, Ph.D.; Barbara Hewitt, PhD; and Jackie Moczygemba, MBA, RHIA, CCS, FAHIMA

Abstract

This paper examines the changes affecting the health information management (HIM) professional skill set and industry demand to determine differences affecting practitioners. As the industry continues to experience technological innovation, the responsibilities of the HIM professional are in flux, affecting the required skill set of the changing environment. This research used the American Health Information Management Association salary survey and current job postings to determine whether the workforce has experienced deskilling and whether a theory-practice-gap exists. It also assesses if industry competencies align with the Health Information Management Reimaged perspectives. The results indicate that the workforce has not experienced deskilling, that a theory-practice gap does exist, and that Health Information Management Reimaged is aligned with industry needs.

Keywords: Health information management, HIMR, HIM, skills, workforce, competencies

Introduction

Health information management (HIM) continues its transformation toward health informatics, big data, and analytics while traditional competencies such as coding are waning as computer-assisted coding moves to the forefront of healthcare information systems.[1] Compounding this skill shift is the adoption of the electronic health record, allowing data to be digitally and globally collected on cheaper, more efficient computers, and software capable of handling big data and predictive analytics.[2] The demand for HIM professionals capable of modeling and performing predictive analytics is growing exponentially, forcing many organizations to scramble to find suitably skilled personnel.[3] This skills shortage provides insight into the changing “supply-side” of the Health Information Management Reimagined equation, but offers little understanding of the “demand-side” of the equation.[4, 5] This research assesses the HIM career skill set, examining current industry needs to evaluate the alignment of skills, knowledge, and abilities with Health Information Management Reimagined (HIMR).

Background

Transitioning from paper medical records to electronic medical records has had a remarkable impact on Health Information Management departments, causing organizations to downsize and eliminate positions based on needed skills.[6] The dominance of paper medical records has declined as healthcare organizations adopt electronic healthcare records mandated in the Health Information Technology for Economic and Clinical Health Act (HITECH).[7] Federal meaningful use requirements have also caused coding and transcription positions to be outsourced while creating new roles and competencies related to informatics, data analytics, information governance, clinical documentation improvement, and big data.[8, 9] Technological change continues to be fueled by new system development and organizational consolidations.[10] While traditional jobs related to billing and coding are still available, less popular careers are evolving, which require skills, knowledge, and abilities such as interface analyst, business intelligence analyst, informatics specialist, data architect, and clinical taxonomy roles.

According to Adler-Milstein and Jha[7], the HITECH Act mandated hospitals to adopt EHR systems. It also included provisions to ensure workforce training in the use of EHR systems, but the implementation of this training remains in question. The Commission on Certification for Health Informatics and Information Management (CCHIM) surveyed 834 HIM respondents, finding that 86 percent recognized the need for education in health data analytics, demonstrating the need for education and redefinition of HIM professional duties.[11] Predictive analytics education is important in helping healthcare professionals make better decisions in both financial and clinical outcomes.[3] With these opportunities come additional challenges, such as incomplete data and insufficient technology. as seen in **Figure 1**.[12]

HIM professionals are aware of the challenges of incomplete records, as evidenced by the prevalence of clinical documentation improvement programs. The healthcare industry has been slow to implement predictive analytics, but as more organizations adopt analytical tools to support decision making, the need for individuals with these skills becomes apparent. Savage[13] suggests that analytical workers are needed in clinical, financial, and operational areas, as shown in **Figure 2**.

To be successful, an HIM professional will have to acquire new skills, continue their education, and obtain necessary new credentials to meet the modern technological changes occurring in healthcare organizations. The need for HIM professionals in traditional roles will decrease as more professionals will be needed in leadership, teaching, and informatics roles. The American Health Information Management Association (AHIMA) has recognized the need to create pathways that support its members preparing for roles in informatics, analytics, and consumer engagement. Thus, a shift to more technical careers and advancements in education is necessary to meet the industry's changing demands.[11] HIMR provides a pathway to successfully update workforce skills, but are those skills demanded by industry today?

The HIM professional's roles and skill set must align with industry needs.[4] Traditional HIM roles will evolve from director, privacy officers, coding staff, and release of information professionals to more modern roles involving big data, statistical analysis, project management, and data analytics.[8] Moreover, these roles will support revenue cycle management, information technology, electronic health records data management and user support, quality, compliance, health information exchange, and clinical documentation integrity.[14] The AHIMA Salary Snapshot,[15] shows the effects of changing skill sets in terms of salary outcomes, as seen below in **Figure 3**.

Some roles that could become obsolete or change due to technological change include file clerks, coders, transcriptionists, and clerical staff. Clerical positions could likely transition into a more electronic data analyst position requiring more education and information literacy. While some positions will disappear, other positions will become more important or evolve into more technologically demanding roles.

Competing for the new evolving HIM professional roles will require a bachelor's and master's degree with robust statistics, quality, and electronic data management. Big data, analytics, and informatics competencies will be among the strongest industry demands for HIM professionals in the coming years.[16] AHIMA's Salary Snapshot collected salary data over several years from 2002 to 2017, using both qualitative and quantitative measures to identify expected competencies. The results of the 2016 AHIMA survey are available on the organization's website at http://www.ahima.org/downloads/2016_salary_snapshot_final_2.pdf. The findings from the survey demonstrate that role changes are occurring for HIM professionals. For example, data scientists who can use Python or develop an algorithm in Hadoop are needed to analyze data and communicate the results.[17]

Competencies represent skills used in jobs and for HIM professionals, these competencies are required and verified via the Commission on Accreditation for Health Informatics and Information Management (CAHIIM). Because these skills can be aggregated around job families, AHIMA has organized the groupings based on its most current survey that includes job family, average salary, and example job titles. Table 1 shows the job families, as described in the AHIMA salary survey.

Table 1

The HIMR initiative was developed to help transform HIM and position professionals to be aware of future job skills, competencies, and role specialties. The initiative recommends three categories, including advanced education, specialized education, and evidence-based practice. HIMR success depends on how the profession responds to the required changes in the delivery of healthcare and the competencies needed to support those changes. The focus is on educational aspects of skills, abilities, and leadership, streamlining education pathways and advancement at the entry level.[9]

The HIMR framework supports transformation of the HIM field into a strong and vibrant profession. AHIMA tasked the Council for Excellence in Education (CEE) with developing a new educational strategy to reexamine current roles, identify future roles, and embrace the opportunities in a rapidly changing profession by instilling processes that build on the strong foundation of skills and knowledge. This venture will introduce new career pathways and academic curriculum to meet future workforce needs, including informatics, big data, analytics, and information governance.

Employers in the HIMR era will look for reputable certifications to guarantee those they are hiring are capable of meeting industry demand.[18] Both public and private facilities are faced with the dilemma of identifying competent knowledge and skills regardless of whether those knowledge and skills were learned at an institute of higher education or on the job.

The HIMR initiative produced recommendations for four main areas:

1. AHIMA proposes to increase the number of members with graduate degrees by 20 percent within the next 10 years.
2. Ensure research is available in both the public and private health organizations to support health informatics and information management skills.
3. Revise HIM curricula to add specialized skills across the degree levels of HIM education, including associate's, bachelor's, and master's degrees to meet the needs of the workforce.
4. Registered Health Information Administrator (RHIA) will be recognized as the standard for HIM generalist practice, and the Registered Health Information Technician (RHIT) (+ specialty) will be the technical level of practice.[18]

The HIMR recommendations provide a road map for future HIM professional success. Moreover, the educational competencies are inherent in data analytics, entrepreneurship, patient advocacy, and information governance to address evolving industry demand.

Research Questions

"HIMR is an AHIMA initiative to transform Health Information Management and position professionals for the future".[9] While limited, reliable data representing workforce competency requirements exists, the development of the internet and job posting websites provides data on industry demands.[19] Since AHIMA introduced the HIMR initiative almost three years ago, HIM professionals might benefit from an analysis of career transition data regarding skill sets necessary in today's changing environment.[15] Therefore, to investigate the alignment of HIM skills, knowledge, and abilities with industry needs, the following research questions were considered.

RQ1 – Has there been a decline in skills of HIM professionals over time?

RQ2 – Does a theory-practice gap exist between workforce skills and industry competency demands?

RQ3 – How are the required skills changing about technological change, innovation, competitiveness, and education?

Hypotheses

Several theories exist that are related to 1) workers' skills and the level of education including Deskilling Theory,[20] 2) the difficulties of training workers in theory and moving them to practice known as Theory-Practice Gap,[21, 22] and 3) workers motivations to obtain education and training as an economic driver in Human Capital Theory.[23]

According to Braverman[20], new technologies often negatively impact a profession by causing the "deskilling of workers." With the increased reliance on technology in healthcare[24], the healthcare industry is experiencing a demand for skill-based employees, which runs counter to deskilling theory. Attewell[25] argues a "countertendency to deskilling" occurs when technology is adopted as observed in an insurance company where skilled workers assessed the validity of claims and unskilled workers performed data entry.

To test the deskilling theory, this study considers educational attainment to measure how new technologies are affecting HIM skills. While Handel[26] noted that using educational attainment to test deskilling was imperfect and other measures may perform better, educational attainment is readily available, as it is captured regularly in the AHIMA salary survey. To test if deskilling occurred, the following hypothesis is proposed.

Hypothesis 1: Deskilling will not occur in HIM professions from 2002 to 2016.

In addition to deskilling, Greenway, Butt and Walthall[27] suggested that theoretical knowledge does not meet practice needs as proposed in the Theory-Practice Gap. This theory has recently been studied in dental education,[28] nursing education,[29] professional sales,[30] teacher education,[31] physical therapy,[32] and other professions. Theory-Practice Gap is routinely mentioned in literature often associated with "bridging the gap," "closing the gap," or "avoiding the gap."

In this work, Theory-Practice Gap will be used to examine differences between existing workforce skills (theory) and industry demands (practice) and provide insight into the formation of this gap with regards to HIM professionals. Given the HIMR initiative, gaps may exist between education in HIM and industry demand. This study compares HIMR prescribed competencies with current industry needs to determine if a Theory-Practice Gap is present as proposed in Hypothesis 2.

Hypothesis 2: A Theory-Practice Gap exists between workforce skills and industry needs.

Another influential theory related to education and workplace skills is the Human Capital Theory.[33] Economic depictions of workforce transformation have included terms such as technological change, innovation, competitiveness, and education.[34] Earlier economic descriptions failed to consider education in the skilled worker equation.[35] In modern Human Capital Theory, education increases earnings and adds to a person's quality of life as investments in human capital.[34] In addition, professional certifications can also indicate specialty training and education obtained by workers.[36]

HIMR suggested traditional roles in coding and record processing will decline while technological improvements will drive new roles in data analytics, information governance, and auditing, requiring additional human capital investment.[4] By comparing skill sets, this study will consider whether HIMR human capital investment is needed to meet current industry needs that are shifting from coding and records administration to compliance, analytics, and informatics. The following hypothesis was created to examine human capital comparisons.

Hypothesis 3: Industry competencies will align with HIMR perspectives on technology, innovation, competitiveness, and education affecting traditional HIM roles.

Methodology

This research uses several approaches to evaluate the research questions and hypotheses. To examine the question regarding "deskilling", AHIMA annual salary surveys from 2002 to 2016 were obtained to compare salaries over time.[15] Historically, the most frequently used measure of worker skill is education level. To evaluate the research question considering the theory-practice skill gap, a granular review and analysis of job board posts identified the current practice skills required by the healthcare industry, which were then compared to the current Commission on Accreditation for Health Informatics and Information Management Education (CAHIIM) educational competencies as adopted by AHIMA.[15] To evaluate aspects of Human Capital Theory, the researchers compared differences between prescribed education and current practice needs identified from job postings on the major online job boards.

Procedures

To test hypothesis one concerning the deskilling of workers, salaries over time were compared based on educational attainment level between 2002 to 2016 using a salary snapshot survey from AHIMA.[15] The level of education included high school, associate's, bachelor's, and master's degrees obtained.

To test hypothesis two and evaluate the practice side of Theory-Practice Gap, the researchers searched major occupational job boards, including careerbuilder.com, monster.com, glassdoor.com, LinkedIn, indeed.com, AHIMA.org, and AAPC.com for job listings that included the term "health information management," in the job title between August and November of 2018. A total of 200 active job listings were included in the analysis. The data was reviewed to eliminate duplicate job announcements prior to analysis. The attributes in the analysis included job title, experience and skills, software skills, salary, and other job requirements. To measure the "Theory" portion of TPG, the AHIMA surveys of salaries and job skills were analyzed for the years 2003-2016.

