# THE VALUE OF A REGIONAL 'LIVING' COVID-19 REGISTRY AND THE CHALLENGES OF KEEPING IT ALIVE

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**Category:** Summer 2021

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**Abstract**

**Background:** The availability of accurate, reliable, and timely clinical data is crucial for clinicians, researchers, and policymakers so that they can respond effectively to emerging public health threats. This was typified by the recent SARS-CoV-2 pandemic and the critical knowledge and data gaps associated with novel Coronavirus 2019 disease (COVID-19).

We sought to create an adaptive, living data mart containing detailed clinical, epidemiologic, and outcome data from COVID-19 patients in our healthcare system. If successful, the approach could then be used for any future outbreak or disease.

**Methods:** From 3/13/2020 onward, demographics, comorbidities, outpatient medications, along with 75 laboratory, 2 imaging, 19 therapeutic, and 4 outcome-related parameters, were manually extracted from the electronic medical record (EMR) of SARS-CoV-2 positive patients. These parameters were entered on a registry featuring calculation, graphing tools, pivot tables, and a macro programming language. Initially, two internal medicine residents populated the database, then professional data abstractors populated the registry. Clinical parameters were developed with input from infectious diseases and critical care physicians and using a modified COVID-19 worksheet from the U.S. Centers for Disease Control and Prevention (CDC). Registry contents were migrated to a browser-based, metadata-driven electronic data capture software platform. Eventually, we developed queries and used various business intelligence (BI) tools which enabled us to semi-automate data ingestion of 147 clinical and outcome parameters from the EMR, via a large U.S. hospital-based, service-level, all-payer database. Statistics were performed in R and Minitab.

**Results:** From March 13, 2020 to May 17, 2021, 549,691 SARS-CoV-2 test results on 236,144 distinct patients, along with location, admission status, and other epidemiologic details are stored on the cloud-based BI platform. From March 2020 until May 2021, extraction of clinical-epidemiologic parameter had to be performed manually. Of those, 543 have had >/=75 parameters fully entered in the registry. Ten clinical characteristics were significantly associated with the need for hospital admission. Only one characteristic was associated with a need for ICU admission. Use of supplemental oxygen, vasopressors and outpatient statin were associated with increased mortality.

Initially, 0.5hrs -1.5 hours per patient chart (approximately 450-575 person hours) were required to manually extract the parameters and populate the registry. As of May 17, 2021, semi-automated data ingestion from the U.S. hospital all-payer database, employing user-defined queries, was implemented. That process can ingest and populate the registry with 147 clinical, epidemiologic, and outcome parameters at a rate of 2 hours per 100 patient charts.

**Conclusion:**

A living COVID-19 registry represents a mechanism to facilitate optimal sharing of data between providers, consumers, health information networks, and health plans through technology-enabled, secure-access electronic health information. Our approach also involves a diversity of new roles in the field, such as using residents, staff, and the quality department, in addition to professional data extractors and the health informatics team.

Initially, due to the overwhelming number of infections that continues to accelerate, and the labor/time intense nature of the project, only a small fraction of all patients with COVID-19 had all parameters entered in the registry. Therefore, this report also offers lessons learned and discusses sustainability issues, should others wish to establish a registry. It also highlights the registry's local and broader public health significance.  Beginning in June 2021, whole-genome sequencing results such as lineages harboring important viral mutations, or variants of concern will be linked to the clinical meta-data.

**Keywords:** SARS-CoV-2, COVID-19, registry, mortality, epidemiology, genomics, genomic epidemiology, electronic medical record

## Background

One dilemma in the attempt to deliver state-of-the-art therapeutics or understand emerging novel infectious pathogens is that the most current data is not always rapidly accessible to clinicians as soon as it becomes available. Hence, living systematic reviews have arisen as a potential solution to narrow the gap between evidence and practice.[1, 2]

Along the same lines, having live access with continuous updates of a patient data base using a standardized, well designed format and a user friendly, interactive software which allows us to also to more rapidly hypothesis test or identify patterns relevant to prevention motivated this effort. Additionally, data from one country or U.S. locality may not be generalizable to others, and data and experience from non-university or rural settings may be underrepresented in the medial literature, or not covered by media.[3] Furthermore, rural areas are currently experiencing some of the biggest increases in new SARS-CoV-2 infections. Fourth, on June 19, 2020, the National Academies of Sciences, Engineering, and Medicine hosted a public meeting on "Data Needs to Monitor the Evolution of SARS-CoV-2". Presenters agreed that regional surveillance nodes were needed. Last, the recently described "tragic data gap", and the federal curtailment of reporting COVID-19 data to the national Health Safety Network, also provided motivation for this intervention.[4] In the current climate, archiving detailed patient data in retrievable, easily analyzable, and share-friendly formats has become crucial for informing responses to current and future pandemics.[4]

Recent guidance[5] and events[6, 7, 8] also underscore the added value having private, nongovernmental alternatives for collecting and analyzing large scale epidemiologic data.

We sought to implement an adaptive, 'living' registry capable of capturing detailed epidemiologic and clinical information from every patient diagnosed with SARS-CoV-2 infection, similar to and more granular than the Danish COVID-19 Cohort or TriNetX network. Examples of the living approach include the living rapid reviews in the Annals of Internal Medicine, and the living systematic review of the University of Toronto regarding secondary infections in patients with COVID-19. However, these are literature reviews and not registries.

Our ultimate goal was to have a minable source of detailed information updated on an ongoing basis, with minimal human effort, and linkable to SARS-CoV-2 whole genome sequences, and other registries across the United States. Perhaps, becoming one of many extra-governmental surveillance nodes in a regional or national network. Additionally, if successful, the approach could then be used for any future outbreak or disease regardless of pathogen or etiologic agent.

**Setting**

The healthcare system consists of five acute care hospitals (ACH) and six long- term care facilities (LCTF) totaling 1056 ACH and 800 LCTF beds. It spans eleven suburban, rural, and urban counties in the Finger-Lakes Region of NY.

**Methods**

All patients in the above healthcare system who had a positive test for SARS-CoV-2 from 03/13/2020 onward were slated for inclusion in the RRH-COVID-19 Registry. Every patient who undergoes SARS-CoV-2 testing in the health system is captured in a cloud-based business intelligence (BI) platform that permits self-service data visualization and guided analytics (QlikView, Lund, Sweden). From this database, the medical record number of each patient is used to drive further queries (either manually or semi-automated) of the enterprise electronic medical record (EMR) (Epic, Verona, WI).

In mid-March 2020, after the first case in our community, demographics, comorbidities, outpatient medications, along with 75 laboratory, 2 imaging, 19 therapeutic, and 4 outcome-related parameters were manually extracted from the electronic medical record of SARS-CoV-2 positive patients. These parameters were developed based on input from infectious diseases and critical care specialists and manually entered on a registry featuring calculation, graphing tools, pivot tables, and a macro programming language (Excel). Initially, two internal medicine residents populated the database, then professional data abstractors populated the registry.

When the U.S. Centers for Disease Control and Prevention (CDC) released their COVID-19 Surveillance Worksheet [9], we used that as a guide to ensure the parameters we were collecting were aligned with national reporting efforts. To those parameters, we added several more such as laboratory values, imaging results, location of admission, length of stay and other outcome data. The initial platform (Excel) was abandoned and the contents transferred to a browser-based, metadata-driven electronic data capture software platform (REDCap, Vanderbilt University, TN)

Eventually, we developed queries and used various business intelligence tools which enabled us to semi-automate data ingestion of 147 clinical and outcome parameters (except imaging data) from the EMR via a large U.S. hospital-based, service-level, all payer database (Premier, Charlotte, NC).[10]

Statistics were performed in R and Minitab.

**Results**

From March 13, 2020 to May 17, 2021, the healthcare system performed 549,691 SARS-CoV-2 tests on 236,144 distinct patients. 30,213 of those tested positive. Everyone, including the negatives are stored, along with location, admission status, and other epidemiologic details are stored on the cloud-based BI platform. Users can partially customize dashboards to view trends, geography, laboratory details and census data. From March 2020 until May 2021, extraction of clinical-epidemiologic parameter had to be performed manually. Of those, 543 have had the more than 75 parameters fully entered in the registry. It took from 0.5hrs -1.5 hours per chart (approximately 450-575 person hours to extract the parameters and enter them in the registry.

As of May 17, 2021, semi-automated data ingestion from the U.S. hospital all-payer database, employing user-defined queries, was implemented. Using that process, all 147 clinical, epidemiologic, and outcome parameters can be accomplished at a rate of 2 hours per 100 patients.

Descriptive statistics of the first cohort of patients are presented in **Table 1**, with mortality associations in **Table 2**. The average follow-up period for those was 25 days (range 21-34 days). Ten characteristics were significantly associated with the need for hospital admiss

ion: age, male gender, occupation as a healthcare worker, diabetes, hypertension, cardiovascular disease, kidney disease, cancer, use of statins, use of ACEI-ARBs, and acid suppressant use. The only characteristic associated with need for ICU admission was a history of close contact w

ith a SARS-CoV-2 infected person. The use of supplemental oxygen, vasopressors, and outpatient statin was associated with increased mortality (**Table 2**).

**Discussion**

The registry revealed local patterns not apparent from less granular databased such as the CDC or county/state health departments, or from reports of other populations. For example, the average length of stay (LOS) for all admitted patients was 8 days (SD 8.6). The average LOS for patients who did and did not require ICU-level care was 13.5 (SD 10.4) and 5.9 (SD 6.8), respectively. This is significant because remdesivir was not available during the follow up period for this initial cohort, and the average LOS without it was already shorter than the 15-day outcome measure used in the final report.[11] Another example is a meta-analysis stating that ACEI or ARB use was associated with a lower risk for severe illness. According to the authors, those results "do not provide enough evidence to draw conclusions about the potential efficacy of these medications in treating COVID-19".[2] In contrast, we found use of angiotensin inhibitors and angiotensin receptor blockers was higher in admitted vs. ED treated-and-released patients ($p \le 0.001$). A third example involves a Chinese report which showed that statin treatment was associated with lower mortality.[12] However in our population, statin use was higher in admitted patients compared to patients who did not require admission (all $p \le 0.001$). Statin use was also higher in those who died than those who survived (**Table 2**) Last, in New York City, viral load was correlated with risk of intubation, but in our more rural and suburban area, we observed that viral load did not correlate with severity of illness.[13, 14]

Despite its benefits, designing and implementing a registry or specific data mart can be fraught-especially for hospitals with limited health informatics and financial support. Registry challenges, pitfalls, and threats to sustainability are presented in **Table 3**. Manual data extraction into the original spreadsheet became prohibitively labor intensive and analytically unmanageable as the number of new cases rapidly increased. Real-time abstraction needed to be suspended for several weeks while contents were transferred to the metadata-driven electronic data capture software platform. Initially, limited by a dependence on manual data extraction registry personnel were able to manually populate all the parameters mentioned above from only a small fraction of COVID-19 patients. Several reasons account for this: the labor intense nature, the unprecedented numbers of patients with the target condition due to pandemic surges or waves, and the number of clinical epidemiologic and outcome parameters we tried to capture. Designers and developers have to keep this in mind as they balance the desire to capture more patents with less data, or less patients with more parameters.

For diseases with lower incidence rates, the sustainability of the initial approach would have been achievable, but the approach became unsustainable given epidemic/pandemic-level volumes of new cases daily and weekly. For optimal sustainability, two full-time experienced data extractors, automation and machine-based learning would be required. The semi-automated process we used also has limitations. Using that, we still have to rely on manual chart review for obtaining imaging data, home/outpatient medication use, and certain health habits such as smoking and alcohol consumption.

## Conclusion

A living COVID-19 registry represents a mechanism to facilitate optimal sharing of data between providers, consumers, health information networks, and health plans through technology-enabled, secure-access electronic health information. Our approach also involves a diversity of new roles in the field such as using residents, staff, and the quality department, in addition to professional data extractors and the health informatics team.

However, due to the overwhelming number of infections that accelerated over the course of the pandemic, and the labor/time intense nature of the project, only a fraction of all patients with COVID-19 had all parameters entered in the registry. Therefore, this report also offers lessons learned and discusses sustainability issues, should others wish to establish a registry. It also highlights the registry's local and broader public health significance.

Robust registries from large EMR vendors take time to build and release, at times waiting for maturing knowledge makes them unavailable to initial nodes of outbreak. At such places, regional nodal registries are critical in early understanding and management of the pandemic. The progress may be limited initially due to the manual process, but they critically guide development of robust semi-automated or automated solutions. In addition, the results from early studies provide direction to broader preparedness and deployment programs. During the early part of a pandemic, focus changes to operational readiness and management, requiring lots of IT infrastructure bandwidth. At such times, having a manual process can be crucial to success of registry effort.

Going forward, the registry is well suited to address a range of hypothesis and is being leveraged by other researchers in our system. It provides a resource for researchers, policy makers, and surge planning. Once established, the informatics processes and parameters can be applied to patients infected with any high-consequence or novel pathogen. Soon, the clinical-demographic metadata will be linked to whole genome sequencing data for patients that had their virus sequenced. A growing number (currently 650) of patients have had whole genome sequence performed on their samples. This approach has been successfully used to improve outcomes for drug-resistant bacteria[15], and our next goal is to do the same for SARS-CoV-2.

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## There are no comments yet.

# SUMMER 2021 INTRODUCTION

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**Categories:** Featured, Summer 2021

*Vol. 18, Issue 3*

The Summer 2021 issue of AHIMA's peer-reviewed research journal, *Perspectives in Health Information Management*, is now available. This issue's topics explore a range of issues, from the RHIA exam to sepsis screening and veterans' issues. Papers include:

- Tabisula B. Association Rules in Heart Failure Readmission Rates and Patient Experience Scores. Read here.
- Martin T, Hamlet G, Gabriella P, Mathew R. A National Survey Assessing Health Information Exchange: Readiness for Changes to Veterans Affairs Access Standards. Read here.
- Sand J. Student Perceptions of an Undergraduate Interprofessional Capstone Course Including Health Information Management. Read here.
- Hyunkyung L. Mapping ICD-11 (The 11th International Classification of Disease) to ICD-10-KM-7th (the Korean Modification 7th of the ICD-10) for Flexible Transition to ICD-11. Read here.
- Fox D, Wiebe N, Southern D, Quan H, Kim E, King C, Grosu O, Eastwood C. The Prevalence of Insomnia and Sleep Apnea in Discharge Abstract Data: A Call to Improve Data Quality. Read here.
- McKeeby J, Coffey P, Houston S, Kennedy R, Chan L, Schacherer R, Alboum S, Bergstrom S, Joyce M. The Evolution of Information Technology Governance at the NIH Clinical Center. Read here.
- Hanna J, Chen T, Portales-Castillo C, Said M, Bulnes R, Newhart D, Sienk L, Schantz K, Rozzi K, Alag K, Bress J, Lesho E. The Value of a Regional 'Living' COVID-19 Registry and the Challenges of Keeping It Alive. Read here.
- Peterson J, Turley J. Predictors of Success on the RHIA Exam. Read here.
- Dokumentov A, Shaalan Y, Khumrin P, Khwanngern K, Wisetborisut A, Hatsadeang T, Karaket N, Achariyaviriya W, Auephanwiriyakul S, Theera-Umpon N, Siganakis T. Automatic ICD-10 Coding Using Prescribed Drugs Data. Read here.
- Liengsawangwong R, Kumar S, Ortiz R, Hill J. Health Informatics Tool Toward Sepsis Screening. Read here.

We hope you enjoy the Summer 2021 issue of *PHIM*. For questions or submissions, please reach out to Alexa Schlosser, Editor, at aschlosser@ahima.org.

## There are no comments yet.

# STUDENT PERCEPTIONS OF AN UNDERGRADUATE INTERPROFESSIONAL CAPSTONE COURSE INCLUDING HEALTH INFORMATION MANAGEMENT

*Posted on August 2, 2021 by Matthew*

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*By Jaime Sand, EdD, RHIA, CCS*

**Abstract**

As the healthcare industry continues to push for better patient care at a lower cost, it is essential that healthcare professionals develop skills in collaboration and teamwork. These skills should be practiced by students in post-secondary institutions, as they also learn to master content and technical skills. Participation of health information management (HIM) students in such activities helps to promote the value of HIM on the healthcare team. This study provides an example of integrating undergraduate HIM students into an interprofessional capstone course with other healthcare majors, summarizing student perceptions of learning activities in applying interprofessional education competencies. The results indicate a positive student perception of activities supporting application of at least three of the four competencies. Comments also highlight the struggles students have with group work, particularly in virtual teams. Sharing these activities and perceptions may contribute to further integration of undergraduate HIM students in interprofessional learning opportunities.

**Keywords:** education, undergraduate, interprofessional, baccalaureate

**Introduction**

Healthcare reform and the complexities of the healthcare system and chronic disease conditions call for collaborative interdisciplinary team-based care.[1] To enhance these collaborative efforts, universities are promoting the need for interprofessional education (IPE) and the opportunity for students in healthcare connected programs to learn with and about a variety of healthcare disciplines.[2] This includes health information management (HIM), aligning with the growing scope of practice and providing a reminder of the importance of HIM on the healthcare team to ensure quality data and information is used to make decisions.[3] This initiative requires intentional effort to bring students from health programs together in a meaningful way, to enhance communication and teamwork skills, and to promote interprofessional learning, interaction, and relationships.

The World Health Organization defines IPE as, "when students from two or more professions learn about, from and with each other to enable effective collaboration and improve health outcomes."[4] The Interprofessional Education Collaborative (IPEC) expert panel identified four practice competency domains: values/ethics for interprofessional practice, roles/responsibilities, interprofessional communication, and teams and teamwork.[5] These competencies are essential in establishing population health programs focused on collaborative partnerships and interprofessional teams that address the needs of the community. These efforts should be driven by the data, establishing the key role of HIM professionals.[6] The need for such collaboration is identified in

AHIMA's Code of Ethics, stating that HIM professionals shall "facilitate interdisciplinary collaboration in situations supporting ethical health information principles."[7] The intent of IPE is to assist healthcare students in fostering the skills necessary to participate in such teams. This study describes the integration of IPE concepts into an online course shared between HIM students and students from various other health programs, summarizing student perceptions of the learning activities in the course in helping them practice the IPE competencies and general comments related to the barriers and benefits of the learning experience.

**Background**

According to the Institute of Medicine, "all health professionals should be educated to deliver patient-centered care as members of an interdisciplinary team, emphasizing evidence-based practice, quality improvement approaches, patient safety and informatics."[8] Traditional methods in which health professional students have minimal contact with each other and few collaborative learning experiences result in graduates that are poorly prepared for a collaborative team environment, lacking knowledge of different roles and teamwork skills.[9] It is important that HIM students are involved in IPE efforts, as quality patient care relies on effective sharing of health information to support clinical decisions and improve patient outcomes.[10] Inclusion in the education setting highlights the skill set of HIM students, helping to demonstrate the benefits of including HIM on the healthcare team and encouraging those students to look beyond the traditional walls of HIM.[11,12]

The first competency domain identified by the IPEC expert panel centers around values/ethics for interprofessional practice, indicating that health professionals should be able to "work with individuals of other professions to maintain a climate of mutual respect and shared values."[13] To achieve this, students and professionals need to learn about patient/population-centered care, respecting the dignity, privacy, and confidentiality of the patient and embracing cultural diversity and individual differences in not only patients, but fellow health professionals and the community. The next domain identified focuses on roles and responsibilities, with the ability to "use the knowledge of one's own role and those of other professions to appropriately assess and address the healthcare needs of patients and to promote and advance the health of populations."[14] To do this, students and professionals must understand their roles and responsibilities within their chosen profession and be able to communicate those to other professionals, patients, and community members. Healthcare professionals must be able to "communicate with patients, families, communities, and professionals in health 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."[15] This domain is primarily focused on effective communication skills, encouraging students and professionals to practice organizing and communicating information, expressing one's knowledge and opinions, listening actively, providing constructive feedback, and using respectful language. Finally, healthcare professionals need to "apply relationship-building values and the principles of team dynamics to perform effectively in different team roles to plan, deliver, and evaluation patient-/population-centered care and population health programs and policies that are safe, timely, efficient, effective, and equitable."[16] Students and professionals need to learn and practice how to work in a team, integrating the knowledge and experience of the team members while constructively managing disagreements and eventually developing consensus.

