A VIRTUAL LEADERSHIP PROGRAM'S IMPACT ON EMPLOYEE LEADERSHIP DEVELOPMENT AT A HEALTHCARE ORGANIZATION

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Abstract

In this study, we explored the effectiveness of the virtual organizational leadership development program at Mayo Clinic. The purpose of this study was to explain how a virtual leadership development program impacted employee leadership efficacy. The research questions addressed how the program affected participant promotions, how the program learning objectives were implemented by participants, and how the program impacted participants. Collection tools included satisfaction surveys, interviews, and data reflecting promotion rates. Participants appreciated the advantages of the virtual format of the program and the quality of the instructors. They completed the program with enhanced communication skills, the ability to influence positive change, and increased self-awareness. Opportunities for program improvement included incorporating real-world projects to give participants the ability to practice the leadership skills taught, the ability to be paired with a mentor, and a second part to the program to explore the leadership competencies at a more advanced level.

Keywords: Healthcare, leadership, virtual, technology, organizational, education.

Introduction

Mayo Clinic, a large interdisciplinary educational healthcare organization, was the study site where we explored how the use of a virtual leadership development program impacted employee leadership development by assessing the promotion rates of those who completed the program as well as the satisfaction rates of participants and their supervisors. The specific area of interest for this study was a program offered by the organization's human resources department–a virtual leadership development program. The program targets employees who are interested in advancing their leadership skills but who do not have a leadership title.

Background

The virtual leadership development program was established in 2016. Its purpose was to prepare candidates for future leadership roles in the organization by equipping them with appropriate skills and competencies. Since the program's inception, no formal assessment of its effectiveness had taken place prior to this study due to competing priorities. Without an exploration of the data associated with the program, it was not known if the program was successfully achieving its goals. This hindered continual improvement of the program without data to support enhancement. The problem was that data existed but had not been analyzed to determine the effectiveness of the virtual leadership development program. The purpose of this study was to explain how an existing virtual leadership development program utilized at a healthcare organization impacted employee leadership efficacy. The program was developed to create an engaging learning opportunity for employees interested in leadership roles within the organization. Leaders at the organization rely on this perpetual building of knowledge for continued organizational success.

The research questions that guided this study were:

1. How did the organizational virtual leadership development program affect participant promotions at Mayo Clinic?

2. How were the organizational virtual leadership development program learning objectives effectively implemented by participants?

3. How were the organizational virtual leadership development program learning objectives effectively implemented by participants from the supervisor's perspective?

4. How did the organizational virtual leadership development program impact participants?

Methods

In the current study, we utilized Charmaz's (2014) constructivist approach to grounded theory. In this view, grounded theory includes iterative logic with a focus on flexible application of the research design. Theory using this research design is based on data directly from those who experienced the phenomena being researched. The data combined with the researcher's investigation generates the explanation and theory. Grounded theory provides guidelines for research that are systematic, yet flexible for data collection and analysis.[1]

Therefore, for the purposes of this study, we utilized the grounded theory design to examine the virtual leadership development program's effects and identify the impact the program has had on participant promotions and participant and supervisor satisfaction rates. It is through interactive and comparative inquiry, which is the coding of numerous comparisons of data[1], that this study explored whether the virtual organizational leadership development program was indeed developing leaders. The perspectives of the virtual leadership development program participants and supervisors were evaluated in this study. Institutional Review Board approval for the study was acquired from the organization.

Participant Selection Logic

Criteria for selection of participants included theoretical sampling which is a data collection process involving the simultaneous collecting and coding of data. This process drives the decision-making for data collection and is central to grounded theory which ensures that the research produces a theory that is truly grounded in data.[2] In this sense, the processes of data collection, coding, and analyses are performed concurrently, and the data directs the researcher in what to collect next.[1] Using this method, the researcher must remain open to following the data and potentially revising what is being asked of participants; hence, semi-structured interview questions offer some flexibility.

Data Collection

Surveys, interviews, and data reflecting promotion rates were the primary data utilized in this grounded theory study. Researchers who use grounded theory typically use interviews as the primary data collection technique.[1] In this research study, we conducted interviews and collected data from surveys and human resource systems. Grounded theory research also focuses on comparing data systematically and allowing categories or themes to emerge as it is collected rather than waiting until all data is received. While the survey and systems data in this study were received in totality at once, we remained true to the concepts of grounded theory and coded interviews as they occurred by immediately transcribing the recorded interviews and codifying themes.

Data Analysis Procedures

For the developers of the virtual organizational leadership development program to understand the perspectives of program participants and their supervisors as well as the impact of the program, a three-fold approach to research was utilized in data analysis: (1) satisfaction survey results from participants and their supervisors were collected and analyzed; (2) interviews of participants were conducted and analyzed; and (3) promotion rates were extracted from the human resource system for all program participants and analyzed.

The satisfaction surveys were already in existence as all participants and their supervisors had been requested to complete surveys since the first cohort in 2016. The questions were not altered to ensure the consistency of the data collected from all cohorts for inclusion in the study.

Results

In this study, participants were selected based on their completion of the virtual organizational leadership development program. All those who had previously completed the program were included in the collection of existing study data which included participant and supervisor satisfaction survey results and promotion rates. The participant list included 435 people who had completed the program at the time data collection for the study commenced. Two additional cohorts were scheduled after the data was collected and were not reflected in the study results. Participants were employees of Mayo Clinic who were not in a formal leadership role at the time of enrollment in the virtual organizational leadership development program. Supervisors of participants were also included in the participant selection for the study as they also completed satisfaction surveys to provide feedback on their perspectives of the impact of the program on participant leadership skill enhancement. Both program participants and supervisors were from diverse areas across the organization which offered an enterprise-wide perspective as displayed in **Table 1**.