To analyze data related to hypothesis three, the active job postings were coded to identify the different skills, certifications, competencies, and education. This data was aggregated to test alignment with HIMR perspectives on technological change, innovation, competitiveness, and education. AHIMA recently updated the educational requirements in 2018 to meet current and future workforce needs as described in the HIMR;[37] hence, the review used the standards from 2016.

Results

To test the deskilling hypothesis, educational attainment was analyzed over time to see if HIM professionals' level of degree increased or decreased. Using the AHIMA annual salary snapshot for selected years, the percentage of professionals with only a high school diploma, associate's degree, bachelor's degree, and master's degree, by year, were calculated as shown in Table 2.

Table 2

The results indicate a decrease in the professionals whose highest level of education was a high school diploma, stable for those at the Associates and the bachelor's levels, and an increase in those with a master's degree or higher. Compared to 2002, when 14 percent of HIM professionals had only attained a high school education, this number steadily decreased to only 2 percent in 2016. The percentage of HIM professionals holding an associate's or bachelor's degree dropped less than 1 percent over this 14-year period, indicating no significant deskilling occurred at the associate's or bachelor's degree level. At the master's level, a steady increase was observed over the fourteen years, from roughly 10 percent in 2002 to 14 percent in 2010 and 15 percent in 2016, as shown in **Figure 4**.

A t-test was performed to determine whether the percent of people holding a high school diploma and associate's degree changed over time. The t-statistic was significant at the .05 level with $t_{(78)} = 3.073$, p=.0015. The result indicated the change between high school and the associate's degree was significant and that deskilling did not occur. **Figure 5** shows the percentage of high school versus associate degrees for comparative purposes.

A similar t-test was performed to determine whether there was a difference between the percent of people holding a bachelor's degree or a master's degree over time. The t-statistic comparing deskilling between the bachelor and master's degree was not significant at the .05 level with $t_{(97)}$ =

0.093, *p*=.0176. The result indicates that deskilling did not occur, and the level of educational attainment remained relatively constant for bachelor's degrees while increasing slightly for master's degrees. **Figure 6** shows the results in a comparison of the bachelor's degree to the master's degree.

We then compared industry demand to HIMR skills to determine if a Theory-Practice gap existed. First, a compilation of industry needs data was extracted from major occupational job boards between August and November 2018. The most popular job listings were coding and billing related (35 percent of all job listings), indicating that Coding and Billing remain important to organizations hiring HIM professionals today. Other predominant job listings included Medical Record Administration at 26 percent, Informatics/Data Analytics at 22 percent, and 6 percent each for Compliance/Risk Management, IT/Infrastructure, and Education/Communications, as shown in **Figure 7**.

Following the industry needs analysis, a similar analysis of the 2016 AHIMA job survey data was used to identify positions that HIM professionals currently hold. According to the AHIMA survey, more than half (53 percent) of the professionals work in Coding and Billing followed, by Operations/Medical Records Administration at 25 percent, Compliance/Risk Management and Education/Communications at 7 percent each, and Informatics/Data Analytics and IT/Infrastructure at 5 percent and 3 percent, respectively. Categorical examples can be viewed using the interactive AHIMA career map (25). **Figure 8** shows these results.

Comparing the 2016 AHIMA job survey to the current industry needs jobs listings indicates similarity across four job families: Education/Communication, IT/Infrastructure, Compliance/Risk Management, and Medical Records Administration. Major differences exist in the Coding/Billing and Informatics/Data Analytics job families. One finding is that an 18 percent difference exists between practitioners with Coding/Billing competencies than industry demands. Thus, a decrease in demand for these skills is occurring. In the case of Informatics/Data Analytics, the data suggests an undersupply with 5 percent of professionals currently holding these skills and the industry demanding a 22 percent or a 17 percent increase in demand for Informatics/Data Analytics capabilities. These job family differences suggest a Theory-Practice gap does exist.

To analyze if skills are changing regarding technological change, innovation, competitiveness, and education, 200 job postings were gathered, and data was coded to align with the AHIMA job survey categories. Percentages were calculated for each job family category based on four levels: Entry Level, Mid-Level, Advanced, and Master. Percentages were also calculated by category, providing insight into the relationship between technological change, innovation, competitiveness, and education. Greater skill level and education would be required to support more technical, innovative, and competitive categories as shown in the AHIMA Career Map.[38]

Positions listed for Operations – Medical Records Administration and Revenue Cycle Management aligned with lower level technical skills and required a high school diploma or associate's degree, as seen in Table 3. Most of the job listings for Informatics/Data Analytics and Education/Communication positions required advanced technical, innovative, or competitive skills with either a bachelor's or master's degree. Privacy and security roles were represented across multiple categories, including Compliance/Risk Management and IT/Infrastructure. Data from the AHIMA Salary Survey was analyzed using the same categories.[15] Currently, 83 percent of those working are in positions that require low technical and less innovative skills such as Medical Records Administration or Coding and Billing. Only 6 percent of participants held skills related to higher technology and innovation work of Informatics/Data Analytics. Table 3 also shows the percentage by job category.

Table 3

A similar mapping was created for the job listings yielding a different perspective. As seen in Table 4, 74 percent of the job postings were for Medical Records Administration and Coding and Billing. There is a notable shift in the industry whereby fewer individuals with low tech/low innovation skills are needed than the AHIMA Survey.[15] In addition, a higher level of technology and innovation is needed, with Informatics/Data Analytics at 13 percent, more than twice the percentage as those working in the industry, according to the AHIMA study.

Table 4

Discussion

This study compared current HIM skills and education to industry needs. Results show that HIM administrative jobs and information technology jobs are transforming to meet industry needs. More individuals will be needed to fill positions in leadership, governance, and informatics. Considering the identified industry demands, there will be a shift towards the more technical aspects of HIM, driving the need for more education.

Technology continues to introduce role changes. For example, many HIM professionals will enter coding related positions today, only to shift to an auditing role in the future. This transition does not mean that coding will no longer be necessary, but it will require higher skill levels focused on advances such as auditing, reimbursement, or case finding. With AHIMA focusing on educational changes, the future HIM professional will be in a better place. These study results align with the HIMR initiative.

In the past, having new employees with no training or certification function in an entry-level position might have been acceptable. AHIMA suggests increasing educational requirements so that the individual can function in more definitive roles such as auditing or billing. This research supports this assessment and the gap between workforce skills and what the industry requires. AHIMA provides opportunities to help fill gaps for those individuals that need additional training. Educated individuals with no actual work experience may have to obtain additional credentials, such as Certified Coding Specialist (CCS) or Certified Professional Coder (CPC), depending on the needs of the facility. Conversely, individuals who have years of work experience and minimal education may have to consider obtaining additional certification.

Considering the abundant amount of data available from electronic health record systems, job announcements are starting to include more advanced departments that are relying heavily on data analytics and information technology. Many HIM professionals may have experience to help them get into these positions but may lack the educational background to support software use and analysis.

Professional organizations such as AHIMA must make changes to their educational requirements to help these professionals attain the skill set required by the industry. The educational levels noted in this study show that the associate's and bachelor's degrees are still the most sought-after degrees in terms of numbers. AHIMA's forward-looking proposal will have to provide competencies for this group to meet workforce needs. The changes AHIMA makes in certification requirements will be the standard for most of the HIM workforce for future jobs. It is noteworthy to add that other organizations such as AAPC offer similar certifications around coding and compliance.

Conclusion

In summary, the HIM profession is changing. Today, professionals operate not only in the HIM department of hospitals but also in many other health care settings. As healthcare and the industry evolve, skills and abilities must change as well. The shift towards higher-level skill sets to meet industry demand may require more education. Currently, many HIM professionals operate in record administration, coding, and billing positions. If job listings are any indication, individuals with lower levels of education and skills should be aware of the industry's expanding needs.

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Table 1. Health Information Management Job Families [39]

HIM Professionals 2016 Survey Job Family
REVENUE CYCLE MANAGEMENT/CODING AND BILLING JOB FAMILY
Coding Professional, Revenue Cycle Manager, Clinical Documentation Improvement Specialist, HIM Revenue Cycle Auditor, Benefits Coordinator, Collections Clerk, and more
OPERATIONS/MEDICAL RECORD ADMINISTRATION JOB FAMILY
Health Information Technician, Meaningful Use Specialist, Patient or Cancer Registrar, Health Information Management Clerk or Manager, Director of HIM, and more
INFORMATICS/DATA ANALYTICS JOB FAMILY
Data Integrity Analyst, Clinical Informatics Coordinator, Project Manager, Research and Development Scientist, Director of Clinical Informatics, and more
EDUCATION/COMMUNICATION JOB FAMILY
HIM Professor, Health Sciences Information Librarian, ICD-10 Educator, Program Director, or Department Chair
COMPLIANCE/RISK ASSESSMENT JOB FAMILY
Credentialing Specialist, Quality Improvement Analyst, Compliance Auditor, Privacy Officer, Information Security Manager, Director of Risk Management, and more
IT/INFRASTRUCTURE JOB FAMILY
Implementation Support Specialist, Data Quality Manager, System Analyst, Data Architect, Chief Technology Officer, and more

Table 2. Educational Attainment *

Highest Degree	High School	Associates	Bachelors	Masters
2002	14%	38%	38%	10%
2003	13%	40%	38%	10%
2004	3%	33%	39%	11%
2006	4%	34%	35%	11%
2010	4%	42%	40%	14%
2016	2%	37%	37%	15%

Note: Data was captured for only the years shown.

Table 3. Percentage of Job Postings by Skill Level and Education

Job Category	Entry-level High School Degree	Mid-level Associate Degree	Advanced Bachelor Degree	Master Master Degree	Category Total
Operations Medical Records Administration	7.2%	51.8%	8.2%	8.2%	75.3%
Revenue Cycle Management Coding and Billing	0.0%	8.4	0.5%	0.0%	8.9%
IT/Infrastructure	0.0%	6.0%	0.2%	0.0%	6.2%
Informatics/Data Analytics	0.0%	1.9%	4.1%	0.0%	6.0%
Education/Communication	0.0%	0.0%	1.9%	0.5%	2.4%
Compliance/Risk Management	0.2%	0.2%	0.7%	0.0%	1.2%
Skill Level Total	7.4%	68.4%	15.6%	8.6%	100%

Table 4. Mappings to Job Listings

Job Category	Percent
Operations Medical Records Administration	41%
Revenue Cycle Management Coding and Billing	33%
Informatics / Data Analysis	13%
Compliance / Risk Management	5%
Education / Communication	5%
IT / Infrastructure	4%
Skill Level Total	100%

Figure 1. A Healthcare Organization's Biggest Obstacle is....[3]

Figure 2. Changing Roles of HIM Professionals [3]

Figure 3. AHIMA Salary Snapshot [15]

Figure 4. Educational Attainment [37]

Figure 5. Percent of High School to Associate Educational Attainment

Figure 6. Percent of Bachelor and Master Educational Attainment

Figure 7 - Industry Needs from Job Listings

Figure 8 - AHIMA Job Survey Results

There are no comments yet.

DEVELOPMENT OF A WEIGHTED WELL-BEING ASSESSMENT MOBILE APP FOR TRAUMA AFFECTED COMMUNITIES: A USABILITY STUDY

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Development of a Weighted Well-Being Assessment Mobile App for Trauma Affected Communities: A Usability Study

By Steve Moeini PhD; Valerie Watzlaf PhD, MPH, RHIA, FAHIMA; Leming Zhou, PhD; and Rev. Paul Abernathy, MPIA

Abstract

A well-being mobile app was built and tested by performing a usability study in a trauma affected community (TAC). Seven usability tasks were given to social workers during Phase 1. Phase 2 of the usability study was a re-test of the same tasks with the same social workers after refinements were applied. The results showed that most users preferred darker foreground colors, lighter background colors, larger fonts, and larger sized UI components. Statistically significant improvements were found after changes were implemented to the app and included time for page navigation ($Z = -2.366$, $p = 0.018$), logout ($Z = -1.997$, $p = 0.046$), and item selection in a page ($Z = -2.371$, $p = 0.018$). UI positioning and size changes proved to be a significant determinant of user satisfaction based on the positive feedback received from the computer systems usability questionnaire (CSUQ). (User1: $p = .000$, User 2 withdrew; User3: $p = .010$, User4: $p = .000$, User5: $p = .001$, User6: $p = .006$, User7: $p = .025$). HIM professionals assisted in the design, development, and administration of the usability study. This is another area in which HIM professionals are needed when assessing health and wellness in communities affected by trauma.