Interprofessional education is a strategy to break down the silo approach to healthcare education and instead promote a team-based mentality. Best practices in IPE draw upon a variety of learning theories to ensure a safe space for collaboration and active learning that offers opportunities for students to draw upon previous experiences and make connections to the real world.[17] Creating and facilitating interprofessional experiences requires an understanding of group learning and group dynamics.[18] Instructors must consider the group balance through knowledge of the different disciplines and current issues in the industry and have the ability to facilitate collaboration. Students must learn good communication skills, respect, and an understanding of each team member's role. Student groups need time to learn about each other and the respective disciplines, to identify commonalities, to overcome disagreements, and to address obstacles along the way. Providing sufficient time allows each group member to learn more about other disciplines and to respect, value, and appreciate those disciplines. Activities such as case-based learning and problem-based learning are essential methods in interprofessional education, allowing students to discuss clinical problems together.[19]

The focus of this study is to describe an implemented online interprofessional course that meets the needs of undergraduate students from a variety of clinical and nonclinical health programs. Including IPE at the undergraduate level fosters an early understanding of the value and significance of other professions and several studies have shown improvement in knowledge, skills, and attitudes when introduced early.[20] Utilizing IPE competencies and best practices in online learning, the course provides an opportunity for students from various disciplines to both reflect upon their own discipline and learn about, with, and from others. Beyond describing the activities in the course as they relate to the IPE competencies, the course evaluations were used to answer the following questions: What are the students' perceptions of the ability of this course to help them practice IPE competencies? What barriers and benefits to learning did students experience?

## Methods

This study describes a one-credit interprofessional capstone course that serves as a mandatory requirement for undergraduate students in a variety of disciplines, including environmental and occupational health, HIM, health studies, nursing, public health, radiologic sciences, and respiratory care. It is a large enrollment course, set up to meet the diverse needs of over 300 students each year that are enrolled part time and full time, in both on-campus and online programs. The course is intended to address the IPE competencies, as well as university learning outcomes related to communication, critical inquiry, and problem-solving. It is structured around the set of core competencies for interprofessional collaborative practice developed by the IPEC expert panel.[21] Student course evaluations were used to investigate student perception of the course's ability to address the IPE competency domains and identified benefits and barriers to learning.

The first general competency statement indicates that health professionals should be able to "work with individuals of other professions to maintain a climate of mutual respect and shared values."[22] To encourage personal reflection on bias and the impact on patient care, students participated in a discussion activity after completing an Implicit Association Test (IAT). To practice working with other disciplines in a climate of mutual respect, students participated in a variety of team activities. The second IPE competency domain centers on roles and responsibilities, both of one's own discipline and those of others. Students recorded elevator speeches related to their chosen discipline to educate their classmates on their qualifications and future roles and responsibilities. In addition, students created one for a discipline not represented in their group. This encouraged them to research the qualifications, roles, and responsibilities of another discipline they may work with in the future. Students also participated in a variety of journal prompts to encourage self-awareness and reflection. The next IPE competency domain highlights skills and abilities related to interprofessional communication. Students had the opportunity to practice these skills through a variety of course activities, including group assignments, discussion boards, and reflection on communication skills such as conflict resolution. Finally, these competencies all rely on competent and productive teams. Students had to practice teamwork throughout the course, participating in team discussions and meetings, agreeing on a team norms document, and creating patient education materials for their culminating project. They had opportunities to lead their team, with many teams rotating leaders throughout the course. Students also did an individual assessment of their leadership style with a reflection prompt. Finally, this class utilized the peerassessment.com program to solicit and collect feedback from each student on their performance, the performance of their peers, and their team overall. This assessment was done multiple times throughout the course to encourage regular feedback and time for self-improvement. Students were instructed on providing constructive feedback to peers and encouraged to consider this feedback as they prepare for their future career.

The instrument used in this study was the student course evaluations, distributed and collected anonymously by the university. In order to assess student response to the above IPE competencies, instructor questions were added to these evaluations for the class over three years. These questions asked the student to assess the usefulness of the course in helping them practice their communication and leadership skills, learn more about their own and other disciplinary roles and responsibilities, and participate in an interprofessional team. The use of these evaluations for research purposes was approved by the university's Institutional Review Board, exempt protocol #186-SB20-071. Anonymous student responses to the instructor-added questions were used to summarize student reactions to nine sections of the course offered over three years, calculating results on a Likert scale. In addition, qualitative comments relevant to the instructor-added questions were analyzed as a supplement to the quantitative data. These were in response to questions concerning the benefits and barriers of the learning experience. NVivo was used to create a coding scheme based on these comments, grouping words and sentences within subcategories of benefits and barriers. The subcodes for barriers included the following: course organization, group work, instructor, online modality, workload, and no barriers. Many comments related to group work and the online modality overlapped. The subcodes for benefits were similar, including the following: course content, course organization, group work, instructor, learning activities, and no benefits.

**Results**

Course evaluations were reviewed for nine sections of the course. Of the 276 students enrolled, 146 completed the evaluation for a 53 percent response rate. All evaluations were complete in answering the quantitative questions, but not all students provided qualitative responses. This research focused on the instructor-added questions related to the IPE competencies and relevant qualitative responses. It is estimated that approximately 72 percent of all respondents provided a written comment.

As seen in **Table 1**, students were asked to rate their agreement with each statement on a Likert scale. Responses from all sections were combined to calculate the mean and standard deviation. The mean for each statement indicates the majority of students agreed or strongly agreed, varying between 4.27 and 4.38.

Students also answered standard open-ended questions included in all university course evaluations related to barriers to learning and valuable aspects of the course. These prompts were not directly related to the interprofessional education competencies, but many student comments addressed opportunities and challenges of working in interdisciplinary teams. Although many of the comments related to course benefits highlighted the ability to practice communication and teamwork skills, students expressed challenges with this process. The majority of the identified barriers to learning in the course highlighted the challenges of working in groups (38), particularly in an online class (29). Comments indicated that the varying schedules and technology created challenges early in the course (10), but many were able to overcome these challenges. This class was the first experience for many students of working in virtual groups, an essential skill in today's work environment. Many students also felt that the workload was extensive for a one-credit course or that it contained too much "busy work" (23), although the course was developed with the recommended time commitments for online learning. A few struggled with the instructor (6), but the second highest subcode for barriers was an indication of no barriers (33).

Student comments related to the aspects of the course that were most valuable to their overall learning experience often contradicted the barriers identified. Many comments were made to the value of team-based learning, the opportunity to work in groups, and learning to work with individuals from other disciplines (27). Students also appreciated the opportunity to reflect on their experiences, roles and responsibilities, and impact in their future careers (39). Several commented on the value of discussion boards around communication and conflict resolution topics, as well as the course reading material related to IPE and collaboration (21). A few comments indicated there were no benefits (2), and another highlighted the instructor as valuable to the learning experience (1). Finally, there were a few positive comments on the overall course structure and organization, chance for self-directed study, and variety of assignments (21).

**Discussion**

The responses to the instructor-added questions and standard university open-ended questions related to the course indicate that the majority of students felt it provided the opportunity to practice at least three of the interprofessional competency domains. The Likert scale responses and qualitative comments highlighted the value in the roles and responsibilities, communication, and teamwork competency areas. However, many of the comments also indicated challenges in establishing a productive team, particularly in an online class.

The first evaluation statement asked students if the course helped them better communicate the roles and responsibilities of their chosen profession, referencing the second IPE competency domain.[23] While the majority of students agreed or strongly agreed (83.56 percent), this was the lowest among the five statements with a mean of 4.27. One comment stated, “I think this class really helped me to understand my own roles and responsibilities and my communication.” Some students felt the course was redundant with previous classes, not seeing the value in doing additional activities to share this knowledge. One student indicated, “It seemed like a bunch of repetitive information from other courses.” As these activities are created, it is important to emphasize the value in sharing one’s roles and responsibilities with students from other majors to improve their understanding of each person’s contribution to the team. Such assignments provide an opportunity for HIM students to create awareness about the critical role HIM plays on the healthcare team, introducing their knowledge of the record, quality improvement, information governance, and data analytics.[24]

In addition to understanding one’s own roles and responsibilities, interprofessional education calls for the understanding of other professions to more effectively engage those healthcare professionals who complement one’s own professional expertise and embrace interdisciplinary relationships to optimize team performance.[25] The next statement asked students if the course helped them learn more about other disciplines, with most selecting agree or strongly agree (90.41 percent). This was the highest scored of all questions with a mean of 4.38, and commonly referenced in the qualitative responses. Other studies have found similar improvements in student knowledge of other disciplines.[26] One student commented, "I think learning about other professions was really valuable to incorporate in the course and helped bring to life the concept of collaborative practice by learning more about those we will work with." To achieve this competency, it is necessary that students and professionals from different disciplines are purposefully integrated into learning opportunities that encourage them to learn from, with, and about each other. HIM students are able to learn more about the other members of the healthcare team and their contributions to patient care.[27]

To build these relationships, it is necessary for healthcare professionals to engage in interprofessional communication.[28] The third evaluation statement addresses this IPE competency domain, asking students if the course helped them with communication and interpersonal skills. The majority of students agreed or strongly agreed (89.04 percent) with a mean of 4.37. One commented, "I think the most beneficial aspects of this course were the lessons that made us think about how vital communication is in the healthcare industry and lessons that made us think and reflect about how we are as communicators." Several favorable qualitative comments related to the conflict management activity, where students responded to a variety of work-related conflict scenarios, indicating an appreciation for a safe space to discuss conflict and the opportunity to hear how different people respond in such situations. Some comments also indicated challenges with communication within groups, highlighting "a few communication hurdles to get over initially" or a "learning curve to find best way to communicate with team." Others indicated some miscommunications or an overall lack of communication within the group. Establishing communication boundaries and expectations is a necessary part of group development. Providing tools and recommendations for students may help them establish this sooner and more clearly. As documentation and medical records specialists, the key patient communication tool in healthcare, HIM students may take a lead in this role for their team and help them establish best practices in their future careers.

To truly embrace interprofessional collaborative practice, healthcare professionals need to be competent in teams and teamwork.[29] Integral to a team is a leader; students and professionals also need opportunities to apply leadership practices and process improvement strategies.[30] This last IPE competency domain was addressed with the final two statements, asking students if the course helped them apply leadership skills and practice teamwork and teambuilding. The majority of students agreed or strongly agreed (88.36 percent and 89.72 percent, respectively) with means of 4.34 and 4.36. As one stated, "I feel that I really stepped up and became a leader in my group during this class. I felt that it was important for myself to take on more responsibility in order to keep everyone motivated and on task, which was something I hadn't really done in past courses." Practicing leadership in the classroom helps build confidence for HIM graduates to take on leadership roles in their future workplace. Another student reflected, "Working in groups allowed me to be a good team member and work on effective communication with other group members." Despite the overall positive response, the majority of the comments related to barriers mentioned working in groups, most notably challenges with the online format. One commented, "Group assignments can be challenging in an online setting with no personal interaction on group work." Most mentioned the difficulty in aligning schedules of all group members, and others indicated unequal contributions from all group members or challenges with individuals each working at a different pace. One recommendation to reduce these hurdles is to pay close attention to group size, as a group too large can be particularly challenging to both schedule and equally distribute the work. Although establishing and working in groups may be challenging online, this form of interaction is more prevalent in the workplace than ever before. Virtual teams and communication can actually provide more equal opportunity for contribution and allows students or employees to process and articulate their ideas before sharing.[31] Interprofessional group work, virtual or in-person, provides opportunities for HIM students to practice being proactive in representing the HIM discipline on the healthcare team.[32]

Group assignments and team-based development activities help students and professionals share accountability and practice working in an effective team characterized by trust, respect, and collaboration.[33] Practicing this in a class affords the opportunity for feedback and reflection.[34] This reflection opportunity was mentioned in several qualitative comments, with one student indicating, "The reflection pieces forced me to look at my weaknesses as a future healthcare provider" and another, "This class showed me what areas I struggle with in a group setting and different ways to improve on them." Students are often afforded these opportunities in a variety of classes, but integrating interprofessional groups adds a different dynamic for students to experience and reflects a more realistic professional situation.

Qualitative comments highlighted a few other barriers and benefits that did not directly relate to the IPE competencies. Several comments related to barriers mentioned the workload of the course as a one-credit class and some felt it included "busy work." As one student stated, "It also had far too many assignments for a one-credit course (20) and took time away from courses that mattered more." These comments prompted revisions in the course to ensure only learning activities directly related to the objectives were included. To enhance the perceived value of a course focused on interprofessional collaboration to students from multiple disciplines, it is recommended that it be worth more credits and be letter-graded. However, finding room in the curriculum of multiple programs for a shared course can be a challenge. It is also important to clearly indicate the value both within the introduction to the course and in the context of the disciplinary curriculum. In contrast, many students also commented that the course was "easy to work on" with "not too many huge assignments" and that "We should take more classes like this one throughout our degree track. This stuff is important." A few indicated some challenges with the course schedule and having multiple due dates throughout the week, but many more commented on the straightforward course structure and appreciated the flexibility of the online format. It is essential in online courses that clear expectations are provided with straightforward assignments and deadlines.[35] The contrasting views may relate to the student's previous courses related to structure and expectations, familiarity with learning online, competing obligations such as work and other courses, and their overall experience within their group.

This assessment is limited to one online course taught at a university utilizing the structure developed by an individual instructor. The sample is limited to undergraduate students in environmental and occupational health, HIM, health studies, nursing, public health, radiologic sciences, and respiratory care. Responses and comments were not differentiated by discipline, and each is not represented equally within every section of the course. Findings are reported in an aggregate format, and the data was not collected with the intention of research. Furthermore, the analysis was conducted of anonymous course evaluations, which are limited to those students who completed them and their perception of the course at the time taken. Despite these limitations, these findings can provide insight into providing interprofessional learning opportunities in undergraduate programs, both clinical and nonclinical, particularly in an online format.

## Conclusion

This study provides an example of how to integrate undergraduate HIM students into an interprofessional capstone with a variety of other majors. Student evaluations suggest an overall agreement that the variety of activities and assessments, including team activities, discussions, personal reflections, and peer evaluations, helped them to apply at least three of the four IPE competency domains. Comments also highlight the need for careful group assignment and facilitation considerations in a clearly organized course format that communicates the importance of interprofessional collaboration and competencies to all disciplines. Although qualitative evaluation statements were categorized by the researcher based on competencies and associated learning activities, future research may conduct interviews or an independent audit to determine which activities the students found most valuable to their practice of the IPE competencies. Such activities and undergraduate course structures facilitating the inclusion of HIM students with other health disciplines is important to showcase the value of HIM on the healthcare team, exposing other disciplines to the HIM skill set and support of improved patient outcomes.

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## There are no comments yet.

# THE PREVALENCE OF INSOMNIA AND SLEEP APNEA IN DISCHARGE ABSTRACT DATA: A CALL TO IMPROVE DATA QUALITY

*Posted on August 2, 2021 by Matthew*

**Category:** Summer 2021

*By Danielle E. Fox, RN, MN; Natalie Wiebe, RN, BN; Danielle A. Southern, MSc.; Hude Quan, PhD; Ellena Kim, RN, BN; Chris King, RN, BN; Olga Grosu, RN, BN; and Cathy A. Eastwood, RN, PhD*

**Abstract**

Insomnia and sleep apnea are associated with a variety of comorbid conditions and carry a symptom burden to patients. As the prevalence of insomnia and sleep apnea continue to rise, it is imperative that appropriate tools are implemented to accurately capture their prevalence in acute care settings. A retrospective chart review was conducted on 3,074 inpatient charts in Calgary, Alberta. The estimated prevalence of insomnia was 10.36 percent, and sleep apnea was 6.56 percent in inpatient visits between January 1, 2015, and June 30, 2015. The sensitivity of insomnia and sleep apnea were low, and the specificity was high when comparing the chart review to the ICD-10. As both insomnia and sleep apnea were associated with various comorbid conditions, it would be imperative that alternate methods are identified to capture and code them. This would enable clinicians to better identify and treat them, and ultimately improve patient care.

**Keywords:** insomnia, sleep apnea, sleep disorders, hospital abstract discharge data, acute care, ICD-10

**Introduction**

Insomnia and sleep apnea are common sleep disorders that have been associated with a variety of comorbid conditions.[1,2,3] The prevalence of sleep disorders vary and, unfortunately, methods to identify people with sleep disorders are limited in administrative.[4] Appropriate methods to accurately identify insomnia and sleep apnea in acute care settings are imperative due to their association with other conditions and the ability of clinicians to intervene to support appropriate treatment.

**Background**

Insomnia is a disabling chronic health disorder[5] that has been associated with reduced health-related quality of life and increased healthcare resource consumption.[6] The prevalence of insomnia is increasing,[7] with 13.4 percent of sampled Canadians meeting the required criteria of insomnia.[8] Insomnia has been associated with a variety of health risks. These include mental health disorders such as anxiety and depression[9]; higher risk of motor vehicle, work, and home accidents;[10] and higher risk of hospitalization for stroke.[11] Insomnia symptoms have been shown to be associated with emotional modulation of pain and emotional blunting[12] and higher work absence.[13] Due to high healthcare utilization, direct and indirect costs of insomnia,[14,15] and obvious patient burden, it is important to identify insomnia as a disorder and begin rigorous treatment early.[16] Despite the high prevalence of insomnia in Canada, few seek treatment, and when they do, medication is normally used as the form of treatment.[17] One study revealed that over 50 percent of those with insomnia were prescribed an anxiolytic/hypnotic,[18] despite alternative forms of treatment, such as cognitive behavioral therapy, being the recommended first line of treatment.[19]

The prevalence of sleep disordered breathing conditions, like sleep apnea, has also risen substantially.[20,21] In Alberta, of people who were classified as sleep disorder positive from a Calgary sleep clinic, 51.1 percent were diagnosed with obstructive sleep apnea.[22] Untreated sleep-disordered breathing has been associated with diabetes, hypertension, cardiac disease, obesity, and depression,[23,24] among other health conditions. Unfortunately, no known systematic programs for monitoring the prevalence of sleep-disordered breathing in the general population exist due to the time consuming, burdensome, and expensive nature of testing.[25] As sleep apnea is treatable, and has adverse impact on quality of life, there is a growing demand to access diagnostic studies and appropriate treatment.[26]

The clinical manifestations of sleep disorders can cause them to be misclassified as other conditions. This is concerning since appropriate treatment is required for the improvement of symptomatic burden and outcomes.[27] Identifying insomnia and sleep apnea may be especially pertinent in acute care settings where they may either exacerbate symptoms of other acute disorders or be misdiagnosed as other conditions. It is thus important to identify and document sleep disorders and their associated testing to ensure they are being appropriately captured and managed. Unfortunately, little is known about the prevalence of insomnia and sleep apnea in acute care settings in Canada and their association with other conditions in this setting.

Disease code accuracy is imperative to reflect the presence of underlying diseases.[28] The International Classification of Diseases (ICD) is the international standard diagnostic classification for many health management purposes, including the monitoring of the incidence and prevalence of diseases.[29]Although ICD codes are used for a variety of reasons, including funding, clinical, and research decisions, each code identified in ICD data has different applications.[30] In Canada, inpatient visits are currently coded using the ICD-10 coding standards.[31] The Hospital Morbidity Database in Canada holds discharge abstract data from acute care facilities across Canada and is frequently used to capture administrative, clinical, and demographic information on inpatient visits.[32] Discharge abstract data may serve as a tool to appropriately capture the prevalence of insomnia and sleep apnea.

**Objectives**

The objectives of this study were 1) to identify the prevalence of insomnia and sleep apnea in acute care hospitals in Calgary, Alberta; 2) to identify the occurrence of these conditions with comorbid conditions; and 3) to identify the degree to which acute care hospital administrative data (as captured by ICD-10-CA coding system) captures sleep apnea and insomnia.