Keywords: Mobile app, wellness, usability study, trauma affected communities (TAC)

Introduction

The collection of health information is paramount in the current information age. Over a decade ago health organizations were embarking toward fluid data warehouse designs and big data strategies. A decade later the focus has shifted toward machine learning and applying techniques of artificial neural networks to gain further insights and to predict future health outcomes. The HIM profession as a whole is one that is highly data dependent and research such as this leads the profession closer to understanding the ever encompassing and newly discovered segments of human populations that generate new clusters of health information. This paper discusses a potential new area for data collection and ultimately discovering new insights in future studies utilizing this data. Individual assessment of health and well-being has far reaching capabilities, which can affect community satisfaction and community well-being.[1] In order to address individual health and wellness, we can leverage mobile technology. One area that can benefit from the ubiquitous nature of mobile devices and social networking are trauma affected communities (TACs). TACs are most often a byproduct of an individual's exposure to violence, sexual assault, and/or disasters. TACs could best be defined as a group of individuals who have been affected mentally and/or physically by violence and/or disaster and who share the same socioeconomic issues as a collective. In addition, trauma affected services are services catering to this at risk cohort with the understanding that the services given are attuned to individuals within this community having suffered past trauma.[2] Due to the nature of trauma, especially in early childhood, higher incidence of chronic disease and behavioral health issues are prevalent, which increase healthcare costs for this population. Moreover, delivery of care issues, such as missed appointments and inability to follow treatment regimens, become increasingly difficult in this segment of the population due to emotional and behavioral instability. In addition, this population also see skyrocketing healthcare costs in the form of high-volume emergency department visits.[3] Given the difficulty to traditional treatment adherence and follow-up within TACs, new healthcare strategies are needed. One such strategy is to gauge the well-being of each individual within TACs via a behavioral health community organizer (BHCO) who utilizes mobile-based technologies to gather wellness data. In a trauma informed service, the BHCOs are similar to social workers and understand the plight of the participants as they too live and work in this community.

The BHCOs who enter into these communities must be highly mobile and be able to track participants who may not be at home. Mobile technology is used to increase productivity and decrease time lost and data management issues prevalent in traditional paper-based approaches. For example, in a traditional clinic-based approach, participants would be required to adhere to a schedule and to follow through with appointments. This is a challenge within this population due to the inconsistency of meeting appointment times, for example. Using a mobile solution solves this problem by creating a point of care service in which individuals, cognizant of trauma, are deployed within these communities to gather data remotely, going into the community to generate data and analytics at the point of care.

It should be noted that even though we are leveraging mobile health-based technologies, the most important piece in this ecosystem is the BHCO. The ability of the BHCO to establish trust and rapport with the community is paramount.

The goal of this research is to provide a quality health and well-being assessment to TACs utilizing mobile technology. A mobile-based weighted well-being scale was leveraged to assess TACs.[4] The benefit of this scale is that it was built from the ground up focusing specifically on the issues facing TACs. Its scale is deployed via a mobile app which runs on tablets. This allowed the BHCO to be highly mobile in capturing population data with the ease of use of the mobile app. In addition, the weighted scale has been validated through expert input and tested in previous research.[5] Research such as this may share some small similarities to other mobile health (mHealth) initiatives that have been deployed in low socio-economic status (SES) countries.[6-9] However, as of this writing, this is the first weighted well-being mobile application to address the area of TACs. The structure of this paper is set up as follows: background information and literature review are provided as well as the methodology for the usability study starting with initial requirements analysis provided by the client, the FOCUS Pittsburgh Free Health Center (FPFHC), which serves this TAC in Pittsburgh, PA. Next, we describe the system design and steps followed in conducting the usability study. Finally, the results of the usability study, discussion, and conclusions are presented.

Background

A literature review revealed a large number of well-being questionnaires. Many of the questionnaires evaluated short and long term disabilities toward quality of life, or to evaluate one domain in general, and others looked at multiple domains,[10-14] while others focused on chronic illness and cancer.[15-18] However, the questionnaires that dealt with multiple domains still focused mostly on the physical/mobility side of well-being with the addition of a relational context.[19] None of the questionnaires found in the literature were specifically designed to evaluate the overall well-being of individuals in TACs. The literature review also indicated that the five domains of physical health,[20], behavioral health,[21, 22], (SES),[23] relationships,[24-27] and spiritual life,[28-30] are directly related to the well-being of an individual. A focus group of community leaders and residents of a TAC in Pittsburgh rated the importance of these domains. Based on the prior research in this area, this research team developed the Well-being Relational Stability Competency Index (WRSCI), which was based off of many well-known and validated questionnaires such as PROMIS,[31-33] Urban Poor Quality of Life, Friedman well-being scale, Adverse Childhood Experience (ACE) test,[34] and survey questions created by the Western Pennsylvania Regional Data Center, to name just a few. The remaining new questions were generated from the research team of experts, with input from members of the TAC from FPFHC in Pittsburgh. Each new question was subject to content analysis, a content validity ratio, and a content validity index determined by a focus group. The WRSCI questionnaire was then reviewed by a group of stakeholders (community leaders and representatives of the Pittsburgh community). The research team then adjusted the well-being questionnaire. Another round of reviews was conducted by the stakeholders and a final version was approved.[5, 35] Both the prior study and this current usability study are part of a larger study called the Neighborhood Resilience Project aimed at addressing the well-being of TACs.

Methodology

Requirement Analysis of Client

The beta version of the mobile app was developed for the Android operating system via Android Studio integrated development environment (IDE). The app is optimized for Android-based tablets (Nexus 9) running version 22 or higher. Prototyping of the app was done based on a set of rules gathered during requirements analysis from the FPFHC and our research team.

Prior to the implementation of a mobile app, the users of the system interacted with the participants and gathered data via paper forms. They would create participant lists and manually go through the paper questionnaire, etc. The goal of the app was to facilitate the real world functions of the users more efficiently, while at the same time maintaining the privacy and security of participants and their data. The mobile app is a digital representation of the WRSCI questionnaire.

Ease of use is vital when developing the mobile app and navigation should be quick and fluid. Therefore, our goal was to perform a usability study to determine usability issues and make improvements for the final version of the mobile app wellness assessment for TACs.

The requirement analysis of the client, FPFHC includes:

1. Authorization of who can access the system

a.) Not storing personal information within the app. A unique identifier was created for each participant. Participant information was stored in a database on a server.

b.) The participants cannot be identified by the app data alone.

c.) Authorized personal (BHCOs) enter the data. Participants do not enter data into the app; they simply respond to the BHCO when asked questions.

2. Large number of question sets

a.) Questions are split into domains and within those domains exist subdomains.

i.) Domains: The survey has five domains (physical, spiritual, relational, socioeconomic, and behavioral) which make up the different sections. Each domain has a set of subdomains associated with it. A user working with a participant will traverse through the main domains. This is the high-level view of the survey.

ii.) Subdomains: Domains are made up of subdomains. Subdomains are bucketed areas that contain all the questions. One or more questions can belong to a subdomain. For example, the Physical Domain is broken up into smaller subdomains, such aspain, fatigue and medication; behavioral domain contains the subdomains positive reactions, negative reactions, traumatic events and resilience etc.

3. Make the design of the questionnaire as simple to use as possible. A justification for speed, reliability, and ease of use must be accomplished.

4. Scalable creating a large social network of patient participants.

a.) BHCOs will target the single participant and then lead to the assessment of the family of the participant, then the street block, next the community, followed by the city and then the state and even the country as a whole.

5. Accessibility built in to address the cohort using the app

a.) Must address usability issues of the BHCOs (such as readability of font size, background color and general usability of user interface components)

6. Data collection must have the ability to send the data to the server at the end of assessment to handle all data storage and analytics and then be displayed on a Web portal. This will be done automatically without user direction.

Implementing the Client's Requirements (System Design)

Listed below are how the design requirements for the mobile app were implemented:

1. The app required an Internet connection to save data to the server.

2. Prior to a live participant assessment on the app, authorized personnel logged in and inputted the participant's private information into a secure server. The system assigns a generic ID to the participant. The app receives the generic ID associated with the participant.

3. Due to the large amount of question sets, all of the loading and storing of questions was done remotely and accessed by the mobile app. A separate database housed all the questions.

a.) The structure of the database was built based on a standard star schema model, with various dimensions and fact tables.

4. The app presented a simplified design to be more efficient than the paper counterpart. Areas of simplicity include:

a.) Large fonts for better readability

b.) Distinct background colors to make text easily readable

c.) Large drop-down menus for easy and quick selection

d.) Linear navigation pane that pulls out data via swipe gestures or a single button press

5. Upon completing the questionnaire, the app displayed the final well-being score and displayed a bar chart showing the domain scores for the given participant. A bar chart was chosen because it's easy to understand and ease its ease of use with the graphic design. We wanted to show the participants and providers the results immediately for ease of understanding and explanation while they are with a healthcare provider such as the BHCO.

Usability Study of Mobile App

To assure a high-quality mobile app that met all of the client and design requirements, a usability study with the BHCOs was conducted. Usability studies are performed to observe users as they perform specific tasks while using a specific system or device. The purpose of the usability study is to determine the user friendliness of the app and determine if there are specific changes that need to be made to improve the initial design of the mobile app. It should be noted, the term user interface (UI) refers to the components that make up the interface of the mobile application. For example, the drop-down box placement, navigational sliders, and radio buttons make up the UI of the mobile application described in this paper. The placement and design of the these components affect the overall experience of the user with the application.

Study Participants and Inclusion Criteria

Inclusion criteria included an English-speaking cohort of varying age and gender who are BHCOs that work/volunteer at the FPFHC where participants may be triaged if needed. All BHCOs were over 18 years of age and had a background in social work or had worked with members of a TAC previously. Almost all the participants use mobile devices on a daily basis and have used a smartphone device or tablets in the past. The demographic backgrounds of participants are shown in **Table 1**. Nine participants were gathered at the start of the study, but two BHCOs were lost to scheduling conflicts and one BHCO was unable to complete the CSUQ in phase 1 and was also removed from that specific portion in phase 2 (this individual was still present for the usability testing portion, even-though they didn't complete the CSUQ responses, leaving a final total of N = 7 for the usability testing itself).

Task Scenarios and Video Recording

Phase 1 of the usability study consisted of 7 tasks (**Table 2**). The prototype app was designed and loaded on the tablet used by the BHCO. An overhead camera was used to capture user tactile response with the mobile app. The camera was an invaluable resource in this study as it helped to aid retro analysis of each users initial learning curve and statistical analysis.

The time on task data was gathered via retrospective analysis of the video recordings. Video recordings were also used to time users on various task scenarios.

The study began with talk aloud scenarios from the principal investigator (PI) who would read aloud each task scenario, followed with the user completing the task. After the user completed one task, they were asked several follow-up questions and to rate their experience. Each BHCO user was also timed on four key areas which made up all of the tasks. Timed tasks included initial login into the app, traversing between domains, traversing between pages inside domains, and logging out. Since a key component of the app is the use of drop-down menu, users were also judged on the time it took to select a value from a drop down.

Phase 2 of the usability study was a refinement of the app considering the changes received from phase 1. The task list for phase 2 was reduced since user preferences were gathered in phase 1 and we wanted to see if the changes made in phase 1 would improve user task performance. Phase 2 usability tasks are shown in **Table 3**.

At the end of each usability study (phase 1 and phase 2) session users were asked to complete the IBM Computer System Usability Questionnaire (CSUQ). (**Appendix A**) The CSUQ was used to measure participants' overall satisfaction with the mobile app. The CSUQ scores are on a seven-point scale, the lower the response, the higher a user's satisfaction with the system.

Data Analysis

Data generated in this research took two forms. We gathered metrics from video recordings such as time spent on task. Descriptive statistics were used to quantify the time on task scenarios. Secondly, a Wilcoxon signed-rank test was used to compare Phase 1 and Phase 2 results for both the time on task scenarios and the CSUQ. Wilcoxon signed-rank test can be used to compare repeated measurements on a single sample to see differences in their mean ranks. In the case of this paper we are repeatedly measuring outcomes pre- and post-intervention.

Results

After each session ended, the user filled out the CSUQ to rate their experience. Based on the Time on Task results in phase 1 and 2 (**Table 4**), in addition to the time it took for and the CSUQ phase 1 results (**Table 5**), it was clear more changes were needed to improve ease of use and overall usability. The results in phase 1 of the CSUQ were fairly scattered with issues still being present in the app build. Most issues were related to sizing and readability of content. Phase 2 CSUQ results showed a more satisfied cohort. A Wilcoxon signed-rank test showed that the CSUQ results post phase 1 user interface adjustments were significantly favorable among participants. All of the participants who re-rated the app saw a significant usability improvement. (User1: $p = .000$, User3: $p = .010$, User4: $p = .000$, User5: $p = .001$, User6: $p = .006$, User1: $p = .025$)

Participants rated each item shown in **Table 6** based on a Likert scale. Table 6 displays the user interface likeability ratings given after each talk aloud scenario in phase 1. The usability components in Table 6 range from common things like different font styles/size and common UI modules. A brief description of each UI component used in the phase 1 trial follow. A listview in software interfaces is merely an itemized list, potentially separated out by small gaps in between each item. The background color of the listview item can be modified for better readability. A radio button is a selected icon in a group/set of buttons, only one of which is selectable at a given time. Drop-down lists are fairly common, made up of a list of items allowing a user to select an item in that list. Slide-out navigation is an interface component that can be activated by a finger gesture usually by swiping the edge of a device and dragging down momentarily. Sliders are activated by finger press and hold of a button and then dragged to its desired location on a horizontal line.

Upgrades to the Mobile App Based on Phase 1 Results:

In phase 2 of our usability study, we summarized all the major issues from phase 1 and presented a finalized mobile app which included modified portions of the apps' UI to better address the shortcomings of phase 1 of the usability study. To increase efficiency and reduce time spent interacting with the UI, most questions from the questionnaire were converted to radio buttons. The logout button was consolidated into the main slide-out navigation window. This allowed us to remove any extra menu items from the taskbar. Having only one navigation pane simplified the user experience. The page selection dropdown also posed an issue in phase 1 mainly due to its small size and location on the screen. It was important to separate anything related to page numbers from any other integer/counter based interface items to limit confusion. In phase 2 we enlarged the drop-down page navigation item and scaled it horizontally almost all the way to the width of the tablet (2d). **Figures 1a-d** and **Figures 2a-f** below shows the comparison between pre and post UI design changes running on the tablet, respectively.

Starting with Figure 2a-f below, the app is made up of the login screen (2a), participant selection screen (2b), which is made up of all patients who belong to a BHCO, slide-out navigation pane used to jump to each wellbeing domain (2c) and the general questionnaire view (2d), which the patient uses to answer each question. Even though there were significant changes to parts of the UI in phase 2, some sections did not change very much. This included the login screen (1a vs 2a) and slide out navigation (1c vs 2c).

Additionally, phase 2 of the app redesign saw the addition of a user session, shown in figure 2e. The intent of the user session is that a patient may have multiple assessments over time. In order to track each snapshot of the progress in time a session variable is needed. Each session can be analyzed independently to see if a patient improved over time. A session can also be paused and later resumed.

Lastly, Figure 2f shows the patient's results once the questionnaire is completed. Upon completion of the WRSCI questionnaire the patient is presented with their well-being score, the outcome of each section of the well-being questionnaire, and their ACE score. It should be noted that a higher well-being score means the patient is doing well in those areas. However, opposite to that is the ACE score. An ACE score is an aggregate of different types of abuse, neglect and other adverse childhood trauma/experiences. Ideally, the goal for a patient is to have a low ACE score. A high ACE score represents a higher probability of increased problems later in a child's life and into adulthood.

Users who had issues with the app in phase 1 saw them reduced in phase 2, mainly due to UI enhancement. **Figure 3** shows a closer view of the redesigned page drop-down which allows participants to move between pages. This was one of the biggest changes in the UI redesign. Subtle changes to this area as can be seen from figure 1d to 2d made a large impact for time on task scenarios and general quality of life improvements for users. Textual and background color changes and clear/large defined fonts seen below helped users with usability and navigation.

In comparison to the time on task of phase 1, a drop in time to completion was seen, most likely due to a decrease in the initial learning curve and UI updates. The total time spent logging into the app dropped by about 41 percent, navigation between domains dropped by 33 percent, navigation within pages dropped 79 percent and total time to logout dropped by 73 percent. A Wilcoxon signed-rank test showed that time on task measurements for a set of scenarios during the mobile app usability test showed statistical significance when the page navigation dropdown values were redesigned from its original app stage build to new version ($p = 0.018$) with ($alpha = .05$). In addition, the changes to the logout placement button ($p = 0.046$) and time from dropdown button press to value selection ($p = 0.018$) were also statistically significant, respectively. See **Figure 4** for time differences (in seconds, total time for all users combined) between the phase 1 and phase 2 navigation, logout placement and dropdown UI changes.

Table 7 below displays a final breakdown of the various components that were rated dealing with satisfaction during the talk aloud task scenarios in phase 2. Quality of life improvements in the UI helped to increase user satisfaction.

Discussion

In this study we tested a wellness mobile app against a cohort of users which consisted of BHCOs from the FPFHC in Pittsburgh. The main purpose of the usability study was to test the ease of use of the mobile app and at the same time administer the well-being questionnaire in the TAC. The implementation of the mobile app along with a web portal administration will reduce paperwork and increase clinical productivity allowing for a smoother rapport between BHCOs and participants. Compared to other studies dealing with well-being questionnaires, this is the first of its kind, to our knowledge, to use a mobile-based weighted well-being questionnaire for TACs.

Most of the usability issues were initially caught by the first five participants, backing Nielsen's postulate of the +5 rule.[36] Despite the background of the participants having used smartphones and who continue to use mobile devices regularly/daily, there was a small learning curve to understand the Android keyboard layout. Some other small issues included understanding the functioning of the Android soft keys found on all Android devices. These are generally the universal back button, the application select button, and the home button, all of which are located at the bottom of the mobile device. Overall, phase 2 proved to be the turning point for a successful completion to the usability study. Almost all users rated with high satisfaction with the following comments:

"The app is much better with increased font and dialog box sizes"

"The app is great"

"App is much easier to use"

"Having used the iPhone for so long it is still difficult because of the small buttons. This version's icons and buttons are larger and easy to select"

The data that is generated from the questionnaire does not reside locally on the tablet. Rather it is sent to the server in real time as the BHCO is selecting answers on the questionnaire. As such, the device requires an always on Internet connection via cell network or Wi-Fi. Therefore, one drawback may be data loss should the cell network connection fail.

Conclusion

In this paper the authors presented a two-phased usability study. The initial phase consisted of the raw app design built for testing. The initial phase posed some usability issues since it presented an alpha build of the app. Phase 2 represented a refinement over phase 1 with some slight modifications of the app design. Based on user response, phase 2 was successful. The app changes for phase 2 testing proved vital to the users and received general praise. Most of the users were happy with its current progress. Having the BHCOs participate in the usability study was important because they were able to improve the very product that they would be using during their participant well-being assessments in the community.

The tasks presented in this study could be applied to future research in which a larger cohort is used with a clear separation in age range to see whether there are differences in time on task scenarios between the age groups.

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There are no comments yet.

DELINQUENT MEDICAL RECORDS: WHO ARE THE STAKEHOLDERS FOR TIMELY MEDICAL DOCUMENTATION?

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Delinquent Medical Records: Who Are the Stakeholders for Timely Medical Documentation?

By Hans A. Puttgen, MD; Maria Stolze-Epple, MHCA, RHIA; Redonda G. Miller, MD, MBA; and C. Matthew Stewart, MD, PhD

Abstract

The explosion of electronic documentation associated with Meaningful Use-certified electronic health record systems has led to a massive increase in provider workload for completion and finalization of patient encounters. Delinquency of required documentation affects multiple areas of hospital operations. We present the major stakeholders affected by delinquency of the electronic medical record and examine the differing perspectives to gain insight for successful engagement to reduce the burden of medical record delinquency.

Keywords

Medical records; delinquency; timeliness; hospital; inpatient; health information management

Introduction

The management of hospital records involves different silos of stakeholders, each with differing perspectives of the importance of the medical record, including bias against financial operations by medical staff. Here we present these perspectives in order to gain insight in how to engage stakeholders, especially relating to the burden of medical record delinquency.

The significance and impact of the Centers for Medicare & Medicaid Services (CMS) Electronic Health Record (EHR) Incentive Programs on the practice of medical care in the United States qualifies as one of the most far-reaching technologically-based changes to practice in medical history. In 2012 US hospitals completed over 36 million admissions resulting in more than 164 million hospital days. In that year, the US hospital use of qualified EHR rose from 27-44 percent overall.[1] In February 2016, 95 percent of all eligible US hospitals had converted to Meaningful Use-certified EHR systems.[2] The implication is clear: nearly all inpatient records are electronic, so with the educated approximation that the average patient needs only 3 notes a day while in hospital, half a billion documents will need composition and processing for inpatient encounters alone. With the addition of emergency department and ambulatory visits, providers in the US will create and finalize billions of records every year.

The American Medical Association sponsored the 2013 RAND report, *Factors affecting physician professional satisfaction and their implications for patient care, health systems, and health policy*. In this report, physicians and practice managers found improved satisfaction with EHR in terms of better access to data and improvement in some aspects of patient care. In contrast, physician satisfaction with health IT was found to have "worsened satisfaction" in the areas of: time-consuming data entry, user interface and workflow mismatch, interference with face-to-face patient care, information overload, threat to practice finances, the requirement for physicians to perform lower-skilled work, and template-based notes which degrade the quality of clinical documentation[3]. In their report titled *Crossing the Quality Chasm*, the Institute of Medicine defines quality to include timeliness ("care should continually reduce waiting times and delays for both patients and those that give care") and efficiency ("the reduction of the total cost of care should be never-ending.")[4,5] In the 2014 Next Accreditation System of the Accreditation Council for Graduate Medical Education, the role of professionalism for residents and fellows of teaching hospitals now requires "training on policies and procedures regarding appropriate documentation of clinical care in the clinical site's electronic health record" (see Professionalism, Pathway 1, Property 2).[6]

Given the promise of meaningful use, the reality of provider satisfaction, the implications for quality and the obligation for training of residents and fellows, we ask about the role of the delinquency of medical documentation. The impact of delinquency of the electronic medical record and the implications for the hospital stakeholders is largely unknown and unpublished. Here we present the major hospital stakeholders for delinquent documentation.

Finance

Each inpatient admission creates a story told by the medical record. The summarization of this story by coding specialists requires timely completion and required elements in order to construct an accurate representation. The comprehensive data elements estimate severity of illness, map and crosswalk the associated diagnoses to diagnosis related groups, contribute to a casemix index, and estimate mortality risk. Professional fees, facility fees, and hospital global charges are reliant on the both the accuracy and the timeliness of medical documentation. During the period of 2014 to 2016 the American Hospital Association monitored the CMS recovery audit program with hospital denials from 7-10% due to "no or insufficient documentation of the medical record."[7]

Delinquency of required documentation affects the ability to submit charges to payers due to filing time limits which vary by payer. For a hospital to maintain provider interim payment status (PIP) 85% of charges must be submitted within 30 days. Billing past the filing limit or submitting partial charges such as PIP both have the same result: hospitals are providing those services for free due to medical record delinquency. A given clinical service line is accountable for balancing revenue with expenses. Clinical service lines and their providers with delinquent or unbilled services negatively impact service line revenue and jeopardize staffing and other expenses.

Risk Management

The narrative of the patient's hospitalization as told by the medical record has an exposition recounted within the admission history and physical (H&P), action described during hospital stay, and a denouement captured by the discharge summary. As with story, gaps or deficiencies in the telling introduce doubts and frustrations, but with far more tangible consequences. A missing or delinquent H&P calls into question what the clinical team knew, when they knew it, and whether a condition or finding was present on admission. Procedural documents, particularly the operative notes, lose accuracy with hindsight. Incomplete and delinquent records make the defense position in legal proceedings untenable. Part of the healthcare journey for high reliability includes identifying risks and developing risk mitigation strategies, and risk management associated with the delinquent medical record is a vital process of this journey.