**Methods**

A validation study was conducted to identify the degree to which clinical coding captured insomnia and sleep apnea in hospital abstract discharge data compared with a chart review data set. This project was part of a larger study aimed at creating a dually coded database (ICD-10-CA, ICD-11, and chart review); as such, full methodological details are published elsewhere.[33]

*Setting*

Three acute care hospitals in Calgary, Alberta, Canada, were chosen as the study sites. In Canada, charts from all acute care admissions are coded following the ICD, 10th version (ICD-10-CA) by nationally certified clinical coding specialists. Calgary is a large urban center that, at the time of study conceptualization, had three primary acute care sites located in different parts of the city. The study location and sites were chosen to allow us to capture a range of types and lengths of admissions.

*Data Collection*

A retrospective chart review was conducted with the intent to identify 50 health conditions derived from the Charlson and Elixhauser lists of conditions as used in prior work.[34] Definitions for insomnia and sleep apnea originated from definitions derived for the larger study and are presented in **Table 1**.

Chart review took place from August 2016 to June 2017; 3,074 charts were randomly selected from the three sites for chart review. Patients were included if they had an Alberta personal health number, were between 18 and 105 years of age, and had an inpatient visit between January 1 and June 30, 2015. Obstetric visits were excluded because of too few chronic conditions.

Six nurses who were trained by the research coordinator conducted the chart review. Inter-rater reliability testing was done until 80 percent agreement was achieved. Chart review data were extracted into a secure data collection platform called REDCap (7.6.9-©2018 Vanderbilt University). The same set of charts had been previously coded by coding specialists using ICD-10-CA.

*Data Analysis*

The ICD-10-CA coded data was compared to the chart review as the reference standard. Chi-square tests and contingency tables were used to analyze and represent the data. Sensitivity, specificity, positive predictive value (PPV), and negative predictive value (NPV) were calculated for both insomnia and sleep apnea, comparing the chart review (gold standard) to the ICD-10 codes listed in **Table 1**.

## Results

Out of the 3,074 charts that were reviewed, those with complete demographic and comorbidity data, 3,051 (99.3 percent), were selected. Three hundred sixteen (10.36 percent) were identified as having insomnia, and 200 (6.56 percent) were identified as having sleep apnea. **Table 2** presents patient baseline characteristics by insomnia and sleep apnea. Sleep apnea was associated with female sex, congestive heart failure, atrial fibrillation, pulmonary circulation disorders, hypertension, chronic pulmonary disease, peptic ulcer disease, renal disease, diabetes, obesity, and alcohol abuse. Insomnia was associated with female sex, peptic ulcer disease, liver disease, fluid and electrolyte disorders, weight loss, drug abuse, psychoses, and depression. Eighty-five percent of people with sleep apnea had three or more conditions, compared to only 61.7 percent of those without sleep apnea. This difference was less pronounced in those with insomnia, which found 74.4 percent of people with insomnia had three or more conditions, compared to 61.9 percent in those without. **Table 3** presents 2X2 contingency tables for sleep apnea and insomnia. The ICD-10-CA data did not capture any cases of insomnia in the administrative data. **Table 4** presents sensitivity, specificity, PPV, and NPV for sleep apnea and insomnia. When comparing the ICD-10 data to the chart review, sleep apnea had a sensitivity of 18.5 percent, a specificity of 99.8 percent, a PPV of 88.1 percent, and a NPV of 94.6 percent. With ICD-10-CA data not capturing any cases of insomnia in the administrative data, the resulting sensitivity, specificity and NPV were 0 percent, 100 percent, and 89.6 percent, respectively.

## Discussion

The data from the chart review revealed the prevalence of insomnia was 10.36 percent, and sleep apnea was 6.56 percent. The sensitivity of insomnia and sleep apnea (**Table 4**) were low, and the specificity was high when comparing the chart review to ICD-10-CA data, revealing that the ICD-10-CA data captured few cases of insomnia and sleep apnea as compared to the chart review (**Table 3**). For example, the ICD-10-CA codes captured 42 cases of sleep apnea, while the chart review captured 200. In the hopes of identifying all cases of insomnia and sleep apnea, broad inclusion criteria were used for this chart review (**Table 1**). This being said, the chart review prevalence of insomnia in acute care settings (10.3 percent) still remained lower than the reported prevalence of 2000 sampled Canadians who met the full criteria for insomnia (13.4 percent).[35] Consistent with the literature, insomnia was associated with depression[1], and sleep apnea was associated with congestive heart failure, hypertension, chronic obstructive pulmonary disease, obesity, and diabetes mellitus.[36,37,38,39] The chart review data also revealed an association between both sleep apnea and insomnia and various other conditions (**Table 2**). Patients with sleep apnea were also more likely to have three or more comorbid conditions, which may be a proxy for complicated cases.

The prevalence rates and comorbid conditions identified in our chart review are specific to the definitions that were derived for this study. A variety of definitions for sleep disorders are used[40,41] that would have impact on prevalence rates. For example, many studies are conducted using self-reporting assessments of insomnia. Many of the presenting symptoms of insomnia (e.g., restlessness, sleepless nights) are also seen with mental health disorders (e.g., depression), chronic pain, or emotional blunting. This emphasizes the importance of using definitions that report primary versus secondary insomnia.[42] It is possible that patients assume their sleep-deprived symptoms are due to insomnia rather than a potentially undiagnosed mental health disorder or chronic illness. This would, in turn, create more false positive results and overestimate prevalence rates. It would thus be imperative that when reporting prevalence rates across studies, consistent definitions be used.

ICD-10-CA coded data was only able to capture a small percentage of the prevalence findings from the chart review (**Table 3**). Other studies have also found that health administrative data for diagnoses, diagnostic procedures, or interventions failed to accurately identify patients with sleep disorders.[43,44] The Canadian Coding Standards for version 2015 ICD-10-CA only captures comorbidities that meet the criteria for significance (e.g., requiring additional treatment, increasing the length of stay, or significantly affecting received treatment).[45] Insomnia and sleep apnea are also not mandatory to capture, unlike other conditions in Canada such as diabetes.[46] These criteria could explain the discrepancies between the chart review and ICD-10-CA data. Clinical documentation has also been cited as a limiting factor for the quality of coded data.[47] As such, poor documentation quality associated with capturing sleep disorders could also explain these discrepancies.

The prevalence of insomnia and sleep apnea in inpatient data and their association with various health conditions make these conditions important to be appropriately identified and documented during hospital admissions. Clear and accurate documentation and coding capture would enable clinicians to connect patients with appropriate assessment and management of their sleep disorders[48,49,50] and, in turn, potentially improve outcomes related to other associated medical conditions and symptom burden. This would be especially pertinent in the inpatient setting, where it is possible that sleep apnea and insomnia are impacting exacerbations of other conditions that have led to their admission. Care on discharge can also be improved by ensuring appropriate continuity of information.[51] Appropriate documentation and tracking would ensure collaboration and continuity of care on discharge and ensure other clinicians (e.g., family physician) have the means and information to set up appropriate follow-up and management. It would also be important to ensure administrators have appropriate access to quality data when making program and funding decisions, as well as researchers when reporting the prevalence of sleep apnea and insomnia. Indeed, it is essential that alternate ways of identifying sleep apnea and insomnia in health information systems are incorporated into acute care settings.

Electronic structured data has been shown to be an efficient and accurate means of extracting data on a variety of health conditions[52,53] and could have future impact on accurately capturing sleep disorders. Electronic medical records could facilitate coding, which could potentially help identify accurate prevalence rates and appropriately allocate funding for the management of high-prevalence diseases. This would also enable clinicians to readily identify and treat cases. An electronic medical record-based system also has the potential to improve data quality, as it could automate coding when sleep disorders are identified by a clinician, reducing the time spent searching different documents for these diagnoses. As healthcare systems move toward electronic medical records, electronic structured data may be an alternate way to accurately capture sleep disorders. However, for this to be an effective solution, it would be imperative that electronic medical records are structured in a way that ensures sleep disorder data is easy and/or mandatory to enter and easily identifiable once entered. The data should then be accessible to all clinicians involved in the patients care, coding professionals, and researchers. It may also be helpful to assess the need for routine screening, documentation, and diagnosis of sleep disorders during acute care admissions.

## Limitations and Future Work

A limitation of our study was the potential for overestimating the prevalence of sleep disorders due to the broad definitions used to identify them in this study. This being said, the definitions were created through an iterative process with the expertise of clinicians. We are confident that the definition used was adequately robust and necessary for the purpose of understanding the potential prevalence of sleep disorders and serves as an appropriate starting point to identify the prevalence of these conditions. Underestimation is also possible in this study, as sleep disorders could only be captured as accurately as what was documented. Details in documentation were also often not specific (e.g., sleep apnea documented with no specification to type, such as obstructive sleep apnea or central sleep apnea). This being said, chart review is a high-quality tool that can be used to assess coding quality and suggest improvements for future ICD versions.

Methods need to be developed to enable clear and consistent documentation of insomnia and sleep apnea and to accurately capture these important conditions in administrative data. Future work should focus on the impact to patient outcomes of inappropriately capturing these conditions and to identify means to improve data quality and appropriately capture sleep disorders.

## Conclusion

The estimated prevalence of insomnia was 10.36 percent, and sleep apnea was 6.56 percent in inpatient visit data between January 1 and June 30, 2015. The sensitivity of insomnia and sleep apnea were low, and the specificity was high when comparing the chart review to ICD-10-CA data. As both insomnia and sleep apnea were associated with various comorbid conditions, it would be imperative that alternate methods are identified to capture and code sleep disorders. We found that ICD-10-CA data was not an effective means to capture sleep disorder data. It would be important for future work to focus on structuring electronic medical records in ways that comprehensively capture sleep disorder data with a goal of making sleep disorder data easily accessible by clinicians, coding professionals, and researchers. This would enable clinicians to better identify and treat sleep disorders, and ultimately improve patient care.

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## There are no comments yet.

# PREDICTORS OF SUCCESS ON THE RHIA EXAM

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*By Jennifer L. Peterson, PhD, RHIA, CTR, and James F. Turley, MS*

**Abstract**

The ultimate goal for most health information management (HIM) program graduates is successful passage of the Registered Health Information Administrator (RHIA) exam. As educators, it is our goal to successfully prepare our students for this endeavor. Past studies in this area have resulted in many recommendations for further research. The current study builds on this past research to provide further insight into predictors of graduate success on the RHIA exam. This study assessed variables impacting student success on the RHIA exam using data from students from one HIM academic program who graduated between 2014 and 2019. Variables included in the study were the dependent variable of the first-time RHIA exam score/pass or fail, and the independent variables of student mock exam score, time between graduation and examination, student self-report of English as a second language (ESL) status, introductory HIM course grade, introductory coding and intermediate coding course grades, overall GPA, and major GPA.

The study found that introductory HIM course grade, mock exam score, and time between graduation and examination were significant predictive factors in HIM graduate success on the RHIA exam. The study also revealed some interesting findings regarding student ESL status and exam success that merit further study. The results of this study provide educators with further insight into predictors of student success on the RHIA exam, as well as provide information that can be used by educators to aid in student RHIA exam success.

**Keywords:** RHIA exam, student success, RHIA exam passage rates, mock RHIA exam, English as a Second Language

**Introduction**

One of the goals for any health information management (HIM) educational program is for their students to successfully pass the Registered Health Information Administrator (RHIA) certification examination. The accrediting agency for HIM educational programs, the Commission on Accreditation for Health Informatics and Information Management Education (CAHIIM), requires that programs track RHIA exam pass rates. In addition, many HIM jobs require RHIA certification, students seek certification, and schools pride themselves on preparing students to pass this exam. At the current time, there is a shortage of credentialed allied health employees, so increasing the ability of students to successfully pass the RHIA exam will also serve the healthcare industry.

Program directors, faculty, and students are constantly working to find ways to adequately prepare students to insure they can successfully pass the RHIA exam. Are there ways to predict which students will pass and which won't? Are there strategies that faculty can use to help students who may not be predicted to pass? What are the metrics that point to this? Answering these questions can enable students and faculty to work together so that students are prepared to successfully pass the RHIA exam.

While there is limited research in this area, a variety of studies have been carried out. In an attempt to predict what factors lead to student success, researchers have looked at grades, GPA, programmatic elements, socioeconomic issues, program format, and program offering of a mock RHIA exam. These studies have led to a variety of findings, at times even to inconsistent findings.

**Background**

An early study in this area was completed by McNeill and Brockmeier in 2005. This study looked at the scores of students who took the exam between 2000 and 2002 based on a variety of programmatic elements. These elements included program resources, expenditures, faculty characteristics, student-to-faculty ratios, curriculum, laboratory facilities, and professional practice hours.[1] The study found that, although "it was expected that significant relationships and differences between an HIA program's percentage of graduates passing the RHIA certification examination and program components would be found. This conclusion was not reached in this study."[2]

Other earlier studies focused on the type of health information educational program. With the advent of increasing numbers of online programs, Russell, et. al., conducted a study focused on the performance of students in online versus face-to-face programs. While this study was designed to evaluate overall performance of students in the two formats, the researchers did find that there was a "statistically significant correlation between overall admission GPA and the RHIA certification examination score" for the combined groups.[3] Interestingly enough, however, when they broke the online and on-campus groups apart, they found that this correlation did not hold for online students. This led to recommendations for further study into the differences between online and on-campus students.

Based on the growth of another type of HIM educational program officering, Condon and Barefield conducted a study focused on RHIA certification exam success between those completing a traditional baccalaureate program and those completing one of the new post-baccalaureate certificate programs. They found that there was no difference between the two groups in terms of RHIA certification exam success. They also found that the "amount of time between graduation and completion of the RHIA certification examination did not significantly impact graduates' scores on the examination."[4] They further stated, however, that there was much conventional wisdom showing that the longer the time between graduation and examination, the lower the scores. They therefore recommended that, "graduates of both programs … still be encouraged to take the RHIA certification examination as soon as possible after graduation."[5] Their study led to recommendations for future study, including further review of other variables that could affect student exam success as well as the relationship between a mock exam and actual exam scores.

McNeill addressed the relationship between administration of a mock exam and student exam success in her study. She analyzed the RHIA exam pass rates of students from 46 schools, some who administered a mock examination and some who did not. She found that "the administration of a comprehensive examination before a student's graduation did not make a significant difference on the HIA program's pass rate."[6] Her recommendations for future study included a deeper look into the development of mock examinations as well as other student variables and their effect on exam pass rates.

In an attempt to look into this issue further, Condon completed a large study in 2013 that looked at a large number of variables and their effect on student success on the RHIA exam. Many of these variables, as opposed to being program variables, focused on student performance in the HIM program. Condon's goal was to create a prediction model for RHIA exam success. He evaluated a number of variables, including HIM course grades, major GPA, demographics, mother tongue, and age at the start of the program. Condon found that certain course grades, major GPA, and mother tongue were significantly associated with exam scores. His predictive model for RHIA exam success was therefore based on age at start of program, core curriculum GPA, introductory and course grades, and mother tongue:

RHIA certification examination score = (age at start ) + (core curriculum score ) + (Intro to HIM grade ) + (Coding grade ) + (mother tongue ) + 21.650 (p. 76)

Based on Condon's findings that student variables had an impact on the certification pass rate, he recommended future research focused on further student-related variables, including evaluation of the time between graduation and examination.[7]

Combining a focus on student variables as well as type of program, Dolezel and McLeod reviewed student success among those taking the exam between 2011 and 2013. They looked specifically at HIM course grades and cumulative GPA, a variety of demographic factors, and online versus on-campus formats.[8] In their evaluation of student grades in specific courses as well as student cumulative GPA as potential predictors of first-time exam success, they found that cumulative GPA and health information technology course grade were associated with higher pass rates on the RHIA exam. They further found that "other variables did not add to the model's predictive ability."[9] Dolezel and McLeod also found that online students had a much higher pass rate on the RHIA exam as compared to on-campus students (81 percent compared to 57 percent).[10] Their explanation for this included the fact that many online students are older, working students who might be more experienced and who may be driven to achieve RHIA certification success. Based on the results of their research, Dolezel and McLeod also recommended that future studies evaluate the time from graduation to exam as well as delve deeper into the online versus on-campus issue. They also recommended including prior healthcare work experience.[11]

While a number of studies have found a variety of elements related to RHIA exam success and have identified some predictive elements, there is obviously further study needed to fine-tune these findings. A study is needed to combine a number of the elements that have been found to be predictive along with other variables that have been suggested for study. This study, therefore, has been designed to focus on select predictive elements as well as variables such as the time between graduation and the examination and the role that mock exams play in student RHIA exam success.

## Methodology

In order to further assess variables impacting student success on the RHIA exam, a study was completed using a convenience sample of one school's students graduating between 2014 and 2019. In order to assess the effect of the variables on the students' passage of the RHIA exam, only students who took the RHIA exam were included. This resulted in inclusion of 83 total students.

Variables included in the study were the dependent variable of first-time RHIA exam score/pass or fail and independent variables: student mock exam score, time between graduation and examination, student self-report of English as a second language, introductory HIM course grade, introductory coding and intermediate coding course grades, overall GPA, and major GPA. Online versus on-campus setting was not evaluated, as all students included in this school's program were enrolled in an on-campus program.

Following IRB review and approval, existing data was compiled for the students who took the RHIA exam. The data was analyzed using descriptive and inferential statistics to determine the correlation between the various independent variables and first-time RHIA exam score/pass or fail status.

## Data Analysis

Data analysis was completed based on 83 total students from the school's HIM program graduating between 2014 and 2019 who had taken the RHIA exam at the time of the study. The data was based on first-attempt results unless otherwise noted. Descriptive and inferential statistical analyses were used to determine relationships between the dependent and independent variables.

*Mock Exam Score vs. First-Attempt Score*

All final semester senior students were given a 180 question, four-hour mock RHIA exam during their final week in classes. Their scores on this mock exam were correlated with their scores on the actual exam. The correlation coefficient (R) for mock exam versus the actual exam score is 0.50. This indicates a positive relationship between mock exam score and first-attempt RHIA exam score. The scatter plot for this can be seen in **Figure 1**.

A review of the mock exam scores indicates that there is a divide between scores of 92 (51 percent) and below and 93 and above. Most students (23.5 percent) who scored 92 or below on the mock exam did not pass the RHIA exam on the first attempt. Likewise, most students (87.9 percent) who scored 93 or above on the mock exam did pass the RHIA exam on the first attempt.

An interesting subgroup of students in this group were four English as a second language (ESL) students. These students were some of the top performers on the mock exam but did not pass on their first attempt at the RHIA exam. Of these four, two subsequently passed the RHIA exam on further tries and two didn't try again. ESL student RHIA exam success rate is discussed further below.

*Time from Graduation to Exam Test Date and Exam Score*

While students are encouraged to take the RHIA exam as soon as possible after graduation, some delay taking the exam for various reasons. These can include financial constraints, job searches, fear of the exam, or delaying until the exam is required for employment.

**Table 1** shows the number of days graduates waited to take the exam, the average scores for each period, the number of graduates taking the exam during each period, and the pass rate for each period. The correlation coefficient (R) for the number of days from graduation to exam data and exam scores is -0.32, which indicates that a longer wait is correlated with lower scores. This can also be seen **Figure 2**. **Figures 3, 4,** and **5** further demonstrate the data regarding the time from graduation to exam date and the average scores, pass rate, and number of graduates taking the exam. As can be seen, average RHIA exam scores and pass rates decrease between zero and three months from graduation to exam date to 12-15 months from graduation to exam date.