Medical Staff

Accredited hospitals have mechanisms for credentialing and monitoring medical staff defined by the Joint Commission such as ongoing provider practice evaluation, OPPE (Joint Commission Medical Standard MS.08.01.03). The monitoring of hospital staff may include a variety of global metrics such as mortality, length of stay, infection, and blood utilization. Without other recourse to effectively set direct consequences for poor EHR performance, Health Information Management (HIM) leadership may need to partner with Medical Staff leadership to set metrics and standards associated with documentation. These may include: unsigned verbal orders, delinquent operative notes, delinquent discharge summaries, and delinquent documentation for ambulatory encounters. As a means of enforcement, several hospital systems have instituted a suspension mechanism whereby providers voluntarily relinquish their privileges when they exceed a threshold metric for the number of delinquent documents. This voluntarily relinquishment is not reportable to state medical boards but still can be an effective mechanism for medical staff out of compliance with global metrics. Hospitals must devote significant administrative effort to the process of suspending and re-instating the privileges, all of which necessarily results in a total, non-recoverable waste of staff effort. HIM leadership bears the accountability and cost of this non-value-added work.

Patient Safety and Quality of Care Coordination

Hospital consumers include patients, families, and also referring providers. Absent and delinquent documentation from hospital admissions does a disservice to referring providers tasked with the transition of care from the hospital to the ambulatory setting. This can prove inherently unsafe for the patient and leads to waste of time and resources spent identifying interventions and avoiding duplication care. Discharge failure due to delinquent documentation has a direct role in pay-for-performance mechanisms such as 30-day readmission rates. Safe, effective care coordination relies entirely on accurate and timely medical documentation. Chronic failure due to delinquency of medical documentation will affect the decision making of all consumers of hospital services.

Conclusion

Health care organizations with HIM and medical staff leadership that implement effective accountability models for improving timely completion of medical documentation has a tremendous potential impact on delinquency of medical records. Finance stands to gain as billings holds are reduced, casemix designations increase in accuracy, and identification of diagnoses present on admission helps to clarify quality metrics for reimbursement. Risk is mitigated with timely and accurate documentation, particularly with production of the medical record. Medical staff credentialing processes that include compliance with documentation standards greatly reduce wasted effort and resources. Both patient safety and quality of care improve as the major stakeholders in medical care, patients and their families, have optimal and timely coordination of their care. Future efforts in accountability models will help delineate the most meaningful metrics of the delinquent record in order to provide management and leadership with effective interventions.

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There are no comments yet.

THE CHALLENGES OF USING ICD CODES TO PERFORM A COMPARATIVE ANALYSIS BETWEEN PATIENTS WITH PENETRATING CARDIAC INJURIES WHO UNDERWENT NON-RESUSCITATIVE THORACOTOMY VERSUS STERNOTOMY

Posted on December 7, 2020 by Matthew

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The Challenges of Using ICD codes to Perform a Comparative Analysis between Patients with Penetrating Cardiac Injuries who Underwent Non-Resuscitative Thoracotomy versus Sternotomy

By Nikolay Bugaev, MD; Janis L. Breeze, MPH; Alyssa M. Tutunjian, MPH; Horacio M. Hojman, MD; Eric J. Mahoney, MD; Benjamin P. Johnson, MD; and Sandra S. Arabian, MBA

ABSTRACT

Background: Comparative morbidity after either sternotomy or non-resuscitative thoracotomy in penetrating cardiac injuries (PCI) is unknown.

Methods: Retrospective review of adults with PCI who underwent either sternotomy or non-resuscitative thoracotomy using the National Trauma Data Bank 2007-2015. Since there is no unique International Classification of Diseases Procedure Coding System (ICD-PCS) codes assigned for resuscitative vs. non-resuscitative thoracotomy, and both procedures were coded as “thoracotomy”, propensity score (PS) methods were applied to avoid inclusion of resuscitative thoracotomy.

Results: Despite well PS matching on injury severity score the non-thoracotomy group compared to the sternotomy group had a significantly increased risk of mortality (30 percent vs 8 percent, p<0.0001). The morbidity differed as well—25 percent vs. 12 percent, p=0.0007.

Conclusions: The differences in mortality in PCI patients who underwent non-resuscitative thoracotomy vs. sternotomy may be biased by unintentional inclusion of resuscitative thoracotomy. To accurately capture thoracotomy type, separate unique resuscitative and non-resuscitative thoracotomy procedure codes should be created in future revisions of the ICD codes.

Keywords: Thoracotomy, sternotomy, resuscitative thoracotomy, penetrating cardiac injury

Introduction

Penetrating cardiac injuries (PCI) present a significant challenge to trauma surgeons. These injuries are largely considered highly lethal because an estimated 60-80 percent of patients will die on the scene or en route to a trauma facility[1-3]; with overall survival to discharge estimated around only 20 percent.[4-6] Factors such as the cause of injury, transport time, and condition of the patient on arrival to the hospital naturally impact outcomes.[3, 7]

However, surgical intervention may increase the chance of survival by 24 percent to 60 percent for selected patients who demonstrate signs of life upon arrival at a trauma center.[8] For these high-risk patients, it is imperative to effectively address the injuries as soon as possible.

For patients sustaining a PCI there are three surgical approaches: resuscitative thoracotomy, non-resuscitative thoracotomy and sternotomy. Resuscitative and non-resuscitative thoracotomies involve surgically opening the left chest in the fifth intercostal space whereas a median sternotomy involves midline division of the sternum. All these approaches allow the surgeon access to the heart in order to repair cardiac injuries. Although resuscitative thoracotomy and non-resuscitative thoracotomy utilize the same surgical incision, they are performed under much different clinical situations, require use of different resources, and result in different outcomes.

A resuscitative thoracotomy is an emergency procedure only performed on moribund patients who are in extremis or without vital signs. It is always performed in the emergency department, often under non-sterile conditions and without general anesthesia. This procedure is performed as a last chance at survival and allows for life-saving maneuvers including the release of cardiac tamponde, direct massage of the heart, and temporary repair of cardiac and other devastating intrathoracic injuries. After temporary control is established, the patient is taken to the operating room for further definitive surgical management. Overall, this procedure carries a greater than 90 percent mortality rate.[9,10]

Non-resuscitative thoracotomy and sternotomy are performed in the operating room, under sterile conditions and general anesthesia, on patients who are not in extremis, and who were stable enough to tolerate the additional time to be brought to the operating room for the procedure. Both surgical approaches have advantages and limitations. A sternotomy provides better exposure of the anterior and lateral surfaces of the heart; however, it is more resource-intensive, time-consuming, and requires particular surgical skills and surgical instruments. It provides less exposure of both lungs and to the posterior surface of the heart.[2] Non-resuscitative thoracotomy allows for quicker access to the heart and can be extended to the right chest if additional exposure is needed. Compared to median sternotomy, it violates the left thoracic cavity, which can potentially lead to lung-related complications.

In patients sustaining PCI without a direct indication for resuscitative thoracotomy, the surgical approach (sternotomy vs. non-resuscitative thoracotomy) is variable. The location of wounds, anticipated cardiac and other associated injuries, patient stability, and surgeon experience are all contributing factors[2,11] to determine the optimal surgical approach (sternotomy vs. non-resuscitative thoracotomy), though specifics vary widely in the literature. Studies that have directly compared these two approaches, particularly with respect to patient outcomes,[12,13] are limited by smaller sample sizes.

The objective of this study was to compare the morbidity of patients with isolated penetrating cardiac injuries who underwent either sternotomy or non-resuscitative thoracotomy using the largest published cohort to date, derived from the National Trauma Data Bank (NTDB). The present study only considered those patients for whom non-resuscitative thoracotomy or sternotomy would have been indicated, based on the available data.

We hypothesized that non-resuscitative thoracotomy patients would have a higher risk of postoperative complications compared to sternotomy.

Material and Methods

This is a retrospective review of the research data sets (RDS) of the American College of Surgeon's (ACS) National Trauma Data Bank (NTDB). The Institutional Review Board at Tufts Medical Center approved the study.

The NTDB RDS for years 2007-15 were queried for adult (15 years of age and older) patients with PCI. The International Classification of Diseases, Ninth Revision, Clinical Modification (ICD-9-CM) was used to identify patients who underwent thoracotomy (34.02) and sternotomy (77.31). We used the ICD-9-CM as oppose to ICD-10-PCS for two reasons. Firstly, only three years of ICD-10 coded data were available in NTDB (2015-2017) so the data from these three years would not provide us a significant number of subjects. Secondly, similar to ICD-9-PCS, no unique ICD-10-PCS codes were assigned for resuscitative and non-resuscitative thoracotomy but both procedures were coded as thoracotomy (**Table 1**).

Cardiac injuries were identified using The Association for the Advancement of Automobile Medicine's Abbreviated Injury Scale 98 (AIS-98) codes that further specify injuries to the heart and pericardium. AIS-98 codes were used as opposed to AIS-05 since the use and reporting of AIS codes to the NTDB between 2007-2015 was not uniform, with AIS-98 coding being more consistent.[14] **Figure 1** represents the cohort selection process.

Since there is no unique ICD-9 code for resuscitative thoracotomy, patients who arrived without signs of life were excluded, to avoid including patients who potentially underwent resuscitative thoracotomy in the non-resuscitative thoracotomy group. To minimize the impact of other significant injuries and procedures on outcomes, patients with associated extra-thoracic injuries with an AIS severity code of ≥ 3; injuries of trunk vessels, long bones and joint injuries; and those underwent surgery for brain, spine, neck, or abdominal/pelvic organ injuries were excluded.

The final cohort was divided into two study groups: those who underwent sternotomy versus non-resuscitative thoracotomy. Data were extracted on patient demographics (age, gender, race), causes of penetrating injury (stab wound or gunshot wound (GSW)), admission vital signs, Glasgow Coma Scale (GCS), presence of respiratory assistance, associated non-thoracic injuries, pre-existing comorbidities, and injury severity score (ISS). Data on outcomes included discharge disposition (including in-hospital mortality), hospital length of stay (LOS), intensive care unit (ICU) LOS, and days on mechanical ventilation. In addition, data were extracted on type of treating institution i.e.: community, academic, non-teaching, trauma level designation, hospital bed volume, number of surgeons, and geographic region.

The primary outcome of the study was a risk of morbidity. Secondary outcomes included days on mechanical ventilation, total ICU LOS, hospital LOS, and mortality.

Statistical Analysis

To further exclude those patients who may have undergone resuscitative thoracotomy, propensity score (PS) methods were used in an attempt to limit the analysis of outcomes to patients who had similar likelihood to have undergone either sternotomy or non-resuscitative thoracotomy based on the data available in the NTDB. Propensity for sternotomy (vs non-resuscitative thoracotomy) was calculated in a logistic regression model that included baseline patient and hospital characteristics potentially associated with choice of surgical procedure, including age, race (white, black, other, missing), year, admission systolic blood pressure, cause of injury (gunshot wound, stab wound), ISS, AIS severity of cardiac injury (range: 1 to 6), presence of extrathoracic injuries, trauma center level (I-II, all others), hospital bed size (1-350, 351-500, >500), US geographic region (Northeast, South, Midwest, West, missing), hospital teaching status (community, non-teaching, university), and number of trauma surgeons (0-3, 4-6, >6, missing). Categorical variables with missing values retained a missing indicator in order to retain those individuals in the PS model. Other admission vital signs and comorbidities were considered for inclusion, but ultimately discarded due to missing data. Sternotomy patients were then matched 1:1 on the propensity score with non-resuscitative thoracotomy patients, using a caliper width equal to 20 percent of the standard deviation of the logit of the propensity score.[15]

The balance of baseline characteristics between the groups (both before and after matching) was assessed using standardized differences, with values ≤0.1 indicating reasonable balance.

The risk of complications and mortality between groups was compared using McNemar's test for matched pairs. Among those patients who survived to be discharged, differences in days on mechanical ventilation, hospital LOS, and ICU LOS were compared with Wilcoxon rank-sum tests. Statistical analysis was performed using SAS v94, and all tests were two-sided with alpha=0.05.

Results

Prior to PS matching, the study cohort included 977 patients; 309 (31.6 percent) of them underwent sternotomy while 668 (68.4 percent) thoracotomy (**Figure 1**). Following 1:1 PS-matching, there were 246 patients in each procedure group. The groups were well matched on baseline demographics, admission blood pressure, injury severity score, and institutional characteristics (**Table 2**).

The majority of patients in both groups were admitted to Level 1 trauma centers, and were seen at academic university hospitals. Hospital size and number of trauma surgeons on staff were balanced between the facilities to which thoracotomy and sternotomy patients were admitted.

Outcomes

In-hospital mortality was higher in the non-resuscitative thoracotomy group (30 percent vs 8 percent, McNemar's p<0.0001). The risk of any complication occurring was significantly higher in the non-resuscitative thoracotomy group compared to the sternotomy group (25 percent versus 12 percent; McNemar's p=0.0007), in patients in whom data were available. The individual types of complications rarely occurred in either group so any meaningful comparison was impossible to perform. Non-resuscitative thoracotomy patients had more days on mechanical ventilation (p=0.0018) and both longer ICU and hospital length of stay (p=0.0133 and p=0.0003, respectively) (Table 3).

Discussion

Our study originally aimed to investigate the rate of complications in patients with PCI who underwent either sternotomy or non-resuscitative thoracotomy using the National Trauma Data Bank data. For the purposes of the study, our intent was to exclude patients who required a resuscitative thoracotomy. We found that patients with PCI in the non-resuscitative thoracotomy group had significantly higher mortality in comparison to the sternotomy group. This finding raises a question about the validity of our non-resuscitative thoracotomy group. First, previous studies directly comparing sternotomy and non-resuscitative thoracotomy in PCI did not demonstrate a significant difference in mortality.[12,13] Second, the lack of a specific code for resuscitative thoracotomy precluded us from confidently excluding these patients from the study cohort. Despite strict exclusion criteria and propensity score matching, it is likely that the non-resuscitative thoracotomy group included patients who were treated with either resuscitative or non-resuscitative thoracotomy, or both.

Our study found that the mortality in the non-resuscitative thoracotomy group was 30 percent, compared to only 8 percent in the sternotomy group. Based on published reports, we did not expect to find such a significant difference in mortality. Besir et. al, retrospectively reviewed the data of 40 patients who underwent surgery for a PCI at a single Turkish hospital over a 10-year period[12]. Twenty-six of the patients underwent a non-resuscitative thoracotomy, and 14 patients underwent sternotomy. Hemodynamic instability was not a determinant on the choice of the incision, and no patient underwent a resuscitative thoracotomy. The results showed the non-resuscitative thoracotomy group had greater blood transfusion requirements and longer LOS, but there were no significant differences in mortality between the two groups: 26.9 percent vs 14 percent, p=0.45. Mitchell et al. reviewed 115 PCI patients who were operated on over a 15-year period at their institution.[13] No significant difference in mortality was found between the non-resuscitative thoracotomy and sternotomy groups (17.5 percent vs 7 percent, p=0.28). The mortality rate was 85 percent in those who required resuscitative thoracotomy.

The extremely high mortality rate of resuscitative thoracotomy is well established and is explained by the moribund conditions of these patients on whom the surgery is performed, rather than by the nature of the procedure itself. The resuscitative thoracotomy is performed in patients in extremis or those without vital signs. The Eastern Association for the Surgery of Trauma Practice Management

Guidelines EAST[10] analyzed data from 64 studies published over 50 years and showed a survival rate of only 10.6 percent (95 percent confidence interval: 9.8 to 11.3 percent) in patients with PCI who underwent a resuscitative thoracotomy. The survival of patients who did not require resuscitative thoracotomy is significantly higher. Morse et al[1] reported their experience of managing PCI at a level one trauma center over a 36 year period. The overall mortality in the study cohort was 31 percent. The subgroup analysis showed a mortality rate of 64 percent in those receiving a resuscitative thoracotomy versus 18.6 percent in those that did not.

During the creation of the study protocol we realized the lack of specific coding for non-resuscitative thoracotomy could skew our findings. Therefore, we attempted to eliminate subjects who would potentially require a resuscitative thoracotomy by applying strict exclusion criteria and using propensity score matching. For example, patients with two common indications for resuscitative thoracotomy: arrival to emergency department with no signs of life, and "death on arrival" were excluded. Next, based on demographics, admission vital signs, and the injury severity score, we performed the propensity score matching between non-resuscitative thoracotomy and sternotomy groups. Both groups were matched appropriately, including the injury severity score. The injury severity score is an indicator of the overall injury significance and is a strong predictor of mortality in trauma patients.

Since institutional staffing and resources can vary, treating facility characteristics were addressed as well to understand procedural differences and patient outcomes. There were no significant structural differences among the treating facilities in our study.

Our study was done based on the ICD-9-CM; however, the recently adopted ICD-10 classification codes similarly do not contain separate codes for resuscitative versus non-resuscitative thoracotomy (**Table 1**). The absence of the unique procedure code for the resuscitative thoracotomy does not allow researchers to perform nationwide analysis of the rate of this procedure and outcomes. The existing literature is limited to the reports from level one and two trauma centers that have the highest level of expertise. The results of these reports cannot be generalized as they are biased by the individual institutions' characteristics. The known differences between non-resuscitative and resuscitative thoracotomy in terms of indications, resources required to perform these procedures, and clinical outcomes are other considerations to suggest the creation of the unique procedure code for the resuscitative thoracotomy.

Conclusions

Analysis of our findings in light of the existing surgical literature suggest that the significant differences in morbidity and mortality in patients with isolated penetrating cardiac injuries who underwent non-resuscitative thoracotomy vs. sternotomy may be biased by the inclusion of resuscitative thoracotomy patients in the non-resuscitative thoracotomy group. The lack of a specific procedure code for resuscitative thoracotomy did not allow us to confidently exclude these patients from the non-resuscitative thoracotomy group. In order to accurately capture thoracotomy type, separate unique resuscitative and non-resuscitative thoracotomy procedure codes should be created in future revisions of the ICD codes. Further studies with ICD codes for resuscitative and non-resuscitative thoracotomy will need to be performed to confirm our findings.

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FIGURES

Figure 1 *Selection of the study cohort*

DOA, death on arrival; SOL, signs of life; LOS, length of stay; SBP, systolic blood pressure. The final "thoracotomy" group (246 patients) was assumed to contain only patients who underwent non-resuscitative thoracotomy.

Table 1 Coding of thoracotomy and sternotomy

Thoracotomy			
ICD-9	Description	ICD-10	Description
34.02	Exploratory Thoracotomy	02JA0ZZ	Inspection of Heart, Open Approach
		0WJC0ZZ	Inspection of Mediastinum, Open Approach
Sternotomy			
ICD-9	Description	ICD-10	Description
77.31	Other division of bone, scapula, clavicle, and thorax	0P800ZZ	Division of Sternum, Open Approach
		0P803ZZ	Division of Sternum, Percutaneous Approach
		0P804ZZ	Division of Sternum, Percutaneous Endoscopic Approach

Table 2. Patient and treating institution characteristics

	Non-Resuscitative Thoracotomy n=246	Sternotomy n=246	Standardized Difference
1. **Demographics**			
Age*	33.6 (13.9)	34.0 (13.1)	0.03
Male	224 (91)	220 (89)	0.05
Race	89 (36)	89 (36)	
White	157 (64)	157(64)	0.07
Non-white			
1. **Admission and Injury characteristics**			
SBP*, mmHg	106.7±44.5	108.8 ±32.6	0.05
AIS severity of cardiac injury >2,	214(87)	208 (85)	0.08
Presence of extra-thoracic injuries (AIS 1-2)	73 (30)	77 (31)	0.04
ISS*	27.7 ± 20.0	25.2 ± 19.4	0.13
1. **Treating institution**			
Community	73 (30)	68 (28)	
University	161 (66)	168 (68)	0.07
Non-teaching	12 (5)	10 (4)	

Trauma Level I-II	240 (98)	241 (98)	0.03
Bed Size	67 (27)	62 (25)	
≤ 350	86 (35)	88 (36)	0.05
351-500	93 (38)	96 (39)	
>500			
Number of Surgeons	13 (5)	12 (5)	
0-3	108 (44)	111 (45)	
4-6	111 (45)	112 (46)	0.09
>6	14 (6)	11 (5)	
Missing			

All data are presented as n (percent) unless indicated otherwise. AIS, Abbreviated Injury Scale; ISS, injury severity score; SBP, systolic blood pressure; *, mean ±standard deviation.

Table 3. *Outcomes*

	Non-Resuscitative Thoracotomy (n=246)	Sternotomy (n=246)	p-value
Any complication(s)*	48/190 (25)	23/190 (12)	0.0007
Mortality	73 (30)	20 (8)	<0.0001
Duration among those discharged alive			
Median DMV (IQR)*	n=66 2 (1, 3)	n=66 1 (1, 2)	0.0018
Median ICU LOS days (IQR)*	n=147 3 (2, 5)	n=147 (3 (2, 4)	0.0133
Median LOS days (IQR)*	n=161 8 (6, 11)	n=161 7 (5, 9)	0.0003

All data are presented as n (percent).

*Denominators differ due to missing data

DMV, days on mechanical ventilation; ICU, intensive care unit; LOS, length of stay; SD, standard deviation; IQR, interquartile range.

There are no comments yet.

BIG-DATA SKILLS: BRIDGING THE DATA SCIENCE THEORY-PRACTICE GAP IN HEALTHCARE

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Category: Winter 2021

Big-Data Skills: Bridging the Data Science Theory-Practice Gap in Healthcare

By Diane Dolezel, EdD, RHIA, CHDA, and Alexander McLeod, PhD

Abstract

Demand for big-data scientists continues to escalate driving a pressing need for new graduates to be more fluent in the big-data skills needed by employers. If a gap exists between the educational knowledge held by graduates and big data workplace skills needed to produce results, workers will be unable to address the big data needs of employers.

This survey explores big-data skills in the classroom and those required in the workplace to determine if a skills gap exists for big-data scientists. In this work, data was collected using a national survey of healthcare professionals. Participant responses were analyzed to inform curriculum development, providing valuable information for academics and the industry leaders who hire new data talent.

Keywords: Big data, analytics, theory-practice gap, data science, Hadoop, Spark, nonrelational, healthcare, curriculum, SQL

Introduction

The use of big-data tools has grown substantially with larger organizations having the highest adoption rates.[1] Although the number of companies using big-data analytics is increasing rapidly, the biggest barrier to adoption of big data technologies is the persistent shortage of data scientists.[2,3] Data sciences jobs are now one of the top five emerging jobs in the United States.[4,5] A 2019 search of job boards showed there were 87,756 vacancies in the United States with 36,608 paying over $95,000 per year.[6] Unfortunately, many job postings are not filled because the demand for data scientists far exceeds the supply, a trend that is predicted to continue.[7]

One factor affecting worker availability is that it takes many years to become a data scientist. Most U.S. data scientists agree that it takes on average 4.9 years.[8] Data scientists must learn multiple programming and database languages and master advanced statistical analysis. Academics institutes struggle to deliver the data science curricular components due the costs associated with providing the hardware, software, and human capital for these courses.[9] In addition, universities may have difficulty hiring knowledgeable professors who will teach these classes. Most professors lack the data science teaching skills, and few institutes have the budget for faculty training at this level.[10] In the end, hiring for data science faculty is financially problematic because educational institutes are competing with companies who can offer higher salaries and better benefits.

Optimally if academia is doing a good job of educating and training, graduate new hires in data science should have a minimal learning curve. There is however a growing concern that data science graduates face a theory-practice gap when they are hired.[11] The purpose of this paper is to 1.) explore the classroom to workplace skills gap for big data scientists using theory-practice gap, 2.) examine big data workplace needs, and 3.) propose resources for curriculum building to better prepare students for the workplace, closing the gap.

Background

Big data is defined as "high-volume, high-velocity and/or high-variety information assets that demand cost-effective, innovative forms of information processing that enable enhanced insight, decision making, and process automation."[12] Thus, the Four Vs of big data are , volume, variety, velocity, and veracity.[13] Currently, volumes are measured in terabytes (1012) however this limit is expected to increase as storage capacities increase and cost decline. It is estimated that 43 trillion gigabytes of data are created each day. Data velocity can range from slow batch processes to lightning fast real-time stream analysis - the choice of which depends on the users' needs. Stream processing is beneficial for updating reports and metrics, but historically batch processing has provided more detailed analyses of the data. Batch processing jobs analyze the data all at once, they may run for a few minutes to several hours. A typical batch process runs at night at a set time to analyze all patient account charges for that day. Conversely, stream processing handles real-time data streams in less than a second, supporting real-time analytics.[14] Data streams can be processed with Apache Storm software or Amazon Web Service. Streams of real-time data could come from medical healthcare monitors, mobile devices, web applications, software log files, or social media streams.