*Self Report of ESL and Exam Score*

There were 9/83 (10.8 percent) students who self-reported that English was their second (or later) language. These students' pass rate was analyzed to determine if ESL has an effect on RHIA exam pass rate. All of these students failed the RHIA exam on their first attempt. As noted previously, five of these nine students failed the RHIA exam in spite of scoring quite well on the mock exam. Of these nine students, three (33.3 percent) passed the RHIA exam on a subsequent attempt, one (11.1 percent) failed on subsequent attempts, and five (55.6 percent) did not retake the exam. To compare the overall RHIA exam performance of native English speaking and ESL students, a two-sample t-test was applied between these two groups assuming equal variances. It was noted that ESL students had lower RHIA exam scores ($M$ = 277, $SD$ = 25.8) than native English speaking students ($M$ = 313, $SD$ = 20.1, $t(81)$ = -5.03, $p$ = 2.92E-6), further demonstrating that ESL students tend to score lower on the RHIA exam.

*Course Grades*

In past studies, course grades in the introductory course as well as in coding courses have been found to be strongly positively correlated with RHIA exam scores[12] In the current study, a review of student grades in the introduction to health information management, the introductory coding course, and the intermediate coding course also found positive correlations between course grades and RHIA exam scores.

There was a strong positive correlation between grade in the Introduction to HIM course and the RHIA exam score (0.51). It was noted that higher grades in the introductory HIM course were correlated with higher scores on the RHIA exam. As seen in other studies, higher student grades in the introductory coding course were correlated with higher scores on the RHIA exam at a correlation coefficient of 0.49.

There was a more moderate positive correlation for student grades in this class and scores on the RHIA exam (0.35). This may be related to the fact that student grades in this class tend to be higher overall than in the introductory course. As coding is a skill, once that skill is learned in the initial course, students tend to do better in subsequent courses. However, again it is noted that higher grades in this course are related to higher pass rates on the RHIA exam.

*Student GPA*

It was found that there was a relatively strong positive correlation between overall GPA and student score on the RHIA exam (0.49). As can be seen in **Figure 6**, higher student GPA was correlated with higher RHIA exam scores.

*Multiple Regression Analysis*

After analyses of individual variables, multiple regression analysis was completed to delve deeper into the relationships between variables and RHIA exam scores. The analysis led to a more fine-tuned understanding of these relationships.

Based on the fact that variables representing course performance and cumulative GPA were suspected of collinearity beyond that of independent metrics, the assumption of collinearity was first applied. Tolerances and variance inflation factors between these variables demonstrated that collinearity between them was not an issue.

Multiple regression analysis was then performed with the knowledge that grades for individual courses were not correlated with grades earned in others. The results of this analysis indicated that 65.35 percent of the variance could be explained by a regression performed on seven explanatory variables ($R$ = 0.808, $R^2$ = 0.654, *Adj.* $R^2$ = 14.427, $N$ = 64, $p$ = 6.778E-11). The significance of this regression is well below the 0.01 level.

The overall regression equation is written as:

Score = 176.153 – 0.001 (Interval) + 0.496 (Mock) + 8.679 (Intro to HIM Grade) + 4.336 (Intro Coding Grade) + 5.562 (Intermediate Coding Grade) + 7.104 (GPA) – 31.417 (ESL status), with each variable being supplied in its proper unit of measure.

The impacts and significances of individual course grades and overall GPA were small in comparison to other variables (Intro Coding Grade, *Coefficient* = 4.336, $p$ = 0.100; Intermediate Coding Grade, *Coefficient* = 5.561, $p$ = 0.175; GPA, *Coefficient* = 7.104, $p$ = 0.328) with the exception of students’

Introduction to HIM grade (Intro Grade, *Coefficient* = 8.679, $p$ = 0.016). It was unexpected that overall GPA was the least significant and least influential of these variables given it is often used to gauge general academic performance.

The effect of the mock exam scores were both significant and impactful. While the effect appeared small due to the range of potential values for scores and the insignificance attributed to individual test points, the significance was clearer when interpreted as every additional point earned on the mock exam correlated with an additional 0.496 points on the actual exam (Mock, *Coefficient* = 0.496, $p$ = 1.73E-4).

The effect of student ESL status, according to multiple regression analysis, was significant and impactful (ESL, *Coefficient* = -31.417, $p$ = 4.434). Unlike other variables, ESL status is of a binary nature (*false* = 0, *true* = 1). While ESL students can have varying proficiency in the English language, in this analysis, this variable was analyzed only as ESL/non-ESL status.

**Discussion**

Analysis of the various metrics used in this study point to some predictors of success on the RHIA exam. It is clear that a higher score on the mock exam was correlated with a higher score on the actual exam. It was noted that there was a significant difference on pass rates on the RHIA exam between those students who scored 92 or below on the mock exam and those who scored above 92. This was further reinforced through the multiple regression analysis that found that each additional point earned on the mock exam correlated with an increase of approximately 0.5 points on the actual exam. This is a particularly meaningful finding because it allows faculty to discuss the student's mock exam pass rate with them as well as best practices for preparation for the RHIA exam. Students who score 92 or below on the mock exam should be encouraged to plan for extra preparation in order to succeed on the RHIA exam.

It was also noted that the pass rate was much higher for students who took the exam within the first few months after graduation. Students who wait to take the RHIA exam 12-15 months following graduation have a significantly lower pass rate. Again, this is helpful information for faculty, as it provides statistical data that can be provided to students to encourage them to take the exam sooner, rather than later, after graduation. It was noted that, in this study, the majority of new graduates took the RHIA exam within one year of graduation.

In other studies, certain course grades were found to be predictive for success on the RHIA exam. This was partially confirmed in this study. Course grades in the Introduction to HIM course as well as the introductory and intermediate coding classes, were found to be correlated with higher scores on the RHIA exam. However, multiple regression analysis showed that the impact of individual course grades for the two coding courses were less significant than other variables. The students' Introduction to HIM grades, however, were a significant predictor of RHIA exam success.

While it was expected that student overall GPA would be a significant predictor, GPA was found to be the least significant variable. It was found that there was a positive correlation between student GPA and RHIA exam score; however, multiple regression analysis found that overall GPA was the least significant and influential variable.

Self-reported ESL students were found to be an interesting subgroup in this study, and analysis of this group led to one of the most significant findings. All of the ESL students included in this study failed the RHIA exam on their first attempt, even though more than half of them scored quite well on the mock exam. In addition, multiple regression analysis identified that student ESL status was quite significant in terms of lack of RHIA exam success.

This is significant in that it seems to point to ESL as being a strong indicator in the pass/fail rate for the exam. In addition, the fact that more than half of these students did not make further attempts to pass the RHIA exam shows that the students lacked the confidence, financial resources, or desire to further pursue the RHIA credential. There are many issues that enter into ESL student success on standardized tests. Faulker-Bond and Sireci state "tests in any subject inevitably end up being partial measures of language proficiency."[13] Beyond basic translation barriers, other issues include test format familiarity and understanding of questions. Multiple-choice questions, such as those used on the RHIA exam, are not used in many parts of the world, and many ESL students are not familiar with and do more poorly on these types of exams.[14] The findings in this area are concerning and this is an area that needs to be studied further. More widespread data should be collected to insure there is no bias against ESL students on the RHIA exam.

While this study was limited to analysis of students in one academic program, the fact that six years of student data was analyzed increase the validity of the study. Further research utilizing student data from other schools could provide additional valuable insight into determinants of RHIA exam success and could strengthen the generalizability of these findings.

**Conclusions**

Based on the data collected and analyzed in this study, it can be concluded that performing well in the Introduction to HIM course, scoring well on the mock exam, and taking the RHIA exam within the first three to six months following graduation are predictors for higher success on the RHIA exam.

However, more research is needed to delve deeper into these success predictors. What factors help determine success on the mock exam? What factors enter into a student's decision to take the exam earlier or later following graduation? How can we, as educators, help our students succeed in the predictive areas, from the introductory course through the mock exam?

In addition, this study raised significant concerns about ESL student success on the RHIA exam. This is an important area that should be studied further. ESL student success in a HIM educational program should be more closely correlated with success on the RHIA exam. Further research into this area of inconsistency should be completed.

Finally, this study elicited some predictive elements that can be utilized by health information program faculty to aid in graduate success on the RHIA exam. By reviewing such data and metrics, program faculty are better prepared to meet their program goals for student success on the RHIA certification exam, to ensure ongoing high student pass rates, and to produce students prepared to meet the needs of the healthcare industry.

## Author Biographies

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## There are no comments yet.

# A NATIONAL SURVEY ASSESSING HEALTH INFORMATION EXCHANGE: READINESS FOR CHANGES TO VETERANS AFFAIRS ACCESS STANDARDS

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**Abstract**

We conducted a national survey of Health Information Exchanges (HIEs), targeting both not-for profit geographic and enterprise or federated exchanges. The aim of this study is to identify current best practices when exchanging information between Veterans Affairs (VA) systems and non-VA health systems. We identified and classified current interactions between HIEs and VA systems given recent passage of the MISSION Act. The MISSION Act allows veterans to seek care outside the VA health system, necessitating the need to reconcile care planning between VA systems and private care settings. We identified several differing best practices concerning information exchange between VA health systems and HIEs and assessed capabilities for HIEs to appropriately identify eligible VA participants within extant databases.

**Keywords:** Health Information Exchange, VA Health System, MISSION Act, HIEs

**Introduction**

The Veterans Health Administration (VHA), one of three administrations within the Department of Veterans Affairs (VA), is the largest integrated health system in the United States. As a large healthcare delivery organization, effective information systems represent a pathway for efficient delivery of services that maximize value.[1] The need for the VHA to adopt new commercial, off-the-shelf electronic health record (EHR) technology is widely documented across peer reviewed and non-peer reviewed literature.[2] Key historical areas of technology focus for the VHA include longitudinal tracking of patient information, increased access to patient information, increasing the number of options for care delivery, and a long-term shift from healthcare facilities to enabling a system of “care anywhere” using telehealth and expansions beyond the VHA.[3]

The VHA has a long-standing practice of exchanging information among its own network of facilities for several years. Examples include exchange between the Department of Defense (DoD) and the current pursuit of engaging in health information exchange (HIE) with non-VHA institutions.[4] The current VA HIE initiative is part of the US government’s Virtual Lifetime Electronic Record (VLER) Health program and is designed for military service members and veterans.[5] Recent policy changes have heightened the importance of understanding what types of patients are most likely to authorize data sharing via VLER Health and underscored the importance of efficient health data exchange.[6] Researchers have learned that there can be some limitations to working with VA data alone, since many Veteran’s using the VA also receive some portion of their care from other healthcare providers, and encounterbased VA data may not capture everything relevant to a patient's health or course of care.[7] For example, 21 percent of Blue Button[8] users shared VA health information with external health care providers. According to Turvey et al, 87 percent of respondents reported that the non-VA provider found the information somewhat or very helpful.[9] Several programs and policies impact a veterans ability to exchange information, including the Veterans Authorization Preferences (VAP) System, policies specific to certain medical conditions, technical platforms enabled by eHealth Exchange standards, and Data Use and Reciprocal Service Agreements (DURSAs).[10] However, much of the exchange of information remains confined to the utilization of information with existing DoD or VA approved systems, not external stakeholders as outlined in this study. The MISSION Act—recently passed legislation discussed below—signals a need to expand the scope of entities with which the VA system engages with to facilitate care.[11] Limited research fully addresses the important step of exchanging information between VA and non-VA locations of care, as most reported metrics skew toward interoperability of systems among non-federal healthcare settings.[12]

*MISSION Act and Insurance Implications*

The VA MISSION Act of 2018 *S.*2372, signed into public law on June 6, 2018, aims to provide greater access to both VA facilities and non-VA facilities under the program titled Community Care Providers.[13] The VA MISSION Act dedicates $50 million per year to a new Department of Veterans Affairs innovation center and would allow the VA to prioritize pilots that counterbalance underlying incentives, test episode-based payment approaches, and to further address veteran-specific needs.[14] The overall purpose of the VA MISSION Act is to establish an effective and more efficient Community Care Program for veterans and create a framework through which to modernize and realign the resources of the VHA.[15] Inherent in this policy approach is the necessity to adequately ensure the transfer of information between facilities and locations of patient care. HIEs provide a structured and geographically broad approach to effectively share information between VA health systems and private sector locations of care.

The approach to privatization of payment for veterans is an ongoing policy discussion.[16] Veterans covered under VA insurance may have additional insurance beyond TRICARE, a form of insurance made available to qualified veterans. Other potential payers include Medicare, Medicaid, or any private insurance. While supplemental insurance is not required, it is often recommended for veterans. VA insurance typically only covers the veteran and not their family. In addition, funding for VA insurance can become limited at any time, and an individual may no longer qualify to utilize VA insurance.[17] We present this information not to provide commentary on appropriate course of action for payment but to inform the reader of the context of findings presented below and related to indexing or identifying patients who require a reconciliation of care resulting from expansion to services laid out in the MISSION Act.

*Public vs. Private or Enterprise Health Information Exchanges*

There are two predominate types of HIEs in existence today. Public or community health information exchanges typically receive public funding, include diverse stakeholders, and traditionally focus on specific geographic locations.[18] Community HIEs include regional health information organizations (RHIOs) and certain state-designated entities.[19]

Conversely, many large multisite health systems and large health information technology firms providing software as a service engage in aggregation and sharing of information at an enterprise level or across potentially siloed systems.[20] This approach is typically referred to as an enterprise or federated HIE model.[21] Patient records contained within federated health information exchanges present challenges related to effective information sharing. While enterprise or federated HIEs are permitted broad access to information within their established pool of medical providers, such as hospitals they affiliate with or certain EHR platforms, these exchanges typically provide limited access by external nonmember institutions.[22] In published research VA physicians indicated the ability to share information with groups both outside and inside of their network, consequently resulting in a better quality of care or outcome for the patient.[23] Both community and enterprise HIEs support the aggregation of clinical data and following patients across settings of care. Although they can be complementary, community and enterprise HIEs nonetheless compete for providers' attention and organizational resources.[24]

*Opt-In vs. Opt-Out Challenges*

An important component of information exchange is establishing consent to share information while ensuring a patient's right to privacy. Two predominant forms of consent are opt-in or opt-out models. To opt in is for the patient to choose to participate in the exchange of patient records. With this, the standard would be to have no records shared unless the patient chooses to opt in.[25] Conversely, to opt out would be to share records automatically unless the patient makes a declaration not to share information, forcing the participation to opt out manually.[26] Both options come with benefits and challenges. Opting out provides greater distribution of data to potential participants and care settings. Opting in provides greater control to individuals over privacy of personal information. In addition, opting in and "signing off" on records forces the patient to become more educated surrounding the benefits of sharing their data.[27]

Currently, there is no universal US national policy enabling information sharing by consent; rather, there exists policies differing by state and legal requirements. According to the Office of the National

Coordinator (ONC) for Health Information Technology, an opt-out policy appears to be the most common across states.[28] Differing policies require individual patients to manually provide consent if the desire is for records to not be shared. Research indicates that opt-in policies are more likely to have barriers at both administrative and technical levels, which contribute to the prevalence of opt-out policies among states.[29] Several respondents to the survey discussed further below indicated the challenges of navigating a patchwork of state policies. At times, existing state case law, vendor implementation of required standards, and technological advancements can converge, creating inconsistencies within a given state's approach to consent, thus creating an additional policy barrier to effective and efficient exchange of health information.[30] Further, consent to exchange data by enrolled veterans remains low and impacts the ability to reconcile disparate records of treatment.[31]

*Query Based vs. Active Data Exchange Protocols*

For a complete overview regarding the current state of information exchange among healthcare providers, we direct readers to technical briefs No. 43 and 51 released by the ONC.[32] A main objective surrounding the adoption of EHRs and creation of HIEs is to share information impacting a patient's course of treatment more effectively. Key trends for effective data exchange outlined by the ONC over time include increased capabilities to send, receive, find, and integrate data into EHR systems.[33] From a technical perspective, there is a need to both send or transmit data (push exchange) as well as receive or reconcile (query) data sources. The treating clinicians must be willing to initiate a query as an end user, which may be automatic (via system alert or notification) or manual in nature (reviewing faxed documentation or opening a new platform). Widely utilized mechanisms for sending summary of care documents are presented below in descending order of stated use indicated among non-federal acute care hospitals responding to the American Hospital Association (AHA) supplemental survey:[34]

1. Utilization of DIRECT messaging – a national encryption standard to send information similar in function to email.
2. Participation in state, regional, or local information organization and outlined above.
3. Participation in single EHR vendor networks, outlined above as federated or private information organizations.
4. Utilization of e-Health Exchange – A large consortium of 293 data-contributing participants, including many not-for-profit HIEs and federated HIEs.

From a study design and background perspective, it is important to note that ONC technical briefs utilizing findings from the AHA supplemental survey on information technology (IT) include responses only from non-federal acute care hospitals. Federal systems do not receive the supplemental AHA survey on health IT. Some researchers have outlined the increased importance and development of a nationwide HIE network as well as the impacts of varied and sometimes fragmented mechanisms to exchange data which informed study design.[35,36] We approached study design cognizant of limited research on information exchange between federal and non-federal locations of care, ongoing issues of policymaking related to system interoperability, and broad approaches to information exchange discussed above.

**Methods**

We conducted a cross-sectional study of HIEs using a novel online survey instrument to determine the HIEs' ability to support expanded access standards set forth in the MISSION Act. We also assessed HIEs' attempts to successfully exchange information with local VA Health Systems. We conducted a pilot assessment of the survey instrument with two regional HIEs to ensure survey instrument validity and respondent comprehension of questions. The pilot survey instrument included a free text response area to capture respondent feedback, issues, or challenges answering any question to improve the quality of the survey instrument. As a result, two questions were changed to further identify mechanisms of data exchange and classification of geographic locations. Prior to survey distribution, the researchers obtained institutional review board (IRB) approval and constructed a novel database of potential HIEs.

The constructed database included approximately (n=65) enterprise, federated information networks, and (n=72) not for profit regional HIEs. Population estimates for active HIEs within the US have ranged as high as 200+ during peak funding associated with the Health Information Technology for Economic and Clinical Health (HITECH) Act circa 2011 to 106 in 2021.[37,38] While respondents were not directly or personally identified, the survey instrument included questions on the name of the responding institution, which was compared against the compiled database of eligible participants to ensure study eligibility. Data collection began in May of 2019 and concluded in October of 2019. Respondents received an email link to a web-based survey tool and subsequent follow-up via email with a request to complete the survey. We conducted three rounds of follow-up communications utilizing the database of potential outstanding respondents. The survey tool collected information ranging from geographic location of HIEs to VA health systems, approaches to information exchange, and capabilities to potentially identify veteran status for care coordination within extant HIE databases. The survey consisted of (n=13) questions with (n=3) questions utilizing pre-programed survey logic to reduce respondent fatigue and increase survey completion rates. We focused study design on the role and impact HIEs play in the active exchange of information between VA health systems and specific to a regional level. In using the term "active information exchange," we limited the scope of the survey instrument to include electronic data transfer mechanisms that can readily be automated and do not require a manual process. As such, we did not focus on the role of mail, fax, or granting access to remote EHRs as covered in other national reports on the exchange of health information. This context is important, as regional or local HIEs represent a critical pathway for the aggregation of patient information and as outlined in the ONC brief and movement toward interoperability of healthcare related systems.[39]

We received a total of 40 complete and semi-complete responses from qualified participants yielding approximately a 56 percent response rate (out of 72 not for profit regional HIEs within our database) for public or community based HIEs when compared against the sample population identified above (see **Figure 1**). Surprisingly, we received no responses for the remaining federated or enterprise information networks contained within the constructed database of potential study participants.

**Results**

All survey responses originated from not-for-profit public or community based HIEs upon review of respondent organization by name. No enterprise or private exchanges participated in the study. **Figure 1** presents the geographic distribution of respondents' organizations by state.

*Geographic Characteristics of Respondents*

Most HIEs operationalized their service area based on either geographic (*n* = 17, 42.5 percent) or statewide level (*n* = 19, 47.5 percent). Almost half of HIEs (*n* = 19, 47.5 percent) were located less than 25 miles from a military base (see **Table 1**), and most respondents indicated a military base within 50 miles of the geographic service location (*n* = 32, 80 percent). In addition to geographic distance to military bases, we probed respondents for geographic distance from VA hospital locations within indicated service areas. Few HIEs indicated that no VA hospitals exist within their defined service area (*n* = 3, 7.5 percent). Most HIEs indicated either one VA hospital (*n* =15, 37.5 percent) or between two or three VA hospitals (*n* = 12, 30 percent) within an area of service. One-quarter of respondents indicated four or more VA hospital facilities located within a geographic service area (*n* = 10, 25 percent).