Big data comes from many sources. Sources could include healthcare activities (151 billion gigabytes), wearable health monitors (420 million), data from 6 billion cell phones or from 4 billion hours of data YouTube videos.[15,16] Big data can be structured, semi-structured, or unstructured. Structured data occurs in patient and administrative medical records. Unstructured data sources comprise emails, mobile devices, digitized radiology images, smart healthcare sensors on connected devices, Facebook posts, Twitter feeds, audio files and encrypted data from business activities. For reference, Facebook users upload over 900 million pictures a day.[17]

Big data analysis requires special tools. The largest provider of free open software for big data development is the Apache Software Foundation (ASF).[18] In particular, the ASF Hadoop project develops distributed processing software.[19] Hadoop is used by an amazing number of companies including Amazon, Adobe, eBay, Google, IBM, LinkedIn, Twitter, *The New York Times* and Yahoo.[20] Hadoop encompasses a huge software library which includes Hadoop Distributed File System

(HDFS) and the Hadoop Map Reduce tools (Hive and Pig).[21] Because of the volume of big data users, the expanded software library and complexity of using Hadoop, data scientist require hands on training.

The complex operating environment of Hadoop provides support tools. Map Reduce applications work on the HDFS, consisting of map tasks, that work separately on data files, and reduce the number of tasks that combine and analyze map data.[22] Pig is a MapReduce data scripting language for extracting, transforming, and loading data into data stores. Hive is an SQL query language for use with HDFS and HBase data warehouses. **Figure 1** shows the relationships between Data Inputs, Hadoop and Processed Data Outputs.

Other related Hadoop software such as Spark and Storm, support big data processing. Spark provides large scale batch and real-time data processing of Hadoop data, machine learning and stream processes. Storm speeds real-time computational processing. Also, there are several ASF NOSQL databases, such as Cassandra, HBase, and CouchDB. Cassandra is a high performance non-relational database that provides excellent data replication with no single point of failure and no downtime. Cassandra is in use at Apple, eBay, GitHub, Hulu, Instagram, Netflix and the Weather Channel.[23] Apache HBase is also used with HDFS, providing real-time read and write of very large tables. If you need a web friendly document database, CouchDB works well with HTTP, JavaScript Object Notation (JSON), MapReduce and mobile applications. CouchDB has large deployments at IBM, Grubhub, and the UnitedHealth Group. Given the large number of big data tools, the complexity of the big data platform and the large number of corporations utilizing these tools, it is easy to see how extensive skills are required to function in the big data environment. Alignment between education and industry is required to provide new hires able to practice big-data skills.

Conceptual Framework

The framework for this paper is the conceptualization of a theory-practice gap between the academic knowledge (the theory) and the hands-on application of that knowledge in the work environment (the practice).[24] The theoretical consideration of a theory practice gap is persistent and has been a topic of interest in many fields.[25-27]

For example in healthcare, the inability to apply evidence-based research to the practice of injury prevention demonstrated a theory-practice gap.[28] In the education field, a theory-practice gap was cited when student teachers' felt unprepared for their teaching internships.[29] Similarly, student nurses in a graduate program reported their clinical supervisors' administration of intramuscular injections was inconsistent with the techniques learned in their classes attributable to a theory-practice gap.[30] This divergence from learned practice confused them about the correct methodology for injections. Engineering students reported problems when implementing telecommunication wireless standards, which is a common engineering task. The telecom standards had complex and cryptic implementation documentation which was unfamiliar to students leading to a theory-practice gap.[31]

Focusing on the healthcare workplace, we found few studies considering the theory-practice gap and guidance related to curriculum development. However, it is important for educators to prepare students to apply the workplace skills, tools and technologies most commonly used by healthcare employers. This is the first step in reducing the theory-practice gap.[32,33]

Research Questions

Given the number of required skills and knowledge needed to operate in the big data environment and the reports of theory and practice gaps in the workplace, the following big data research questions were developed:

- What is the overall usage level of big data tools in industry and academia?
- Which skills are needed for big data analysis in the workplace and by educators?
- What database skills are used by industry and in academia?
- What data science tools used in the workplace and by educators?

We developed a methodology to explore these research questions using a survey of industry professionals and educators.

Methodology

The aim of this study was to identify if a theory practice gap existed in the healthcare big data environment. The study originated at a large university in the southern United States after an Internal Review Board approval process. A survey was created by the researchers to measure the desired variables and data were collected during the summer and fall of 2018. After cleaning the survey data an analysis took place using SPSS 25. Demographics and descriptive statistics were then generated from respondent data.

Participants

The researchers obtained approval from the American Health Information Management Association (AHIMA) to survey their professional members. AHIMA assisted with the study by providing the email link to the survey to their professional members. Specifically, the link was emailed to members having job titles that reflected potential knowledge of big data skills, tools, and technologies usage. Survey respondents who failed to complete the entire survey were excluded from analysis, leaving a total of 492 participants’ responses that were analyzed.

Instrument

The survey was designed to determine perceptions of big data skills and the frequency of use. **Appendix 1** provides the questions used in this measure. The survey used Likert scale questions with responses ranging from very frequently to never. Other questions asked participants how frequently they used big data skills, what types of relational and non-relational databases were used, what statistical and data visualization software they used or planned to use in the future. Response data were split into two groups—Educator and Workplace (i.e. all non-educator professional responses). Both groups were analyzed in SPSS to determine the frequency and percentages of the usage of big data skill, tools, and technologies and the gap between workplace and educators was examined. Demographic questions on participant's education level, years of healthcare education experience, job level, job setting, and work role were analyzed.

Results

Demographics

There were 492 respondents in the study providing a good range of responses. The educational levels reported were master's degree (67 percent), doctorate (13 percent), baccalaureate (12 percent), and associate degrees (8 percent). The years of healthcare education experience varied, responses included none (n=11), less than 1 year (n=1), 1-5 years (n=80), 6-10 years (n=69), 11-5 years (n=74), 16-20 years (n=60), and over 20 years (n=197). **Figure 2** charts the respondent's years of healthcare experience.

Respondents were typically employed in acute-care hospitals (22 percent), clinic/physician practices (5 percent), consulting services (8 percent), or integrated healthcare delivery systems (7 percent).

Figure 3: Job Settings of Respondents

Participant job settings are displayed in **Figure 3**. Educators made up the greatest number of respondents at 37 percent. **Table 1** list the Job Setting, Count and Percentage of respondents.

Job Settings (n=492)	Count	Percent
Acute Care Hospital	107	21.7
Ambulatory Surgery Center	3	0.6
Behavioral/Mental Health	16	3.3
Clinic/Physician Practice	26	5.3
Consulting Services	38	7.7
Educational Institution	181	36.8
Health Information Exchange	3	0.6
Home Health/Hospice	1	0.2
Integrated Healthcare Delivery System	37	7.5
Non-Provider Setting	20	4.1
Other Provider Settings	4	0.8

Regional Extension Center	1	0.2
Long-Term Care	17	3.5
Other	38	7.7

Table 1: Respondent's Job Setting

We also collected information about respondents' Job Level in order to classify whether they were working in industry or academia. The job levels were predominantly Educator (39.2 percent), Director (19.2 percent), or Manager/Supervisor (19.4 percent). Other job levels denoted were clinician, consultant, executive/president/vice president, and technology role.

Job Levels (n=490)

Characteristic	Number	Percentage
Clinician	13	2.7
Consultant	47	9.6
Director	94	19.2
Educator	192	39.2
Executive/President/Vice President	22	4.5
Technology Role	27	5.5
Manager/Supervisor	95	19.4

Table 2: Respondent's Job Level

The primary work roles were Education (n=189) and Coding and Revenue Cycle (n=113). To divide the data based on education and workplace, we considered job settings. Those classified as educators, versus workplace respondents who designated non-educational job settings. Workplace respondents (63 percent) outnumbered educators (37 percent) nearly two to one.

Figure 4: Respondent's Work Role

Current Level of Usage

Participants were first asked about the current level of big data analytics usage in their organization. Respondents rated the level of overall big data technology usage as Very frequently (daily), Frequently (1-2 times a week), Occasionally (a few times a month), Rarely (a few times every three months (i.e., every quarter), and Never (not used at all). Twenty four percent of all respondents had high usage levels, which we defined as very frequent use.

Frequency of Use

Next, participants were asked about how frequently big data skills were used at their organization. These skills included artificial intelligence, data mining, data visualization, java, machine learning, natural language processing, structured query language, python, and statistical analysis. Considering the most commonly used workplace skills shows a distinct gap between educators and workplace percentages of use. Figure 5 presents big data skill.

Across the board, workplace usage exceeded education: artificial intelligence (Workplace 10.9 percent, Educators 4.3 percent), data mining (Workplace 25.2 percent, Educators 11.6 percent), data visualization (Workplace 25.6 percent, Educators 21.3 percent), java, (Workplace 15.1 percent, Educators 5.5 percent), machine learning (Workplace 12.8 percent, Educators 2.4 percent), natural language processing (Workplace 14.7 percent, Educators 4.9 percent), structured query language (Workplace 27.1 percent, Educators 12.8 percent), python (Workplace 5.8 percent, Educators 2.4 percent), statistical analysis (Workplace 33.7 percent, Educators 29.3 percent.

In terms of the skills gap, **Table 2** list the differences between the Workplace and Educators.

Big-Data Skill	Difference
Structured query language	14 percent
Data mining	14 percent
Machine learning	10 percent
Natural language processing	10 percent
Java	10 percent
Artificial intelligence	7 percent
Statistical analysis	4 percent
Data visualization	4 percent
Python	3 percent

Table 2: Big-Data Skill Differences

Relational Database Skills

Next, we considered which relational databases were very frequently used. The relational databases included IBM DB2, Microsoft SQL Server, MySQL, Oracle database, SAP HANA, Teradata and other. **Figure 6** displays relational databases skills reported as very frequently used. These included IBM DB2 (Workplace 2.9 percent, Educators 1.7 percent), Microsoft SQL Server (Workplace 43.7 percent, Educators 43.9 percent), MySQL (Workplace 15.4 percent, Educators 28.9 percent,) or Oracle (Workplace 19.3 percent, Educators 18.3 percent), SAP HANA (Workplace 1.9 percent, Educators 1.1 percent), and Teradata (Workplace 2.6 percent, Educators 2.2 percent). Figure 6 shows relational database skill differences between the workplace and educators.

Here the workplace and educator usage are similar for all relational databases, except for the much larger levels for MySQL among Educators. Table 3 shows the difference in percentage reporting frequent use by relational database.

Relational Database	Difference
MySQL	14 percent
IBM DB2	1 percent
Oracle	1 percent
SAP HANA	1 percent

Teradata	0.4 percent
Microsoft SQL Server	0.2 percent

Table 3: Relational Database Usage Difference

Nonrelational databases are used in big-data environments. **Figure 7** displays non-relational databases skills with high usage. The most commonly used nonrelational databases were: Apache Cassandra (Workplace 10.0 percent, Educators 6.7 percent), Couchbase (Workplace 2.9 percent, Educators 1.7 percent), Apache Hadoop (Workplace 5.0 percent, Educators 3.5 percent), and Apache CouchDB (Workplace 8.0 percent, Educators 3.9 percent).

Here the workplace and educator use are similar, with the exception that educators having higher use of Apache Hadoop/MapReduce and lower usage of the remaining listed databases. Table 4 shows the differences between Workplace and Educators for nonrelational databases.

Non-Relational Database	Difference
Apache CouchDB	4 percent
Apache Cassandra	3 percent
MongoDB	3 percent
Apache Hadoop/Map Reduce	2 percent
Couchbase	1 percent

Table 4: Non-Relational Database Usage Difference

Data Science Tools

Data analysis is an important function directly tied to big data. **Figure 8** displays data science tools results. The frequency of use reported for these data science tools were: Apache Hadoop HDFS (Workplace 11 percent, Educators 8 percent), Apache Hive (Workplace 11 percent, Educators 4 percent), Apache HBase (Workplace 6 percent, Educators 2 percent), JAQL (Workplace 23 percent, Educators 10 percent,) Jaspersoft BI Suite (Workplace 3 percent, Educators 0 percent), or IBM Infosphere (Workplace 21 percent, Educators 7 percent),

Apache Mahout Machine Learning (Workplace 7 percent, Educators 3 percent) and the most frequently used Tableau Desktop and Server (Workplace 70 percent, Educators 73 percent). The differences between the Workplace and Educators is detailed in **Table 5**.

Data Science Tools	Difference
IBM Infosphere	14 percent
JAQL	13 percent
Apache Hive	7 percent
Apache HBase	4 percent
Apache Mahout Machine Learning	4 percent
Apache Hadoop HDFS	3 percent
Jaspersoft BI Suite	3 percent

Tableau Desktop and Server	3 percent

Table 5: Data Science Tool Usage Differences

Here the Workplace and Educator use are lower, except for Tableau software. Table 5 shows the percent difference between Workplace and Educators with regard to data science tools.

Statistical Tools

Statistical tools provide needed data transformation and analysis. Expertise in statistical analysis is required of data scientist dealing with big data. **Figure 9** displays the frequency of use of statistical tools with R (Workplace 35 percent, Educators 47 percent), JMP (Workplace 35 percent, Educators 41 percent), Minitab (Workplace 12 percent, Educators 14 percent), Matlab (Workplace 6 percent, Educators 4 percent), SAS

(Workplace 53 percent, Educators 41 percent), SPSS (Workplace 28 percent, Educators 65 percent), Stata (Workplace 9 percent, Educators 11 percent), and Statssoft Statistica (Workplace 16 percent, Educators 16 percent). **Table 6** shows the percent difference between Workplace and Educators.

Statistical Tool	Difference
SPSS	37 percent
R Statistical Software	12 percent
SAS	12 percent
JMP	6 percent
Minitab	2 percent
Matlab	2 percent
Stata	2 percent
Statssoft Statistica	0 percent

Table 6: Respondent's Statistical Tool Differences

Data Mining and Analysis

Big data provides an opportunity to dig into data and perform analyses. **Figure 10** presents data mining and analysis tools.

Figure 10: Data Mining Tools Usage

The most commonly used were: SAS Enterprise Miner (Workplace 45 percent, Educators 37 percent,), IBM SPSS Modeler (Workplace 23 percent, Educators 28 percent), Dryad Parallel Processing (Workplace 1 percent, Educators 2 percent), IBM Watson Analytics (Workplace 7 percent, Educators 0 percent), R Software (Workplace 15 percent, Educators 43 percent), Rapid Miner (Workplace 9 percent, Educators 4 percent) and Weka/Pentaho (Workplace 0 percent, Educators 3 percent). **Table 7** shows the data mining and analysis tools differences.

Data Mining Tools	Difference

R Software	28 percent
SAS Enterprise Miner	8 percent
IBM Watson Analytics	7 percent
IBM SPSS Modeler	5 percent
Rapid Miner	5 percent
Weka/Pentaho	3 percent
Dryad Parallel Processing	1 percent

Table 7: Data Mining Tools Differences

Data Visualization

To extract meaning from big data, many data scientist use data visualization tools. **Figure 11** shows the frequency of data visualization tools.

The tools included Fusion Charts (Workplace 9 percent, Educators 3 percent), Google Analytics (Workplace 36 percent, Educators 40 percent), IBM Watson Analytics (Workplace 12 percent, Educators 4 percent), Microsoft Power BI (Workplace 34 percent, Educators 15 percent), Oracle Visual Analyzer (Workplace 31 percent, Educators 16 percent), QlikView (Workplace 5 percent, Educators 10 percent), SAP Analytics Cloud (Workplace 17 percent, Educators 5 percent), Tableau (Workplace 46 percent, Educators 72 percent) shown in **Table 7**.

Data Visualization Tools	Difference
Tableau	26 percent
Microsoft Power BI	19 percent
Oracle Visual Analyzer	15 percent
SAP Analytics Cloud	12 percent
IBM Watson Analytics	8 percent
FusionCharts	6 percent
QlickView	5 percent
Google Analytics	4 percent

Discussion

To close the theory-practice gap, educators work to produce more data scientists with the workplace skills needed by industry. This theory-practice gap study informs healthcare educator's capacity building for big-data education to maximize their limited human and financial capital. Interestingly, we discovered that the theory-practice gap can be forged in one of two ways. Either Workplace use can be ahead of Educator use or the reverse situation may exist where Educator use is ahead of Workplace use. In either case, better alignment might equate to better qualified new data scientist.

Overall, results of this study showed higher Workplace use of big data and data science tools. In four of the seven big-data tools examined - Data Analytics, Non-Relational Database, Data Science Tools, and Data Visualization Tools, industry perceptions of usage exceed academic perceptions of usage. This is not surprising given the utility and newness of big-data tools and the perception of strategic advantage achievable with large data sets. Skills across the board are more highly regarded in industry and a gap does exist with relation to education. An average eight and half percent skills difference gap exists across the board for Artificial Intelligence, Data Mining, Data Visualization, Java, Machine Learning, Natural Language Processing, Structured Query Language, Python and Statistical Analysis skills with industry ahead of academia.

Not surprisingly, perceptions of Relational Database skills are very similar between workplace and educators. For IBM DB2, only a 1.2 percent difference exists and this is similar with Microsoft SQL Server, Oracle, SAP HANA and Teradata. The major difference is MySQL showing a 13.5 percent gap with academia far ahead of industry. One reason for this might be low cost and greater adoption by educators looking for inexpensive technical solutions for the classroom.

Non-relational database skills are newer than relational database skills and in this case the workplace is more advanced than education. For all non-relational database tools except Apache Hadoop/MapReduce, industry perceives greater usage than education. With regard to Apache Hadoop/MapReduce use, educators are 1.5 percent ahead of the workplace.

Perceived usage of data science tools in the workplace is greater than educator's perceptions but not by a lot. On average there is only a 6.4 percent difference with IBM Infosphere being the greatest difference at 14 percent. Still the frequency of use is relatively low for all data science tools except Tableau which is used by 73 percent of educator and 70 percent of industry respondents. These numbers indicate close alignment between industry and academia.

With regard to Statistical Tool usage, education seems to be ahead of industry usage. On average there is a 9.1 percent difference with education scoring higher in percent of use for R, SPSS and STATA. Industry has an edge in use of SAS. Given that R is a free statistical tool, we thought that usage in academia would be greater than industry and this is the case, however SPSS is used more in education in spite of its costs. Schools do get a price break which might be driving usage but there is a 37 percent gap for SPSS and only an 8 percent gap for R. Possibly R is gaining ground in industry as a standard because of its compatibility to Python and large library of free code. Interestingly, SAS is the strongest of the statistical tools in the workplace with 53 percent reporting usage.

There are a number of quality data mining tools and in our survey and there appears to be greater usage in academia than industry. The use of R software for data mining purposes is high in education at 43 percent but only 15 percent for industry. Also, IBM SPSS Modeler and IBM Watson are stronger in education however, SAS Enterprise Miner Dryad Parallel Processing and Rapid Miner see more usage in the workplace. There is an obvious gap of 28 percent in R software tool usage in academia.

Data Visualization software has become more available and easier to use with industry a little ahead of education for Fusion Charts, IBM Watson, Microsoft Watson, Oracle Visual Analyzer and SAP Analytics but education is much stronger in the use of Google Analytics and Tableau. Here again these differences may be due to low cost acquisition for schools. Overall there is an average of 11.9 percent difference in data visualization tool usage.

In summary, the largest theory-practice gap exists in the areas of data visualization, statistical tools, big-data skills and data mining tools. Given high educational and industry usage of data visualization and statistical tools, these areas may require greater attention in academia to facilitate alignment as new graduates enter the marketplace.

Topic	Avg Pct Difference
Data Visualization	11.9 percent
Statistical Tools	9.1 percent
Big-Data Skills	8.5 percent
Data Mining Tools	8.0 percent
Data Science Tools	6.4 percent
Non-Relational Database	5.6 percent
Relational Database	2.9 percent

Limitations

As with all research, there are several limitations. First, there were 492 respondents, but there were more workplace respondents (63 percent) than educators (37 percent). Still the number of respondents in each group provides good insight into perceptions of usage. Second, all respondents were members of a healthcare professional organization, thus a survey of a different population could produce different results. In addition, educators who responded to the survey will naturally focus on technologies available and used in their classes and may not have been aware of the full range of data science tools and technologies at their facility.

Future Studies

Future research should include a wider range of industries to determine big-data technology use. There may be specific tools used in different organizations. Another approach to this research would be to interview employers to gain insight into the knowledge or skills gaps they are seeing with newly hired data scientist graduates. In addition, future research may look at job postings to see what big data and data science skills are in demand in industry.

Conclusion

This paper explored the classroom to workplace skills gap for big-data scientists using theory-practice gap. Reducing this gap is a two-pronged approach. First, surveying the big-data skills that employers want can help bridge the gap between what schools teach and what employers need. Schools could then adapt their curriculum to more closely fit the needs of industry. Second, educators must provide real world big-data activities so that new graduates are better prepared to use what the learned at university. Results from this study should inform curriculum development and provide valuable information for academics and industry leaders who hire new data talent. When creating course content, professors must be frugal and careful with their software choices. Certainly, there exists free commercial software for Microsoft SQL Server Express and Oracle

Express and education licenses for SAS. These products are easy to install and use.[34,35] However, the ASF software suite (e.g. Apache Hadoop, MapReduce) is the most used big-data software and it runs on a distributed computer system. To setup such a system in a complex, requires a collaborative effort between educators, management and IT. In many cases, the faculty provide debugging support and performs installations for these data science systems. Professors should contact data science employers and document their needs. Faculty could visit the employer's sites to see demonstrations of software for potential course development. Data scientists could visit campuses for guest lectures which builds enthusiasm and shares knowledge among faculty and students. To develop experience-based learning, classroom simulation and application building could be employed. Internship programs with big-data employers would provide students with realistic experiential learning.

The addition of problem-solving assignments and mentoring of faculty and students should be evaluated to prepare students for employment.[36,37] Professional data science organizations could be encouraged to mentor data science students to help close the theory-practice gap.

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Appendix 1 Survey Instrument

What is the current overall level of big data analytics usage at your company? Very Frequently, Frequently, Occasionally, Rarely, or Never.

How frequently are these big data skills used at your organization? Please answer with Very Frequently, Frequently, Occasionally, Rarely, or Never.

- Artificial Intelligence
- Data Mining
- Data Visualization
- Java
- Machine learning
- Natural Language Processing

- Structured Query Language
- Python
- Statistical Analysis

Indicate which relational databases are in use at your organization. Select all that apply.

- IBM DB2
- Microsoft SQL Server
- MySQL
- Oracle database
- SAP Hanna
- Teradata
- Other please specify

Indicate which NoSQL non-relational databases are in use at your organization. Select all that apply.

- Apache Cassandra
- Couchbase
- ArangoDB
- Apache Hadoop MapReduce
- Apache CouchDB – document db
- Apache Hbase
- MongoDB – document db
- Other

Indicate which big data tools are in use at your organization. Select all that apply.

- Apache Hadoop HDFS distributed file system
- Apache Hive Query Language
- Apache HBase column-oriented database
- JAQL query language
- Jaspersoft BI Suite
- IBM InfoSphere
- Apache Mahout machine learning
- Tableau Desktop and Server
- Other

Indicate which data analysis tools are in use at your organization. Select all that apply.

- Microsoft Dryad
- IBM SPSS Modeler
- IBM Watson Analytics

- R Statistical Software
- RapidMiner
- SAS Enterprise Miner
- Weka/Pentaho
- Other

Indicate which statistical analysis tools are in use at your organization. Select all that apply.

- R
- JMP
- Minitab
- Matlab
- SAS
- SPSS
- Stata
- Statsoft Statistica
- Other please specify

Indicate which data visualization tools are in use at your organization. Select all that apply.

- FusionCharts
- Google Analytics
- IBM Watson Analytics
- Microsoft Power BI
- Oracle Visual Analyzer
- Qlikview
- SAP Analytics Cloud
- Tableau
- Other

There are no comments yet.