*Current Approaches to Information Exchange*

In addition to understanding HIE service areas and geographic relationships to either military bases or VA hospitals, our survey instrument included questions regarding HIEs' capabilities to either identify or index veteran's status within existing data repositories. The majority of HIEs (*n* = 23, 62.1 percent) either did not have a capability to identify or indicated difficulty calculating the percent or number of individuals eligible to utilize VA health systems or services within their clinical data repository or exchange (see **Table 2**). Approximately 11 percent (*n* = 4, 10.8 percent) of respondent HIEs had identified current VA eligibility within the HIEs' data repository, and a further 27 percent of respondents indicating a calculation could be made if needed but has not been conducted (*n* =10, 27 percent).

Our survey instrument also explored current practices regarding active exchange between HIEs and VA hospitals. Most HIE respondents (*n* = 23, 62.2 percent) did not engage in active exchange of information with regional VA health systems (see **Table 2**). Only 14 HIEs (37.8 percent of respondents) indicated a current active exchange of information with any number of VA hospitals within their coverage area (see **Table 2**). Based on logical question programming within the survey tool, HIEs indicating active exchange were provided an additional question to further understand technical aspects of information exchange between parties. Among the most popular mechanisms of information transfer are via eHealth Exchange (10 HIEs). eHealth Exchange is a query-based platform leveraging unique access to multiple regional not-for-profit and some enterprise HIE networks. Participation in eHealth Exchange occurs via establishment of a DURSA and common login to initiate a query and based on prioritization of potential volume.[40] Only four HIEs indicated utilization of Health Level 7 (HL7) interfaces (which, at the time of writing, these include Fast Healthcare Interface Resource Application Programming Interface (FHIR API), Consolidated Clinical Documentation (C-CDA), Admit Discharge Transfer (ADT), or other common encounter notification messaging), and another four respondents employing direct messaging as formats to exchange information. **Table 3** presents the cross-tabulation of the extent of engagement and information transfer mechanisms.

*Post Hoc Stakeholder Follow-Up*

Upon review of the findings, we initiated a post hoc stakeholder follow-up using email to better understand responses to questions and skewed responses. Our questions focused on the opportunities to improve access to VA health data, common challenges to reconcile care for VA patients, and barriers to the identification of veterans status among extant health information exchanges.

**Question 1:** What is the easiest data exchange query method to obtain information on VA patients?

HIE 1 Response: eHealth Exchange

HIE 2 Response: eHealth Exchange

**Question 2:** What are the biggest challenges or opportunities with providing a continuum (reconciliation) of care to VA patients?

HIE 1 Response: Data quality issues.

HIE 2 Response: Large volumes and duplicate data in clinical document architecture (CDA).

**Question 3:** What is the challenge with identifying veterans status within current HIEs/RHIO data repositories?

HIE 1 Response: No eligibility files, which makes it difficult to identify veterans.

HIE 2 Response: No mechanism to identify veterans other than review VA eHealth Exchange query audit logs.

**Discussion and Recommendations**

Most not-for profit HIEs reported limited ability to adequately identify a patient based on a designated veteran's status within their respective patient databases. In addition, a majority of HIEs reported no real-time active data exchange with VA Health systems despite a high number of HIEs indicating a VA location in close geographic proximity to the HIE region. While several respondents did indicate limited interactions with VA systems using query-based search or pooling of data using eHealth Exchange as an intermediary, these findings suggest potential future problems in the reconciliation of care as patients increasingly move between VA and non-VA healthcare systems.

Limitations of our study include the lack of participation by any private or enterprise wide HIEs. We note the opportunity to focus additional research efforts on this specific demographic in future work. Our relatively small sample size of not-for-profit HIEs (n=40) also prevented attempts at generalized linear regression modeling to identify any causal associations or interactions. However, we do note that a strength or our study is a robust response originating from not-for profit HIEs. Our findings suggest an ongoing patchwork approach to HIEs engaging with regional VA Health Systems for the purpose of exchanging information in line with findings in other peer reviewed literature.[41] There is limited evidence among survey participants to suggest that VA Health systems routinely connect to both public and private HIEs to engage in real-time data exchange to support goals outlined within the MISSION Act. To this end we provide the following recommendations considering the findings above.

1. Increase the Utilization of HIEs by VA Health Systems – A key finding of our work is limited utilization of not-for-profit HIE services and diffuse practices with regards to establishing connectivity between regional VA Health Systems and public not-for-profit HIEs. Search based or end-user-initiated queries were the most common approach to exchange information using a portal to access the HIE by the VA Health System conducting a search. Real-time exchanges of information such as active alerts or encounter notifications services were less frequently reported by HIEs when interacting with VA Health Systems or VA locations of care. A key advantage of real-time information exchange is the ability to automate a service fully or partially, or to reduce potential errors in preforming a user-initiated search (e.g., misspelling of names or change of patient residency).[42]
2. HL7 Capability to Document Eligibility or Insurance Status – Another key finding of this work is in highlighting the difficulty for HIEs to appropriately index existing databases for patient status based on VA health system or TRICARE eligibility. The ability to appropriately convey and exchange "veteran status" is a necessary step in fulfilling the requirements associated with the MISSON Act and to reconcile care among potential insurance types. To appropriately index extant databases for information on current VA health system reliability, we recommend consideration by HL7 to update Level 3 Administrative FHIR[43] frameworks to include veteran status as a base resource. HL7 operates on a consensus and member-driven voting process with open commenting on changes to proposed standards. Inclusion of a criterion as a

standard for information exchange would assist in future data exchange efforts. This resource would aid in determination of eligibility, resource management, and establishing continuity in the delivery of care.[44] We also note an ongoing discussion for the inclusion of veteran status within SNOMED CT, HL7 data standards as well as United States Core Data for Interoperability (USCDI) future versions where the findings of this work support the inclusion of such a data class.[45]

3. Identification of Current Best Practices to Exchange Information – We note several emerging best practices for successful engagement between HIEs and regional VA Health Systems. Real time push of data, which includes encounter alerts and sharing of lab results, is critical to reduce the duplication of tests and make sure the primary care physicians and care coordinators get information as a push transaction versus the current query only model using eHealth Exchange or the Sequoia hub. The VA and DoD should publish all their provider DIRECT addresses and establish internal workflows that support transition of care (ToC) documents. Notifications should be channeled to providers who are managing the care of the veterans resulting from increased access to non-VA health systems and the community care program.

In summary, the most prevalent approach employed between HIEs and regional VA health systems is utilization of eHealth Exchange as a common platform to query (post hoc) patient eligibility. Another notable finding is that the majority of not-for-profit HIEs lack the ability to identify or index existing databases to further understand potential veteran populations. A key directive of the MISSION Act is to increase access to care for veterans into the private sector. However, the ability to fully reconcile eligibility or status within existing HIE databases remains problematic when surveying public not-for profit HIEs, making coordination of care problematic for HIEs. We recommend continued support of existing query-based models of data exchange. However, given the complex issues surrounding increased access by veterans, a shift should occur toward utilization of active data exchange protocols.

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## There are no comments yet.

# MAPPING ICD-11 (THE 11TH INTERNATIONAL CLASSIFICATION OF DISEASE) TO ICD-10-KM-7TH (THE KOREAN MODIFICATION 7TH OF THE ICD-10) FOR FLEXIBLE TRANSITION TO ICD-11

*Posted on August 2, 2021 by Matthew*

**Category:** Summer 2021

*By Hyunkyung Lee, MPH*

**Abstract**

In the World Health Congress in May 2019, ICD-11 was approved, This study aims to analyze the classification system of the 11th revision of the International Classification of Disease mapping with the ICD-10-KM-7th (ICD-10 Korean Modification 7th) to identify the characteristics of ICD-11 so that it can be flexibly linked to KCD-7 when introduced in Korea.

The mapping was conducted based on the ICD-11 frozen version (April 2019). Most of the ICD-11 codes were mapped to a single ICD-10 or KCD-7 code. However, for the diabetes code, more than 80 percent of KCD-7 codes needed to be mapped to one or two post-coordination codes, along with one stem code in ICD-11.

ICD-11 is a great classification that has an excellent taxonomy system to express detailed information. For the codes that have been changed or removed, a proper guideline might also be useful for users to understand the changes made in KCD-7 or ICD-10 code.

**Keywords:** ICD-10, ICD-11, Mapping, Post-Coordination, Granularity

**Introduction**

Patient information collected for care delivery can be used for research and billing purposes as well as accreditation of health facilities.[1] ICD-10 (International Classification of Diseases 10th revision) has been used for more than 25 years in 115 countries for disease classification. The International Classification of Diseases (ICD), used to classify and report health conditions and factors, provides a basis for health statistics.[2]

The World Health Organization (WHO) has been developing the International Classification of Diseases 11th Revision since 2007 with the aim of comparing the statistics compilation for diseases and causes of death between countries.[3,4] ICD-11 addresses the needs of medical innovation and changes in the digitized healthcare system.[5]

One of the important features of ICD-11 is that it has a post-coordination system. ICD-11 has two types of codes: stem codes and extension codes. Similar to ICD-10 PCS, stem codes provide basic information, and by adding extension codes, which specify other things such as laterality, severity, etc., a code can have detailed information as a modifier. In some cases, more than two stem codes can be combined to express one diagnosis. Cluster refers to combined codes, which includes stem codes and extension codes, and it is a post-coordination system in ICD-11. Another feature of ICD-11 is that the ICD-11 codes have short or long descriptions, which helps the users to understand the diagnosis and the way of use.[6] Descriptions are provided in the ICD-11 tabular list.

After the World Health Congress approved ICD-11 in May 2019, the members of the WHO will switch from ICD-10 to ICD-11, and health statistics reports based on the new system will begin on January 1, 2022.[7]

In this regard, Statistics Korea, which manages disease classification and statistics in Korea, conducted the first research project in 2018, a structural analysis and field test for chapters 1, 2, 3, and 4 of ICD-KM-7 (the Korean modification 7th of the ICD-10 (KCD-7)). It contains unique codes that are used in Korea and that are not included in ICD-10; therefore, separate study about KCD-7 was needed. (See **Table 1**.)

Statistics Korea has been performing an ICD-11 study with a plan to finish before the implementation of the ICD-11. As a consecutive research project of 2018, a structural analysis and code mapping, which maps ICD-11 codes to KCD-7 codes for Chapter 5 (endocrine, nutritional or metabolic diseases), Chapter 9 (diseases of visual system), and Chapter 10 (diseases of the ear or mastoid process) were performed in 2019. The chapters that are going to be covered by the study were decided by Statistics Korea, reflecting on the budget and amount of study. This study will report the result of chapters studied in 2019; other chapters were studied by other researchers.

This study aims to analyze the classification system of the ICD-11 along with those of KCD-7 to identify structural and content differences of ICD-11 compared with KCD-7 so that it can be flexibly linked to KCD-7 when introduced in Korea and help to achieve more stable transition.

**Method**

A total of 1,485 codes (625 in Chapter 5, 710 in Chapter 9, and 150 in Chapter 10) were analyzed. Six health information managers with disease classification experience of more than 10 years who are working in secondary and tertiary hospitals in Korea participated in the mapping research.

Before the researchers started the mapping, sample ICD-11 to KCD-7 mapping on about 30 codes from each chapter was conducted by the principal researcher and the manager of the analysis team, and the needed analysis items and method were set.

First, for the structural analysis, the ICD-11 web browser contents for ICD-11 Mortality and Morbidity Statistics (ICD-11 MMS) frozen version of 2019 were studied. Second, the ICD-11 codes and the KCD-7 (with ICD-10) codes were mapped to compare the detailed level of the two systems and analyze their differences.

For all the codes, the participants were asked a question about comparison of granularity between ICD-11 and KCD-7.

After the end of the mapping, the mapped ICD-10 code was compared with the ICD-11 to KCD-7 mapping in the WHO's one category ICD-11 to ICD-10 map table. Using this comparison data, the missing codes or different mapped codes each other were studied.

*1. Data Source*

- ICD-11 codes (Downloaded from WHO ICD-11 website MMS 2019. APR)
- KCD-7 code master table (Provided by Statistic Korea)
- One category ICD-11 to ICD-10 Map -each ICD-11 code maps to only 1 ICD-10 code (Downloaded from WHO ICD-11 website) MMS 2019. APR
- One category ICD-10 to ICD-11 Map – each ICD-10 code maps to only 1 ICD-11 code (Downloaded from WHO ICD-11 website) MMS 2019. APR

*2. Structural Analysis of ICD-11 and KCD-7*

In the ICD-11 MMS frozen version, some items, such as "description," "inclusion," "exclusion," "note," and "post-coordination," are presented for each code depending on characteristics of a code, and it is called "foundation" structure. Foundations include all the contents included in the alphabet index and a tabular list of the code to provide a knowledge base.[5] It is designed to flexibly respond to science and medicine, which are changing constantly. The researchers reviewed which items are on each code for structural analysis. The items reviewed for each code as structure analysis include inclusion, exclusion, note, post-coordination, etc. (See **Figure 1**.)

*3. Mapping Method*

Based on the title of the ICD-11 codes in the MMS frozen version of April 2019, most of the ICD-11 codes, except for the diabetes codes, were reclassified in both KCD-7 and ICD-10. The total number of ICD-11 codes is 1,485, and about 250 codes were assigned to each researcher.

Segments were not overlapped in the performance, and after the first mapping, two members re-examined the mapped codes with each other. A doctor consultation was performed to resolve any difficulties the researchers faced in the mapping or differences in opinions regarding codes. More than two ICD-10 codes (KCD-7 codes) could be mapped in case it is needed to express one ICD-11 code.

Mapping example (ICD-11 to KCD-7 and ICD-10)

The ICD-11 code 9C83.5 has a title of "Internuclear ophthalmoplegia." Researchers classified H51.2 as both KCD-7 and ICD-10.

In cases where the codes that are only used in Korea are found in the ICD-11 code, both the ICD-10 and KCD-7 codes were mapped. For example, the ICD-11 code "9A78.51 Corneal Staphyloma" could be mapped to KCD-7 code "H18.79 Corneal Staphyloma"; however, ICD-10 did not have any specific code that could be mapped. Hence, "H18.7 Other Corneal Deformities" was mapped.

To map ICD-11 code "5B80 Overweight or localized adiposity," two ICD-10 (KCD-7 codes) codes, "E65 Localized Adiposity" and "E66.9 Overweight Unspecified," were required.

Mapping Example (KCD-7 to ICD-11) – Diabetes Mellitus

For diabetes codes, based on the KCD-7 code title, KCD-7 codes, including diabetic complication, were reclassified with the ICD-11 codes. There were 250 diabetes mellitus codes on KCD-7, including the fifth code. In ICD-11, all complications have to be described by using post-coordinations. For example, for ICD-10 code "E10.0 Type 1 diabetes with coma," two ICD-11 codes ("5A10 Type 1 diabetes" and "5A23 Diabetic coma") were required to fully explain the ICD-10 code. The KCD-7 codes, which are only used in Korea, was also mapped with ICD-11. (See **Figure 2**.)

**Results**

*1. Analysis of ICD-11 Structure Performed by Chapters*

The percentage of the cases where "description" was presented is as follows: 45.9 percent in Chapter 5; 24.8 percent in Chapter 9; and 33.3 percent in Chapter 10. Other items, such as "inclusion" and "exclusion" are presented at around 10 percent in each chapter. (See **Table 2**.)

*2. Analysis of Post-Coordinations by Chapters*

In chapters 9 and 10, most of the post-coordinations seen were "laterality." In Chapter 9, the most appeared post-coordination was "has manifestation." "Specified anatomy" was also frequently seen. (See **Table 3**.)

*3. ICD-11 to KCD-7 Mapping*

Mapping ICD-11 to KCD-7 Using the ICD-10's Digit Codes

Most of the ICD-11 codes were mapped to four-digit code in ICD-10 (81.3 percent). Because KCD-7 has unique codes in five or six digits, 64.5 percent of the ICD-11 codes were mapped to four-digit KCD-7 codes; 16.8 percent were mapped to five-digit codes; and 0.2 percent were mapped to six-digit KCD-7 codes.

3.2 percent of ICD-11 codes were mapped to a range of codes and not mapped to one code in specific (e.g., ICD-11 code AA4Z).

The ICD-11 code AA4Z Noninflammatory disorders of the external ear, unspecified could not be mapped to one code; therefore, it was mapped to a range of codes from ICD-10 (KCD-7), H61-H62 ("H61 Other disorders of external ear," "H62 Disorder of external ear in disease classified elsewhere").

About 3 percent of the ICD-11 codes needed two ICD-10 or KCD-7 codes. For example, the ICD-11 code "5B55.5 Vitamin A deficiency with xerophthalmic scars of cornea or blindness" was mapped to two ICD-10 (KCD-7) codes, "E50.5 Vitamin A deficiency with night blindness" and "E50.6 Vitamin A deficiency with xerophthalmic scars of cornea."

There were some codes that were moved from other chapters. For example, ICD-11 code "9A00.Z Atopic eczema of eyelid" was moved to the chapter on visional system from the chapter of skin subcutaneous. (In ICD-10, it was labeled "L20.8, Other atopic dermatitis.") (See **Table 4**.)

Comparison of HIMs' ICD-11 to ICD-10 Code Mapping and the Codes Provided on the WHO's Mapping Table.

On the WHO's ICD-11 to ICD-10 mapping table, each ICD-10 code was mapped to a single ICD-11 code; 2.7 percent of the codes were not mapped to individual codes but were mapped to chapter codes. The concordance rate of the mapped codes of the WHO and the mapped codes suggested by the researchers was 63.1 percent. The concordance rate of Chapter 5 was the highest with 74.7 percent.

Among the nonconcordant codes, the cases where researchers used specific codes that are unique to Korea, while the WHO's mapping table used a range codes showed the highest nonconcordance with 34.6 percent. For example, the ICD-11 code "AA6Z Diseases of external ear, unspecified" was mapped to a range code "H60-H62 disease of external code" on the WHO's mapping table; whereas the researchers mapped the code to one specific code, "H61.9 Disorder of external ear, unspecified."

Survey Results on Granularity Comparison

HIMs answered that 52.2 percent of ICD-11 codes were more detailed than KCD-7, and 47.3 percent were similar to KCD-7. Especially for Chapter 10, 69.4 percent of health information professionals answered that "granularity was similar." (See **Table 5**.)

KCD-7 to ICD-11 Mapping Result for Diabetes Mellitus

Around 18.2 percent of the KCD-7 diabetic codes showed a one-to-one match. Only stem codes were required to describe the KCD-7 codes. However, for 63.5 percent of the KCD-7 codes, a single post-coordination (extension or associated/manifestation code) was required. (See **Table 6**.)

For 18.2 percent of the KCD-7 codes, more than two post-coordination codes were required to fully explain the diabetes codes. In ICD-10, 20 percent of the codes only required stem codes to describe the diabetic codes.

Comparison of the Mapped KCD-7 Codes and KCD-7 Master Table Code

After finishing ICD-11 to KCD-7 mapping, the mapped KCD-7 codes and the codes in the KCD-7 master table from Statistics Korea were compared. Through this process, the unmapped KCD-7 codes were reviewed to re-examine the reasons why they remain unmapped. It was found that there were many cases where the diseases with specific KCD-7 or ICD-10 codes belonged to "all index terms" or where the codes were deleted or moved to other chapters in ICD-11. "All index terms" are terms that are provided in the ICD-11 code browser, and the terms can be searched on the browser. However, the terms do not have specific codes. (See **Figure 3**.)

The total number of KCD-7 codes not presented in ICD-11 was 598. Of them, 297 cases (49.7 percent) were unique Korean codes that were not listed in ICD-10. Of the total 598 codes, 39.5 percent of the codes were not included in ICD-11; 55 percent of the codes were included as "all index terms"; and 5.5 percent of the codes were moved to another chapter.

For example, two ICD-10 codes, "E15 Nondiabetic hypoglycaemic coma" and "E16.0 Drug induced hypoglycaemia without coma," are all included in the ICD-11 code "5A41 Hypoglycaemia without associated diabetes" as an "all index term." (See **Figure 3**.)

For the ICD-10 codes that are not the codes that are unique to Korea, 21.6 percent of the 301 codes were deleted, 24.4 percent were changed to "all index terms," and 4.2 percent of the codes were moved to another chapter. (See **Table 7**.)

**Discussion**

*1. Structural Analysis Review*

There were many new codes in ICD-11. The code description was helpful for the researchers to understand what the diseases were and how to use the codes. For chapters 5, 9, and 10, about 34.5 percent of ICD-11 codes had descriptions in the tabular list, which were useful for mapping.

In some cases, "exclusions," which were provided in ICD-10 (KCD-7) codes, were not provided in ICD-11. Therefore, it was discussed that a future study should perform the comparison of the structure between ICD-11 and ICD-10 (KCD-7).

Post-coordination was another factor that affected the mapping, as it adds detailed information about the code. However, the researchers had difficulties using them because they were confused about how to arrange the order of the codes and how many stem codes or post-coordination codes could be used.

In some cases, an extension (e.g., laterality or manifestation) that should have been added to a stem code was not provided in the stem code. Some researchers put extension codes by researching the codes in the main web browser; however, others did not put any extension codes. A unified rule for post-coordination may be required to receive a coherent data.

*2. Mapping Result Review*

Changed Codes

There were many KCD-7 codes that were removed or changed to "inclusion" or "all index terms" in ICD-11. Codes could have been deleted for logical and clinical reasons; therefore, a guideline must be provided to fully explain the change, including the rationale behind the change to guide users and prevent confusion.

In addition, a detailed review of the subdiagnostic terms of ICD-10 or KCD-7 is required. In some cases, it was found that only a term among multiple subdiagnostic terms of an ICD-10 code was presented in a code that has been changed to different chapters in ICD-11.

For example, in the case of ICD-10 code "H02.8 Other specified disorders of the eyelid," subterm 1, "hypertrichosis of eyelid," is listed in the chapter on visual system in ICD-11. Subterm 2, "Retained foreign body in eyelid," was moved to the chapter on injury in ICD-11, indicating the necessity of a prior review and analysis of subtitle for smooth calculations in the future. (See **Table 8**.)

Comparison Results of Mapped KCD-7 Codes and KCD-7 Master Codes

There were many KCD-7 codes that were mapped to multiple ICD-11 codes. Thirteen KCD-7 codes were mapped from two ICD-11 codes to 30 ICD-11 codes. For example, KCD-7 code "E88.8 Metabolic disorders" was mapped to 39 ICD-11 codes, including "5C50.G Trimethylaminuria," "5C53.1 Disorder of citric acid cycle," and "5C63.2 Disorder of Vitamin D transport or metabolism." To help coding professionals after ICD-11 implementation, KCD-7 codes that are mapped to multiple ICD-11 codes should be informed.

In a comparative analysis of ICD-11, ICD-10, and ICD-10-CM, a round-trip method was used to identify the equivalent codes between ICD-10 and ICD-11, which were validated by limited manual review. In conclusion, with post-coordination, it is possible to fully represent the meaning of a high proportion of ICD-10-CM codes.[8]

Therefore, to make the transition of going from using the KCD-7 classification to the ICD-11 classification smooth, there is a need to present mapping tables (KCD-7 to ICD-11 mapping table and ICD-11 to KCD-7 mapping table), especially with post-coordination information, to present KCD-7 as clearly as possible so that hands-on workers can use the codes by directly comparing them in the two classification systems.

The American Health Information Management Association (AHIMA) introduced a mapping schema for mapping of SNOMED to ICD-9-CM. In this schema, four tables (Concept Table, Cross Maps Sets Table, Cross Maps (Maps Table), and Cross Maps Target Table) were used for systematic mapping. By using terminology concepts and tables, mapping process can be conducted clearly systematically, even in the case of an ambiguous guidance in ICD.[6]

Moreover, in the paper about ICD-11 framework for classifying patient safety events, field trials were conducted on the application of the ICD-11 classification system. The results were analyzed by dividing the cases into the case where the code could be applied and the case where the code could not be applied.[9]

In this research, the most suitable KCD-7 codes for all ICD-11 codes were selected using ICD-11 title and were mapped by manual coding. Only one ICD-11 code, "9D42.1 Normal visual field," remained not mapped, as there was no suitable code for it in ICD-10 (KCD-7). After the research, there was an opinion that the code that could not select a suitable code should remain unmapped because some new ICD-11 codes could not be perfectly matched with an ICD-10 (KCD-7) code. In subsequent research, the mapping rule, including mapping range, should be restudied.

Importance of Detailed Mapping Guidance

The mapping results appeared quite differently depending on the researcher's experience and the ways the researchers used to apply coding rules. Malaysia and Sweden used SNOMED CT to map the acute coronary syndrome registry and performed comparative study. The conclusion of the study showed that in order to ensure reproducible and reusable maps, special actions were required. Especially, the importance of the detailed mapping guidance was reaffirmed to reduce the deviation by coding professionals' opinions.[10]

The symbols * and + are no longer used in the section on complications of diabetes. Instead, users have to select related complications from the post-coordination, which has an extensive list of diseases. This caused confusion for the researchers, as deep clinical knowledge was required to select proper a manifestation. With this, it can be suggested that an intensive training of clinical knowledge may also be essential to carry out an accurate classification.

Limitations

This study was performed based on the 2019 WHO mapping table and 2019 ICD-11 MMS.

It was found that the mapping table provided on the ICD-11 web browser in 2021 showed different data from the mapping table provided on the same web browser that was studied in 2019.

Specifically, in 2019, some of the ICD-11 codes were mapped to chapters; whereas, in 2021, there were no ICD-11 codes that were mapped to chapter. Due to such circumstances, minimum level of WHO mapping table comparison study was reported in this article.

## Conclusion

ICD-11 is a great classification that has an open structure to meet the modern and innovative era with post-coordination system. The description provided in the tabular list also helps coding professionals to easily understand the new diseases and adapt to the new classification system. Using this excellent taxonomy system, various codes that have detailed information can be used in many areas, including research and healthcare planning.

ICD-11 is still changing, and a dual mapping table (the ICD-11 to KCD-7 and KCD-7 to ICD-11) with post-coordination information might be useful for users to understand the changes that are made in KCD-7 or ICD-10.

Also, a guideline for the mapping process should be developed by multidisciplinary experts to keep the consistency of the work.

For the changed codes, such as the ones that were removed or moved to another chapter, it is necessary to make an easy-to-use code book to avoid any confusion.

Further study and mapping, including code-specific research by chapter, will be needed to make the transition from KCD-7 to ICD-11 smooth.

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**Author Biography**

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## There are no comments yet.

# HEALTH INFORMATICS TOOL TOWARD SEPSIS SCREENING

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*By Raweewan Liengsawangwong, MD, MHIM, RHIA; Sajeesh Kumar, PhD; Ruben A. Ortiz, MS; and Jason Hill, MD, MS*

## Background

Sepsis is a syndrome without, at present, a validated criterion standard diagnosis test.[1] Sepsis can rapidly progress to septic shock, multiple organ dysfunction syndromes (MODS), and death.[2] Mortality of intensive care unit (ICU) patients with severe sepsis or septic shock is as high as 30 percent to 40 percent, even with comprehensive treatment.[3] Prompt management of sepsis can decrease the risk of complications, organ failure, and mortality. Initial clinical presentation of sepsis can be nonspecific and obscured by underlying morbidity of a patient, which makes sepsis challenging to detect until the condition becomes deteriorated. The clinical decision support (CDS) system for sepsis can play a critical role in improving sepsis management and outcomes. Many healthcare institutions have been increasingly leveraging clinical data captured in electronic health records (EHRs) and CDS systems to alert clinicians to the possible presence of sepsis and other clinical deteriorations.[4] However, the significant challenge is creating a CDS tool that is intuitive, user-friendly, and has effective protocols for alarms, alerts, and decision-making pathways.[5]

In 2011, Ochsner Health System launched EHRs at all its facilities and had actively engaged CDS in clinical settings. In October 2015, the Centers for Medicare and Medicaid Services (CMS) enacted a national quality measure (NQF #0500) for reporting on sepsis called the Severe Sepsis and Septic Shock Early Management Bundle (SEP-1).[6] Medicare included the SEP-1 quality measure in the Medicare Hospital Compare reports, a publicly available database rating on a hospital, based on each CMS captured measure.[7] Ochsner developed the sepsis order set that contains recommended treatment guidelines based on the SEP-1 measure. However, Ochsner faced low usage of the sepsis order set; hence, the compliance rate of SEP-1 measure was lower than Louisiana average and national average. Ochsner aimed to improve patient care quality, increase performance metrics, and standardize sepsis treatment by promoting adherence to SEP-1. In January 2018, the Ochsner informatics team launched the sepsis screening tool to improve adherence to standard treatment by raising awareness of the providers, encouraging sepsis order sets usage, and increasing compliance to SEP-1. This study's objectives were to determine the association between the sepsis screening tool, the use of sepsis order set, the compliance with SEP-1, and the primary outcomes. The primary outcomes were 1) time zero to antibiotics; 2) inpatient length of stay; and 3) survival at discharge.

## Materials and Methods

*Study Design and Population*

This retrospective study was conducted at a tertiary academic hospital (Ochsner Medical Center, New Orleans, Louisiana). Data were extracted directly from EHR. The population was adult patients admitted through the emergency department that had a diagnosis of sepsis or septic shock during admission from July 1, 2017, to July 31, 2018. The diagnoses of sepsis/septic shock based on the International Classification of Disease (ICD)-10. The exclusion criteria were a) referral patients from outside facilities; b) who had antibiotics started before arrival at the emergency department; and c) transferred patients to outside facilities. The time that a patient arrived at the emergency department was the time zero. In January 2018, the sepsis screening tool was launched and incorporated into the EHR at the triage station. The sepsis screening tool contained clinical history and screening criteria based on SIRS criteria (**Figure 1**). If there were positive at least two out of three criteria, a patient would be considered to have sepsis, an automatic alert in the provider's EHR would be triggered, and that patient would be brought in to have prompt evaluation and intervention by the emergency team. The physician could use the sepsis order set, which was incorporated in the EHR but does not have a direct link from the sepsis screening tool. The sepsis order set contains a package of treatments including antibiotics recommendation, laboratory testing orders, and other recommended standard management based on SEP-1.

This study collected patients' data during the six months before and six months after the launch of the sepsis screening tool, which would be called the pre-intervention and post-intervention group, respectively. The compliance with each element of the SEP-1 measure at three hours and six hours was collected based on the eligibility of a patient's conditions that met the criteria for the intervention. The perfect care was achieved when a patient received all required elements according to the protocol at three hours (3H perfect care) and six hours (6H perfect care). The total perfect care was the group of patients who completed both three- and six-hour requirements. Total perfect care represented the compliance to the SEP-1 measure and was used for reporting to CMS Hospital Compare.

First, we compared the pre-intervention and post-intervention group to assess the association between the sepsis screening tool and the usage of sepsis order set, the sepsis screening tool, and the compliance of the SEP-1 measure, and the sepsis screening tool and the primary outcomes. Second, we regrouped the whole population to be the group that used the sepsis order set and that which did not use the sepsis order set. Then, we assessed the association between the sepsis order set and total perfect care, and the association between the sepsis order set and the primary outcomes. Last, we regrouped the whole population into the group that achieved total perfect care and did not achieve total perfect care. We then assessed the association between total perfect care and the primary outcomes.

This study was approved by the University of Tennessee Institutional Review Board as meeting the criteria for exempt status for nonhuman subjects research status; 18-05810-NHRS.

*Statistical Analyses*

The chi-square statistic was used to assess the association between the categorical variables for the sepsis screening tool and the order set usage, the sepsis screening tool, and total perfect care, and the order set usage and total perfect care. An independent t-test was used to assess the association between time zero to antibiotics and a) the sepsis screening tool; b) the order set usage; and c) total perfect care. The negative binomial regression statistic was used to assess the association between the inpatient length of stay and a) the sepsis screening tool; b) the order set usage; and c) total perfect care. The logistic regression statistic was used to assess the association between the survival at discharge and a) the sepsis screening tool; b) the order set usage; and c) total perfect care. All analyses were performed using SPSS version 26 (IBM Corp., Armonk, NY). The p-value of less than 0.05 was considered to be statistically significant.

**Results**

The final population for analysis was 632 (**Figure 2**). The collected data comparing the pre-intervention group and post-intervention group is shown in **Table 1**. Our results showed that the usage of the sepsis order set increased significantly in the post-intervention group ($p = 0.001$). We found that the post-intervention group was 1.8 times more likely to use the order set than the pre-intervention group. The average time zero to antibiotics in the post-intervention group was 17.7 minutes lower than the pre-intervention group. However, there was no significant association between the pre-intervention and post-intervention groups and primary outcomes or total perfect care.

The association between using the sepsis order set and the primary outcomes (**Table 2**) showed that the average time zero to antibiotics in the order set usage group was 54 minutes shorter than the group that did not use the order set ($p = 0.001$). The average length of stay in the group that used the order set was 1.8 days shorter than the group that did not use the order set ($p = 0.002$). There was a non-significant trend toward improvement of survival in the group that used the order set.

We found that the number of total perfect care increased significantly in the group that the order set was used with the p-value $<0.001$ (**Table 3**). The group that achieved total perfect care had 102.4 minutes shorter average time zero to antibiotics ($p < 0.001$), 1.5 days shorter average length of stay ($p = 0.004$), and better survival at discharge ($p < 0.001$, 95% CI 0.02 – 0.206, OR 0.064) than the group that did not achieve total perfect care.

**Discussion**

Our findings confirmed that the sepsis screening tool improved adherence to standard treatment. The sepsis screening tool raised awareness of the emergency department personnel by showing that the usage of the sepsis order set significantly increased in the post-intervention group ($p = 0.001$). The post-intervention group was 1.8 times more likely to use the sepsis order set than the pre-intervention group, despite no direct link within the sepsis screening tool. Even though the sepsis screening tool did not improve primary outcomes, the post-intervention group received antibiotics 17.7 minutes earlier than the pre-intervention group.

Our study found that the usage of the sepsis order set improved the adherence to the treatment guidelines and reduced time to antibiotics and length of stay. The utilization of the sepsis order set streamlined and standardized the sepsis management, which resulted in a shorter time to antibiotics by 54 minutes ($p = 0.001$) and shorter length of stay by 1.8 days ($p = 0.002$). However, there was no significant difference in survival between the group that used the order set and the group that did not use it. Our results showed a significant association between sepsis order set usage and total perfect care ($p < 0.001$), which indicated that the order set usage increased the compliance with SEP-1 measure.

National Quality Forum (NQF) stated that an absolute reduction in mortality over 20 percent was reported with the compliance rated of 52 percent of the sepsis management bundle.[8] The survival benefit of the compliance of SEP-1 remains unclear. The association between SEP-1 measure and mortality was evaluated in a multicenter retrospective study[9]. Rhee et al. reported that the crude mortality rates were higher in sepsis cases that failed to comply with SEP-1 measure when comparing with sepsis cases that passed, but the difference was not significant after adjusting for clinical characteristics and severity of illness.[10] Rhee's study concluded that detailed adjustment was necessary to properly interpret associations between SEP-1 compliance and mortality.[11]

Our results showed that the compliance of SEP-1, by achieving total perfect care, significantly improved all primary outcomes. The group that achieved total perfect care had significantly shortened the average time to antibiotics by 102.4 minutes ($p < 0.001$), shortened length of stay by 1.5 days ($p = 0.004$), and improved survival at discharge ($p < 0.001$, 95% CI 0.02 – 0.206, OR 0.064). Even though our results showed strong association between the compliance of SEP-1 and primary outcomes, more study is needed to confirm these findings because we did not adjust for clinical characteristics and severity of illnesses.

Our study had some limitations. The first limitation was the data lacked the details of clinical characteristics and severity of illness of the studied group. The second limitation was the nature of a retrospective review with the data extracted directly from the EHR, which might be confounded by the incompletion of the data. The third limitation of our study was that the number of studied populations might not be enough to detect significant differences. The last limitation was the confounding effect of partial treatments on the outcome of the study. Many patients underwent parts of the bundle elements but did not complete the required interventions per SEP-1 measure in which the benefit of partial treatments could become confounding factors of this study.

## Conclusion

Performance metrics could drive change in clinical behavior, improve quality of care, and may decrease mortality in patients with severe sepsis and septic shock[12] Our study showed that the sepsis screening tool raised awareness of emergency department providers and improved adherence to standard treatment. Furthermore, our study confirmed that adherence to the standard treatment guidelines improved the treatment outcomes. Even though the overall compliance of the SEP-1 measure in this study was 46 percent, our study demonstrated the benefits of the sepsis screening tool, the benefits of the sepsis order set, and the benefits of compliance of SEP-1 measure. More study is needed to confirm the association between compliance of SEP-1 measure and patient-related outcomes.

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## There are no comments yet.

# THE EVOLUTION OF INFORMATION TECHNOLOGY GOVERNANCE AT THE NIH CLINICAL CENTER

*Posted on August 2, 2021 by Matthew*

**Category:** Summer 2021

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**Abstract**

An information technology governance (ITG) program has helped the National Institutes of Health (NIH) Clinical Center (CC) in the implementation of many systems and has guided the organization through the maturity of its project management methodology. The NIHCC Department of Clinical Research Informatics (DCRI) maintains an electronic health record (EHR) called the clinical research information system (CRIS) along with many clinical information systems (CIS) and research information systems, supporting approximately 3,200 users.

ITG involves establishing processes to guide the review, selection, implementation, management, and setting of the IT strategy representing the business owners, stakeholders, and IT.[1]

Research conducted by Levstek, Hovelja, and Pucihar[2] identified that different organizations may need different ITG structures, frameworks, and strategies. The path to achieving strong ITG is a continuous journey. This paper reviews the evolution of the NIHCC IT governance strategy.

**Phase 1: NIHCC IT Governance**

The path of the NIHCC for IT governance started as the NIHCC implemented a new EHR in 2004, the decision made by the EHR Steering Committee was to ensure the use of best practices of project, risk and configuration management.

Following the implementation of the EHR, the complexity of the NIHCC's IT environment began to increase as new clinical applications were implemented and integrations across systems were developed. These activities were captured in a project dashboard, as the NIHCC developed a new Project Management Office (PMO). By 2005, the PMO was actively tracking five IT projects, which quickly ballooned to 24 active projects in 2007. Although there was some growth of the IT department during this time, it did not keep up with the evolving state of the IT architecture. Resources that normally would spend the majority of their time supporting existing systems were now shifting their time commitments to the implementation of new systems—all of which would then be added to their normal operational activities. At the time, the default arbiter of prioritizing these activities was the responsibility of the chief information officer (CIO). As the IT complexity continued to grow, it was clear that there was a need for a more robust governance process with input from the organization's business stakeholders on the authorization and priority of new requests. Without IT governance, projects fail, resources become unavailable, systems are not managed properly, and expectations between the IT department and system business owners are not met. Houston and Kennedy[3] explain that "having a robust governance process in place ensures that the right projects are done at the right time, while ensuring alignment to the organization's mission and vision. Projects can be major undertakings, requiring multiple resources, time, and money, so it is crucial that these efforts are understood and monitored on a regular basis."

The road to IT governance at the NIHCC started with the adoption of a systems-thinking approach to understand the organization from a big-picture perspective to develop communication, collaboration, and teamwork skills.[4] Way and McKeeby[5] identified the benefits of the systems thinking approach as follows:

- Give customers choices, so it is not an absolute "no."
- Manage customer expectations.
- Let customers have a voice in project prioritization.
- Enlist management support.

The first milestone of ITG was a disciplined approach to create a shared understanding of the scope of workload internally within the DCRI. The NIHCC CIO started the process with the creation of a comprehensive inventory of projects. Each member of the DCRI leadership team validated the list, identified missing items and items no longer valid, and returned the annotated list to the NIHCC CIO.

As we started IT governance, we created an IT PMO with two project managers. The PMO developed a process to maintain the list, adding new requests, putting projects on hold, and removing projects.

**Phase 2: NIHCC IT Governance**

The second milestone for ITG at the NIHCC in 2006 was to prioritize the CC's most impactful projects. The organization introduced the term cornerstone project and defines it as a project that combines many resources across multiple departments and is typically a mission-driven strategic initiative that spans multiple years. A cornerstone project identifies a priority in respect to resource utilization and implementation dates. All other projects are coordinated and scheduled with cornerstones as the baseline.

A sample list of the cornerstone projects is in **Table 1**.

At this time, the PMO increased to five. As part of Phase 2, we started a monthly project management team (PMT) meeting. The attendees included DCRI senior leadership, all DCRI project managers, a representative from the Office of Purchasing and Contracts (OPC), and all DCRI supervisors. DCRI supervisors includes service center, user support, system and network, database administration, CRIS build, NIHCC chief technology officer (CTO), and the NIHCC CIO.

**Phase 3: NIHCC IT Governance**

From 2007 to 2016, the NIHCC performed operational reviews across departments to identify areas of improvement. In 2009, an operational review of the NIHCC's DCRI found that there were over 120 open or pending projects, there was no vetting of the prioritization of projects outside of DCRI, and there was no stakeholder involvement in the prioritization process.

The only directive from the 2009 operational review was the development of the Information Technology Advisory Group (ITAG). The mission of the ITAG is to plan, approve, prioritize, and direct NIHCC initiatives with the goal of meeting customer expectations regarding the implementation and support for developed information technology (IT) solutions. A secondary goal is the management of the project scope and risks to ensure we meet the clinical, administrative, and IT requirements.

DCRI added a chief of the portfolio and PMO (PPMO). The PPMO oversaw the PMO, enterprise architecture, configuration management, and testing. The PMT meeting expanded the agenda to include OPC and ISSO announcements and the review of the monthly CM calendar of system updates and activations.

Phase 3 institutionalized a formal governance organization to serve as the guiding force over IT projects. The first two critical components in devising an ITG model include the development of a charter and the identification of key stakeholders.[6] The charter provided the NIHCC a clear roadmap of the mission, vision, roles, and responsibilities for the new governance organization. However, to be successful, it was important to ensure critical input was provided by key stakeholders and IT expertise across the NIH.[7] ITAG was comprised of seven to eight senior business leaders from the NIHCC, one from the NIH CIO's office; a member of the Medical Executive Committee (MEC) Clinical Information Management (CIM) Subcommittee; and a member of the EHR Prescribers' Group and one to three additional institute/center representatives; and one member of NIH IT leadership.

In addition to the official members, we added several other key NIHCC staff to provide input for decision-making, including the NIHCC CIO, NIHCC chief financial officer (CFO) and the NIHCC chief medical information officer (CMIO). Of note, none of these members are able to vote, thereby allowing all decisions made based on the business needs of the organization.

Figure 1 illustrates the ITAG process.

The ITAG charter contains the following mission and responsibilities:

**Mission**

The mission of the ITAG is to plan, approve, prioritize, and direct NIHCC initiatives to meet customer expectations and organization requirements regarding the implementation and support for information technology solutions.

**Responsibilities**

The ITAG has the following areas of responsibility:

- Determine and consistently apply criteria for prioritizing and recommending NIHCC IT investments to the NIHCC CEO.
- Ensure that all projects selected align with the NIHCC Strategic Plan.
- Review IT resource requirements, scope, and/or schedule changes to IT initiatives.
- Re-evaluate, prioritize, and recommend approval as needed.

**Project Review Process**

One of the early steps in the development of the ITAG was to narrow the scope of what constitutes a project. Specifically, a project is a piece of work that has the following distinct characteristics:

- Requires over 40 hours of staff time to complete.
- Has a time limited duration.
- Produces a specific and distinguishable product, service, or result.
- Serves a specific purpose.
- Has interrelated activities or tasks.

Under the newly defined process, NIHCC departments, NIH institutes, and other NIH committees submit new IT project requests to the NIHCC's Office of Financial Resource Management (OFRM). OFRM reviews the request for any financial obligations to the NIHCC and shares the request with a DCRI portfolio manager. The DCRI portfolio manager works with the requestor to document the business and technical requirements, justification, expected timeline, funding needs, and resource requirements into a project charter or business case, depending on the situation.

The DCRI portfolio manager submits the request and the details to the OFRM/DCRI Project Evaluation Committee. The OFRM/DCRI Project Evaluation Committee submits any item that fit the definition of a project, and require new capital IT equipment, new applications, or major version upgrades that consisted of new functionality, to ITAG. Based on defined criteria, many requests submitted are identified as routine operations and maintenance or mandates due to regulatory or security requirements. These types of requests were not vetted through ITAG but are reported due to their resource requirements.

ITAG met four times per calendar year. Requests, project charters, and/or business cases are distributed electronically one week prior to the meeting for the voting members to score the requests. The criteria for scoring is: 1) Areas of Benefit; 2) Strategic Alignment; 3) Operational Efficiencies; 4) Impact to Quality of Patient Care; 5) Impact to Satisfaction of Patient Care; 6/7) Number of Patients and Protocols Impacted.

At the meeting, the project requestors present their respective project requests. After the presentations, the ITAG voting members review the scoring summary. The committee also reviews a current list of all projects along with a staffing report, which includes available versus allocated project resources. With this information, the ITAG discusses each request and identifies a recommendation decision, to approve, needs more information or to deny. The ITAG chair then provides the recommendations to the NIHCC CEO for final disposition. The approval decision does not specify a start date. DCRI then works with the requestor on determining when resources would be available to start the project and assigns a project manager from the NIHCC PMO.

**Phase 4: NIHCC ITG**

The scope of the ITAG expanded in Phase 4. In 2019, the NIHCC CIO acknowledged that there was a substantial amount of work considered routine or mandatory, which compete for the same resources, allocated for the formal ITAG projects. As a result, it was difficult to manage the resources for projects. Requestors became frustrated that their projects were not being scheduled and project delays were frequent; staff morale was negatively affected by this long list of projects and feeling unable to meet the expectations of the organization.

In reviewing this issue with the NIHCC CEO, ITAG chair and NIHCC leadership, the NIHCC CEO identified that without improved and more comprehensive governance, it would be impossible for the DCRI staff to complete the project list of over 260 items. The scope of governance over IT work needed to improve; as such, the role of ITAG expanded to review all activity that fit within the definition of a project. With over 40 ITAG projects and over 200 other items, it would be very difficult for the ITAG to review all the activities independently.

In reviewing the list of activities that had IT components and met the definition of a project, it was determined the project categorization as ITAG Projects, Complex System Change Requests (SCRs), Security & Infrastructure Operations, and Maintenance (O&M).

1. ***ITAG Projects*** are projects that require a full review and scoring as an individual project by the ITAG committee. Examples of these projects include:
    1. New capital IT equipment
    2. New functionalities, interfaces or applications
    3. Major upgrades
    4. New CC IT investments that require implementation and ongoing support
2. ***Complex SCRs*** are projects managed through multiple SCRs. The NIHCC Functional Review Board (FRB), the Enterprise Scheduling Advisory Group (ESAG), or the CIM reviews these request. A voting member from ITAG participates in this review and presents the recommendations back to the full ITAG committee. Examples of these projects include:

1. Large-scale configuration changes
2. Significant IT work
3. Limited updates to existing applications

1. ***Security and Infrastructure O&M*** are projects reviewed by the Architecture Planning Board (APB), Technical Review Board (TRB), and/or the Security TRB (STRB) for security and

infrastructure implementations and updates. A voting member from ITAG participates in this review and presents the recommendations back to the full ITAG committee. Examples of these projects include:

1. Large-scale hardware and OS updates
2. Mandates due to security, privacy, or architecture regulations
3. Infrastructure updates and implementations

**Figure 2** reviews the updated process.

**Six Months Later, Post-Phase 4**

The initial list presented to the NIHCC CEO had 262 ITAG projects, Complex SCRs, and Security & Infrastructure O&M projects. The first review by ITAG of this the list included a recommendation to remove 45 projects, as they included duplicates, projects already completed, or projects that had not been approved. Additionally, 37 projects were placed on hold based on a lack of funding or approval. As a result, the list presented at the first ITAG meeting was reduced to 180 projects.

In the most recent six months, since the new ITAG processes came into practice, DCRI completed 35 unique projects. This nearly doubled the typical average of 15-20 project completions over other six-month time frames. The rate of new submissions has also increased to nearly 30 additional project requests in the same six-month time frame, which indicates that more stakeholders are becoming aware of the project governance requirements.

Along the road to the development of this now robust IT governance process, the organization's health information (HI) professionals remained well integrated and involved in the various components of the process in addition to team members from IT and other organizational leaders. The NIHCC values and understands the critical input from HI professionals and the unique skill set they have regarding project management, EHR configuration, documentation requirements, IT knowledge, privacy and security, and more. Nearly all IT projects have one or more of these components, and HI professionals bring value to the NIHCC's process by managing and/or participating on the organization's Clinical Documentation Control Board, Clinical Information Management Committee, Functional Review Board, EHR Stakeholder User Groups, and more.

**Lessons Learned**

The NIHCC's road to a robust programmatic review of information technology initiatives has been a learning experience for the organization, including the primary fact that governance is not easy, but it is important to maintain the integrity of prioritization and the overall governance process. Organizations must ensure that all stakeholders are represented in some way throughout the various components and steps of the process. Finally, in order to be effective, all information technology efforts must be governed across the organization in a transparent manner.

The evolution of information technology governance at the NIHCC has resulted in many tangible benefits. In addition to the effects on completion, the morale of both the staff and stakeholders has markedly improved. DCRI and ITAG membership and the extended ITAG membership review the project list more, providing increased transparency as well as an opportunity for discussion that has improved the understanding the alignment of projects, staff resources, and needs of the organization.


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The authors have no competing interests to declare.

## Contributorship Statement

All authors wrote and reviewed the final manuscript.

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## There are no comments yet.

# AUTOMATIC ICD-10 CODING USING PRESCRIBED DRUGS DATA

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## Abstract

This article discusses the emerging trends and challenges related to automatic clinical coding. We introduce an automatic coding system, which assigns short ICD-10 codes (restricted to the first three symbols, which define the category of the disease) based only on drugs prescribed to patients. We show that even with limited input data, the accuracy levels are comparable to those achieved by entry-level clinical coders as depicted by Seyed Nouraei et al.[1] We also examine the standard method for performance estimation and speculate that the actual accuracy of our coding system is even higher than estimated.

## Introduction

Clinical coding involves assigning medical records universal codes such as ICD-9 explained by Melissa Wei et al;[2] ICD-10 introduced next and further explained by Donna Cartwright;[3] and in the upcoming ICD-11 discussed by Carla Smith et al.[4] It supports comparability in the collection, processing, and presentation of health statistics. Such coding makes it easy to store, retrieve, compare, and analyze health information for evidence-based decision-making. The increase in complexity and granularity of the codes from one classification version to the next can lead to increasing difficulty in achieving accuracy in clinical coding. This increasing technical challenge can lead to performance degradation for health systems that operate activity-based funding models shown in the study of Pamela Baxter et al,[5] which can result in financial losses, as explained by Charland Kim, Morgan  Haefner, Lani Knight et al.[6,7,8] Recent advances in machine learning (ML)—a branch of artificial intelligence based on the idea that systems can learn from data by identifying patterns and make decisions with minimal human intervention—and more specifically deep learning, as explained in Jürgen Schmidhuber's study,[9] which is a subset of ML techniques wherein its networks are capable of learning unsupervised from large amounts of data that is unstructured or unlabeled. It provides great potential to develop effective systems to partially automate the clinical coding process and support the sustainability of clinical coding activities.

## Methodology

This study was conducted between June 2019 and January 2020. We were granted an approval with number "6152/2019" from the Research Ethics Committee of the Faculty of Medicine at Chiang Mai University to use the anonymized data for the purpose of this study. We use ML to build two automatic coding systems. ML approaches learn and improve from experience without being explicitly programmed and make predictions on unseen data. Although there are various types of patient-related data, we have built a novel supervised ICD-10 prediction model using only prescribed drugs data. Among the reasons for using such data are:

- Prescribed drugs appear to be very informative to predict ICD-10 codes, as it is often the last step of the episode of care.
- The data is mostly complete (fewer missing data) per diagnosis.
- The problem is challenging, as drug association with the disease is not one-to-one (e.g., co-morbidity prescriptions).

Neural networks (NNs) are artificial networks consisting of multiple layers, each with many neurons (learning units) trying to simulate the human brain, as shown by Zenon Waszczyszyn.[10] It has many layers of "neurons" that receive inputs that go through all the layers, and the output of one layer is fed into the next layer. We adopt NNs to extract drug-disease associations from data to predict ICD-10 codes. The use of NNs is driven by a few factors; the main one is the inherent high complexity of the problem due to the nonlinearity of relations found in drug-disease associations. NNs can automatically learn hidden intrinsic complex features without any manual hand-crafted feature engineering. Moreover, NNs are now thoroughly investigated and well established with a wide range of supporting software and well-written documentation.

**Related Work**

To the best of our knowledge, this work is the first to address the ICD-10 coding prediction from this angle. However, previous related work to the prediction of diagnosis studied by Julia Medori et al, Svetla Boytcheva, and Keyang Xu et al[11,12,13] relied mainly on discharge notes and using very specialized datasets that do not contain many diverse real-world complex cases. These techniques range from rule-based (e.g., coding frequency and gender-specific) using Naive Bayes classifiers, to text-based, as shown by Julia Medori, from free-text death certificates using term-based concepts (SNOMED CT) and employing a support vector machine (SVM) classifier as shown in Shihong Yue's study.[14] Moreover, in Jürgen Schmidhuber's study, they used medical terminologies (UMLS) to formulate features to train their models, while in the study of Bevan Koopman et al,[15] they matched ICD-10 codes to diagnoses extracted from discharge letters using a multiclass SVM. However, SVMs cannot support the case of extreme multiclass, multilabel problems that this paper tackles. On the other hand, Julia Medori incorporated more data sources (structured, semi-structured, and unstructured) and employed an ensemble method to integrate all modality-specific models to predict codes. However, this approach requires large amounts of data, suffers from high dimensionality, and was only tested on a very small subset of 32 frequent ICD-10 codes. In summary, these models are too specific to a small subset of the real-life clinical coding, and neither reflect the real complexity or the true figures of coding prediction accuracy.

**Dataset**

We used clinical data (inpatient and outpatient datasets) from the electronic health records of Maharaj Nakhon Chiang Mai Hospital (Thailand), which was recorded between 2006 and 2019. **Table 1** contains a few important statistics for each available dataset.

**Evaluation Measures**

Our main task is predicting the set of ICD-10 codes assigned to a patient that belongs to a class of ML problems called multilabel, multiclass classification problems. We calculate the accuracy of the trained systems by randomly splitting the data into training and test (holdout) subsets. The training set (subset) is used to extract the knowledge (to train the systems), and the test set is used only to check the accuracy of the predictions similar to Ron Kohavi's study[16.] For evaluation, we use the Jaccard similarity score to measure accuracy of the predictions. The Jaccard similarity score was introduced by Paul Jaccard's study[17] and is calculated as an average of scores for all cases in the test set, while one score is calculated as a ratio of two numbers: the number of correctly predicted ICD-10 codes and the number of ICD-10 codes in the union set of correct and predicted codes:

,

where N is the number of cases,  is the set of correct ICD-10 codes for case , and  is the set of predicted ICD-10 codes for case .

The main reason is that the Jaccard similarity score covers the most intuitive meaning as shown by Krzysztof Dembczyński et al[18] for both types of ICD-10 coding errors: undercoding and overcoding.

For example, in **Table 2**, there are three rows. The Jaccard similarity score is calculated as an average over three scores: 0.25, 0.5, and 0.25 and equal to 1/3 (33.3 percent).

The first row in the dataset is giving an example of undercoding (when predicted codes are the subset of the correct codes), the second row is an example of overcoding, and the third case is a mixture.

However, when we predict the primary diagnosis (one code), we use a different accuracy measure:

For example, in **Table 3**, there are three rows, and, in two cases, the primary diagnosis is predicted correctly; thus, the accuracy is 2/3 (66.6 percent).

**Proposed Model**

We use NNs to train two automatic coding systems. The structures of both NNs are the same and appear in **Figure 1**. In both cases, the neural networks predict only first three symbols of ICD-10 codes.

Both models are feedforward (FF). The reason these models are called feedforward is because information flows through the function being evaluated from x (input), throtaugh the intermediate computations (hidden layer(s)) used to define f, and finally to the output y as explained by Han Jun et al.[19] Our proposed NN model comprises two trainable layers. The input layer is of the size of number of drugs in the dataset. Since the number of drugs vary for inpatient and outpatient datasets, the size of the input layers differs respectively. For the inpatient dataset, the size of the input layer is 4,986 and for the outpatient is 3,008. The output layer is of the size of the number of the ICD-10 codes with three-letter prefixes in each dataset. For the inpatient dataset, the size of the output layer is 1,941 and for the outpatient is 1,751. The input is weighted in hidden layer by weights learned through the training process. Then, an activation function is needed to transform the sum of the weighted input to output of that layer. Rectified Linear Unit (ReLu) is a short piecewise linear function that will output the input directly if it is positive; otherwise, it will output zero as shown by Abien Fred Agarap.[20] The choice of this activation function is because it overcomes the vanishing gradient problem (when gradients of the loss function approaches zero), allowing models to learn faster and perform better. We chose the hidden layer of our model to contain 600 neurons with ReLu activation. It is a piecewise linear function that will output the input directly if it is positive; otherwise, it will output zero. The dropout layer is set with a rate of 0.35 that follows the hidden layer.

Since the first NN is trained to predict sets of ICD-10 codes, the loss function used there is binary cross entropy as explained by Shie Mannor,[21] while the second neural network, which needs to predict a single ICD-10 code, has categorical cross entropy as loss function. Both NNs used the Adam optimizer with a batch size of 2,048.

During the prediction phase, in the case of the first network, the set of outputs with output probability value greater than 0.5 is counted as the predicted ICD-10 codes. When no neurons output a value greater than 0.5, the neuron with maximal value will be counted as the only prediction. For the second network, a neuron with maximal value is always counted as the prediction.

**Experimental Results and Discussion**

The data was collected during the period between 2006 and 2019 from the Maharaj Nakorn Chiang Mai Hospital medical record system. Python Statistical Software version 3.5[22] was used for all computations. Python deep learning Keras library[23] was employed for implementation. Pre-processing, building the model (layers and activation functions), and training were performed on a 2-GPU (GTX 1060 6GB) machine. Inpatient medications comprises 5 million unique medications with 13.47 average prescriptions per patient. Outpatient comprises 3 million unique medications and 3.22 prescriptions on average. The data was extracted by grouping all prescriptions related to each episode-of-care ID. Data was grouped by each episode of care. The only pre-processing for the medications dataset was to remove canceled prescriptions and to binarize into multilabel sparse vectors.

Table 4 presents the prediction accuracy for both inpatient and outpatient datasets, respectively.

As mentioned above, for accuracy testing, we followed a well-established procedure explained in Ron Kohavi's study, which we believe gives a very conservative estimate of accuracy performance. We speculate that, in our case, the actual accuracy is higher by about 15 percent to 20 percent. In fact, the existence of label noise in the dataset has many negative potential consequences, such as increasing the model complexity and the degradation of the accuracy of predictions as shown by Benoît Frénay et al.[24] To get a rough estimation of the accuracy over a noisy test set, we assume that there is a correct test set and there is a noisy test set . The noisy test set is the test set where every case coding is randomly changed: some correct codes are removed, and some new random incorrect codes are added. The whole procedure is performed that way that the Jaccard similarity between and is about 70 percent (based on Haefner, we can speculate that the datasets we have contains at least 30 percent of errors).

Suppose the predicted set has a Jaccard similarity score of 60 percent with the correct test set . Thus, every case t from has, on average, 60 percent of labels guessed correctly (out of union of labels from and ) by the corresponding prediction . Out of that 60 percent of correct labels, only 42 percent are deemed correct in the set (since has noise). If we assume that probability to guess noise labels from by the algorithm is very low, then if the algorithm scores actual accuracy of 60 percent, it will only show an accuracy of 42 percent on the noisy dataset .

Thus, the figures in Table 4 are very conservative estimates of the real prediction performance and, according to the explanations above, they reflect approximate accuracy of as high as 55 percent to 65 percent over clean test sets.

**Limitations of the Study**

ML approaches suffer from some limitations for practical applications. One of them is that new, complex, or rare cases cannot be handled directly by the system, as it has no prior familiar examples to learn from. This means that even if a much more advanced system that is accepted for production use, it will only replace a limited amount of coding work, leaving the most complex, new, and borderline cases for professional medical coders to confirm.

Other limitations are more on the technical side of the approach. One of them is that assigned ICD-10 codes are treated as a set, which is not always the case, as some ICD-10 codes can work as modifiers. Another limitation is that only first three symbols of ICD-10 codes are used for prediction. This limitation comes from restricted data we had for prediction (we are considering prediction full ICD-10 codes in the future). The last limitation is that all data rows are considered without any chronological order while, in practice, predictions are done using only past data.

## Applications

Our internal evaluation of the system shows that, currently, the system allows for short-listing and automatically recommending relevant ICD-10 codes. This can improve the performance and accuracy of professional medical coders and save both time and effort in the process. Another possible application of the system is ICD-10 auditing, which is a critical procedure carried out by medical authorities to assess the quality of coding in health organizations. This can be done by the system through short-listing complex and extreme cases for human investigation.

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# There are no comments yet.

# ASSOCIATION RULES IN HEART FAILURE READMISSION RATES AND PATIENT EXPERIENCE SCORES

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*By Braden Tabisula, MBA, RHIA, CHDA*

**Abstract**

**Objective:** Thirty-day readmission rates are closely monitored in today's healthcare ecosystem to prevent higher-than-average rates in inpatient settings. Excess readmission rates result in decreased reimbursement for healthcare facilities. Additionally, feedback from patients about their hospital experience may indicate areas of improvement for healthcare facilities. This feedback is a national survey that collects data on patient experience through a standardized survey called Hospital Consumer Assessment of Healthcare Providers and Systems (HCAHPS). The objective of this study is to identify significant patterns between readmission rates and HCAHPS survey data through the application of association rules.

**Materials and Methods:** Publically accessible HCAHPS survey data and 30-day readmission rates provided by the Centers for Medicare and Medicaid Services (CMS) were utilized for this study. Through the implementation of association rules using SAS Enterprise Miner, significant rules were identified in the data.

**Results:** Association rules were developed in SAS Enterprise Miner and produced three significant rules associated with high heart failure (HF) readmission as the right-hand rule. The rules indicated that a high pneumonia readmission, a low cleanliness star rating, and a low medication communication star rating were associated with a high readmission rate for heart failure.

**Conclusions:** The rules provided strong associations between HCAHPS star ratings and determining a high readmission rate for HF. It was interesting to find that pneumonia readmissions exist as well with a high HF readmission. Hospitals should work on improving their star ratings for the HCAHPS domains identified and work on lowering pneumonia readmissions to lower their HF readmissions.

**Keywords:** hcahps, readmission rate, heart failure, association rules, patient satisfaction

## Background and Significance

### *Hospital Readmission Rates*

Coding professionals and health information professionals play a huge role in assuring the appropriate documentation and applying accurate diagnosis codes to properly identify any hospital readmissions. A particular quality of care indicator are 30-day readmission rates. When patients return to a hospital for the same condition within 30 days of their discharge, this brings into question a possible case of inadequate care. With the average length of stay scrutinized in the current healthcare ecosystem, the faster hospitals get the patients out, the less a hospital incurs in costs for providing care to the patient. However, hospitals must still maintain their quality of care while implementing ways to reduce costs. This important indicator is not only monitored internally, but by a major external organization.

The program, designed by the Centers for Medicare and Medicaid Services (CMS) to begin monitoring these high readmission cases, meant hospitals would begin to see a reduction in their reimbursement when readmission volumes are higher than the national average. Identified in the program are six diagnoses that CMS has deemed crucial enough to monitor. The Affordable Care Act initialized monitoring and controlling of healthcare spending toward excessive readmissions on October 1, 2012. The Hospital Readmissions Reduction Program (HRRP) is a Medicare value-based purchasing program that reduces payments to hospitals with excess readmissions.[1] According to CMS, acute myocardial infarction, chronic obstructive pulmonary disease, heart failure (HF), pneumonia, coronary artery bypass graft surgery, and elective primary total hip arthroplasty and/or total knee arthroplasty are the conditions and procedures currently monitored by the program for excess readmissions.[2] These conditions are recognized by CMS to have excess readmissions in the acute, inpatient settings. One of these conditions are identified below as impacting Americans and the readmission to hospitals.

*Heart Failure (HF)*

This study will specifically look at heart failure readmissions. The focus on heart failure is due to its widespread prevalence in American hospitalizations. Chronic heart failure (CHF) affects over 5 million Americans and accounts for over 1 million hospitalizations annually.[3] In order to predict the risk associated with heart failure readmission, the Readmission After Heart Failure (RAHF) scale was developed.[4]

Subsequently, CHF is the most common indication for admission to the hospital among older adults.[5] The older adult population indicated in the study is the population primarily funded through Medicare. Behavioral factors, such as poor compliance with treatment, frequently contribute to exacerbations of heart failure, a fact suggesting that many admissions could be prevented.[6]

In a study conducted by the Veterans Health Administration, results indicated that two hospitals (2 percent) had a CHF risk-stratified readmission rate (RSRR) worse than the national average, whereas no hospital demonstrated worse-than-average RSRR for AMI or pneumonia.[7] Additionally, the study attempts to combine three years of data indicating hospitals had RSRRs worse than the national average for all three conditions.[8] Another study found that of patients with HF, about 23 percent of them were readmitted or died within 30 days of hospital discharge.[9]

The studies introduced above from the literature review indicate a presence of readmission rate studies due to the impactful nature of HRRP on reimbursement. However, many of these studies were conducted without the use of the Hospital Consumer Assessment of Healthcare Providers and Systems (HCAHPS) data for patient feedback on their hospital experience. This allows for further research into the predictive power of HCAHPS scores on readmission rates for CHF.

As a government payer, Medicare seeks to reduce payment for subpar care. Readmission rates above the average for the nation are penalized.[10] Hospitals will continue to lose money if readmission rates are not lowered. Hospitals in this situation try to implement changes and improve processes to get readmission rates below the national average. To see a reduction, the right change must be implemented.

*HCAHPS Surveys*

HCAHPS provides scores for domains related to the patient's experience during their stay. HCAHPS are patient-completed surveys that are provided to the patient once they have been discharged. According to CMS, the HCAHPS survey asks discharged patients 27 questions about their recent hospital stay. The survey contains 18 core questions about critical aspects of a patient's hospital experience (e.g., communication with nurses and doctors, the responsiveness of hospital staff, the cleanliness and quietness of the hospital environment, pain management, communication about medicines, discharge information, overall rating of hospital, and would they recommend the hospital).[11]

The HCAHPS scores are a way to gather valuable feedback from the patients on the quality of their hospital stay. This data could assist the healthcare facility in further determining areas of improvement or to boast areas of excellence. As indicated, the survey measures multiple areas, addressing communication, cleanliness, and many more. The HCAHPS survey addresses 10 of these domains in total.

For each domain question, a patient has the option to select an answer from varying degrees. For most of the questions, the available responses are on a scale of "Always," "Usually," or "Sometimes/Never." For the question on whether the patient would recommend the hospital, only responses of "Yes" or "No" are provided. Other domains include binary responses, as well, such as "Agree" or "Disagree."

The survey results are analyzed by the Agency for Healthcare Research and Quality (AHRQ) and provide an overall star rating for the hospital and each domain. This normalizes the varying samples of the hospitals and provides every hospital a 1-5-star rating for each of the 10 domains. The healthcare consumers, healthcare providers, and third-party payers can better understand a star rating when comparing healthcare providers.

HCAHPS scores can provide insight into the quality performance of the hospital. Using star ratings, a hospital could have low star ratings on the quietness or cleanliness domain, which may influence a healthcare consumer's decision to choose that site for a procedure. Other domains identify the healthcare provider's level of engagement with their patients. The star ratings in the domains of nurse communication or communication about medications may indicate high or low engagement between clinicians and their patients. Overall, star rating and recommendation domains may indicate whether a patient will return to that facility for future procedures or decide to acquire their healthcare needs elsewhere.

Both HCAHPS and readmission rates are publicly available datasets published by CMS, and several studies are utilizing both datasets. The previous studies indicate heart failure readmission rates as an area of study and interest in the healthcare domain. One group attempted to find a link between the HCAHPS responses and readmission rate, and conducted a retrospective analysis using 10 years of HCAHPS and readmissions data. Results indicate that patients who responded after readmission were significantly more dissatisfied with physicians, staff responsiveness, pain control, discharge plan, noise, and cleanliness of the hospital.[12]

Another study, explicitly focused on total hip arthroplasty readmissions and HCAHPS data, reports 30-day readmissions were associated with a significantly lower likelihood of rating the hospital a 9 or 10 out of 10.[13]

A retrospective, cross-sectional study examined the relationship between communication and discharge HCAHPS questions and readmissions at 30 days, specifically at the patient level. In conclusion of their study, six of the eight items analyzed were found to be significantly associated with 30-day readmission, and two of the HCAHPS questions (relating to “help after discharge” and “receiving written information after discharge”) had higher top box responses for readmitted patients than non-readmitted patients.[14]

*Association Rules*

Association rules analyze items or attributes in transactional datasets that are commonly found together. In market basket analysis, association rules can identify which items are frequently purchased together. This data-mining approach can support decision-making to optimize item purchases in a market setting. An example of such an association rule is the statement that 90 percent of transactions that purchase bread and butter also purchase milk. The antecedent of this rule consists of bread and butter, and the consequent consists of milk alone. The number 90 percent is the confidence factor of the rule.[15]

One study sought to use association rules in finding interesting patterns in hospital infection control and public health surveillance data.[16] Association rules utilizing the HCAHPS data and readmission data would identify interesting patterns among the different HCAHPS domain star ratings and readmission rates for hospitals. Each transaction in this dataset is a healthcare provider. In pursuit of finding meaningful and accurate association rules, the study excludes the other conditions and procedures indicated by CMS in the right-hand rule. The target right-hand rule, or consequent, for this study will be a high or low readmission rate for CHF. Left-hand rules, or the antecedent, will include domain star ratings for the facility from the HCAHPS data, as well as all types of readmissions found in the 30-day readmission dataset. The solution will be built using SAS Enterprise Miner (SAS EM) to develop these association rules.

**Materials and Methods**

*Data Extraction and Collection*

HCAHPS data was downloaded from the CMS website for the latest year available. The Readmission rates for hospitals were also downloaded from the same source. The data collection period for the HCAHPS data set was 2017-2018, and the readmission rates dataset had a collection period of 2014-2017, as well. The datasets were available in CSV format and imported into Excel for data preparation and cleanup.

*Data Preparation*

Since both datasets came from CMS, all records came with an identifier assigned by CMS. This made the process of merging the datasets seamless. The HCAHPS dataset included the following hospital attributes: HCAHPS Measure ID, Provider ID, Hospital Name, Address, City, State, ZIP Code, County Name, Phone Number, HCAHPS Question, HCAHPS Answer Description, Patient Survey Star rating, Patient Survey Star Rating Footnote, HCAHPS Answer Percent, HCAHPS Answer Percent Footnote, HCAHPS Linear Mean Value, Number of Completed Surveys, Number of Completed Surveys Footnote, Survey Response Rate Percent, Survey Response Rate Percent Footnote, Measure Start Date, Measure End Date, and Location.

Attributes from the HCAHPS dataset were removed except for Provider ID, HCAHPS Question, and Patient Survey Star Rating. Additionally, the only rows retained from the dataset were the rows pertaining to the HCAHPS Question that measured “Star Rating” of the domain. After filtering out the other questions, there were 10 rows remaining for each unique Provider ID. The Star Rating for that row was in the Patient Survey Star Rating column. The 5-star rating was further categorized as “high” or “low” to represent a 4- or 5-star rating, or a 1- to 3-star rating, respectively. This created a new derived attribute to represent the star ratings such that Patient Survey Star Rating was no longer required for the dataset.

Utilizing association rules for this study requires all the data to be represented in two columns. The first column indicates the Provider ID, later to be recognized in SAS EM as the ID. The second column will be each unique attribute related to the provider. After preparing the HCAHPS dataset, three columns were retained, one column containing our derived attribute. To utilize this dataset in SAS EM, HCAHPS Question and our derived attribute needed to be concatenated in Excel. While retaining the original data values in the two attributes, a new derived attribute was created. An example of this new attribute is, “Low Discharge Information - Star Rating,” which represents a provider’s star rating for Discharge Information domain between 1 and 3.

A similar process was followed for the Readmission Rate dataset. The dataset began with the following attributes for the Readmission Rate dataset: Hospital Name, Provider ID, State, Measure Name, Number of Discharges, Footnote, Excess Readmission Ratio, Predicted Readmission Rate, Expected Readmission Rate, Number of Readmissions, Start Date, and End Date.

After reviewing the attributes, the only attributes retained were Provider ID, Measure Name, and Excess Readmission Ratio. For the determination of a “high” readmission rate and a “low” readmission rate, the excess readmission ratio was categorized to low or high. Since the ratio represented a comparison of the provider’s rate to the national rate, anything above a 1 would be interpreted as a higher-than-average readmission rate. A provider with a number less than 1 would have a lower-than-average readmission rate. A formula was created in Excel to translate values in excess readmission ratio greater than 1 to be high and all else translated to low. This became our new Readmission Rate, and Excess Readmission Ratio was removed from the dataset. Additionally, to create one field from the two (Measure Name and Excess Readmission Ratio), another attribute was created to concatenate the value in each column. An example of this derived field is High READM_30_HF_HRRP, representing a greater-than-average readmission rate than the national rate for heart failure.

When both datasets had been separately cleaned, they were merged into one CSV file. Each Provider ID would include several rows of attributes, including each Domain Star Rating and the Readmission Rate category. The data was now prepared for the SAS EM environment and was imported into the application.

*Data Analysis*

The File Import node was placed into the workspace. This allowed the file to be imported. The variables of the dataset need to be assigned roles. The Provider ID field was given the role ID, and the attributes column was assigned the Target role. Additionally, the parameters need to be adjusted in the File Import node to indicate transactional data. The Association node was placed on the workspace and ran.

*Post-Pruning*

With the initial output of rules resulting from the analysis, the right-hand rule of “High READM_30_HF_HRRP” needed to be retained and the rest of the rules filtered out. Once the other rules were removed, to find strong rules from those that remain, the parameters to prune the rules were adjusted. Confidence was set to 60 percent or higher, Support was set to 20 percent or higher, and Lift was set to >1. Three rules remained after post-pruning. Additionally, it was important to identify the statistical significance of each rule. To find out if any of the remaining association rules were significant, the first step was to find the reliability of the rule that was calculated by finding the difference between expected confidence and confidence.

To measure the statistical significance of the rule, a t-test was performed to evaluate the significance of the difference in expected confidence and confidence, represented as reliability. The three remaining rules after post-pruning were identified as significant according to our t-test statistic. The following association rules remained after post-pruning was completed:

Rule 1 Low Cleanliness - Star Rating & High READM_30_PN_HRRP ==> High READM_30_HF_HRRP
Rule 2 High READM_30_PN_HRRP ==> High READM_30_HF_HRRP
Rule 3 Low Communication About Medicines - Star Rating & High READM_30_PN_HRRP ==> High READM_30_HF_HRRP

**Results**

As a result of the data-mining process and using association rules, three interesting rules were produced with a high readmission for heart failure as the right-hand rule. Two of the rules were three-item rules, and one of the rules a two-item rule. All three rules contained high readmission for pneumonia in the left-hand rule. The three rules are explained below.

Rule 1 indicates that if there was a low cleanliness star rating and a higher than the national average readmission rate for pneumonia, it is associated with a high readmission rate for heart failure. A low cleanliness rating indicates that the cleanliness domain was scored below a 4-star rating. This domain primarily covers the aspects of care related to how clean a patient felt the room was during their stay. In the study by Siddiqui, et al. (2018) above, they found that patients who were readmitted were dissatisfied with cleanliness, among other domains.

Rule 3 suggests that if a hospital has a low star rating for communication about medicines and a high readmission for pneumonia cases, then a high readmission rate for heart failure followed. Patients who have come into the hospital with heart failure tend to go home with some type of medication. The common ones are ACE inhibitors, beta-blockers, digoxin, and diuretics. When low communication star ratings are assigned, patients are indicating that they were either not shown how to take their medications or feel there was enough explanation about their medications. When a patient does not follow medication instructions regularly, it may lead to poor management of their heart failure condition at home. This can lead to a readmission to the hospital because the patient may have not been following their prescribed medication regiment appropriately. This low rating, along with a high pneumonia readmission, also associates with a high HF readmission.

Rule 2 is explained, as it exists in Rule 1 and 3. The rule states that if the hospital has a high pneumonia readmission, then a high heart failure readmission is associated. Since heart failure and pneumonia are part of the cardiopulmonary system, when a hospital poorly manages the care of pneumonia cases, it is possible that it associates with poorly managed HF cases as well.

**Discussion**

A major strength of this solution is that the association rules data-mining technique has not been applied to the readmission dataset and the HCAHPS dataset in previous literature. Other attempts at using association rules were applied to different datasets, but not the two used in this study.

Association rules can provide insight to the probability of a HCAHPS domain associating with a high readmission for heart failure, but the study also found that there were association rules between the high readmission types being monitored by CMS. It was identified that cleanliness, high readmission for pneumonia, and communication about medications reveal an association to high heart failure readmissions.

A limitation of the proposed solution is the varying response rates from the HCAHPS data. Since the dataset comes from patient responses, it may be difficult to get a response from every patient that comes in. A second limitation is the age range of the individuals captured from the surveys. As Medicare beneficiaries are typically aged 65 or older, there is not a full representation of the entire healthcare population. This means that results from these association rules may only apply to a certain age demographic covered by Medicare and Medicaid programs.

**Conclusion**

In this study, the data-mining technique of association rules was implemented to explore any patterns between HCAHPS domains and readmission types. Since the diagnosis of heart failure is a major condition that affects millions of Americans each year, and frequently brings patients to the hospitals, the readmission rates for this specific condition were the focus. The Excess Readmission Ratio and the HCAHPS Domain Star Rating were used to find any association with a high readmission of heart failure.

The analysis produced three significant rules from the combined datasets. High heart failure readmission was the determining right-hand rule for the association rules that remained after pruning. In the left-hand rules, we identified high pneumonia readmission, a low cleanliness star rating, and low star rating for medication communication. The results from this analysis would indicate that if a healthcare provider has a high readmission rate (i.e., greater than the national average) for heart failure, they might also have high readmission rates for pneumonia cases. Furthermore, it was identified that low star ratings in the HCAHPS domains of the hospital's cleanliness and communication about medications were strongly associated with high heart failure readmissions. If a healthcare provider wants to improve their high heart failure readmissions, these two areas may be considered to focus improvement efforts.

In future work, this analysis could be expanded to focus on finding other patterns among the other excess readmission types monitored by CMS. Other data-mining techniques could also identify relationships among the domain star ratings themselves or find connections to other areas like hip replacements or acute myocardial infarctions, which are other conditions that frequently bring patients to seek care.

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## Notes


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## There are no comments yet.