The study also incorporated interviews of participants. An invitation to participate in an interview was sent to all program participants via e-mail. The first 12 participants to respond with an interest in participating were selected for interviews. This was consistent with the recommendation that 12 interviews are sufficient for most research studies to gather data and generate themes on

participant perspectives and experiences. Guest, Bunce, & Johnson (2006)[3] Charmaz (2014) concurred with this recommendation and it proved to be true as saturation was reached within 12 interviews when no new ideas were being shared by participants. Participants interviewed represented all geographic locations of the organization, again providing an enterprise-wide perspective in data collection through interviews as displayed in **Table 2**.

Summary of Findings

Follow-up Survey to Participants. Of the participants who completed the virtual organizational leadership development program, 149 completed the follow-up survey, which was sent via email immediately following program completion, a 34-percent response rate. The results of that survey are outlined in **Table 3**. Based on the responses, 82 percent indicated they were applying what they learned in the program. Regarding receiving coaching and support from their supervisor in applying their newly acquired skills and knowledge, 57 percent said they had received the support they needed. In addition, 75 percent stated that the program had supported them in their career development.

Follow-up Survey to Supervisors. Of the participants who completed the virtual organizational leadership development program, 130 of their supervisors completed the follow-up survey which was sent via email 60 days following program completion, a 30-percent response rate. The results of that survey are outlined in **Table 4**. Based on the responses, 83 percent indicated their employee was applying what they learned in the program in their current role. Regarding providing coaching and support to assist their employee in applying their newly acquired skills and knowledge, 88 percent said they had provided the support they needed. In addition, 81 percent stated that they valued the communications from the program throughout their employee's cohort, stating it had helped them coach and support the employee through the process.

Post Program Survey to Participants. Of the participants who completed the virtual organizational leadership development program, 284 completed the post-program survey which was sent via email three months following program completion, a 65-percent response rate. The results of that survey are outlined in **Table 5**. Based on the responses, 93 percent indicated they developed skills and gained experiences that aligned with organizational leadership capabilities of inspiring values, engaging colleagues, bold and forward thinking, and driving results. Regarding identifying and practicing skills related to change agility, influencing without authority, building relationships, team dynamics, and communicating effectively, 91 percent said they had met these objectives. In addition, 97 percent stated that the program had helped them differentiate and recognize the impact of leadership with a coaching mindset versus management.

When asked about engagement in self-assessment opportunities in preparation for future leadership roles, 94 percent indicated this had been accomplished in the program. Also, 83 percent of participants believed that the format of the program was conducive to their learning style and preferences. Regarding the time commitment both in and outside of class, 90 percent of program participants believed it was just right and did not need any changes. The majority of participants, 66 percent, thought that program participants should be allowed to miss only one session and watch the recording to receive credit for program completion.

On a scale of one to 10, with 10 being the highest, when asked their level of confidence to apply what they had learned, 98 percent scored greater than five. Five is the mid-point on the scale which would be considered average. In this study, we looked at those scores considered above average. Regarding their level of commitment to apply what they had learned, 100 percent scored greater than five. In regard to expecting positive results from applying what they had learned in the program, 98 percent of program participants scored greater than five. When asked if they would recommend the virtual organizational leadership development program to others, 96 percent scored greater than five on a scale of one to 10.

Promotion Rate Results

Of the participants who completed the virtual organizational leadership development program, 30 participants were promoted to a formal leadership role with direct reports after completion of the program, a 7 percent promotion rate, which is displayed in **Figure 1**. Of the 30 participants who were promoted, three were promoted while enrolled in the program. The average time to acquire a promotion after completion of the program was seven months. In addition, 103 participants were promoted to a role with increased responsibility, but not a formal leadership role with direct reports, a 24 percent promotion rate of informal leaders. In total, 31 percent of those who completed the virtual organizational leadership development program received promotions, while 69 percent of participants did not receive promotions of any kind. Both participants and supervisors indicated that potential to move into formal leadership positions was hindered by limited opportunities for advancement within the organization, rather than the effectiveness of the program.

Research Question 1. *How did the organizational virtual leadership development program affect participant promotions at Mayo Clinic?*

All participants interviewed cited organizational barriers associated with a lack of opportunities for advancement rather than promotion rates being connected to the effectiveness of the virtual organizational leadership development program. This common theme was repeated in the participant satisfaction surveys. Promotion rates indicate that 31 percent of participants were promoted after completion of the program, 7 percent of those to formal leadership roles, while 69 percent of participants did not receive a promotion after completion of the program.

Research Question 2. *How were the organizational virtual leadership development program learning objectives effectively implemented by participants?*

The four objectives were: (1) develop skills and gain experiences that align with the organization's leadership capabilities; (2) identify and practice skills related to the leadership capabilities; (3) differentiate and recognize the impact of leadership (coaching mindset) and management; and (4) engage in self-assessment opportunities in preparation for future leadership roles.

Based on the participant post-program survey, 93 percent indicated they developed skills and gained experiences that aligned with organizational leadership capabilities of inspiring values, engaging colleagues, bold and forward thinking, and driving results. Regarding identifying and practicing skills related to change agility, influencing without authority, building relationships, team dynamics, and communicating effectively, 91 percent said they had met these objectives. In addition, 97 percent stated that the program had helped them differentiate and recognize the impact of leadership with a coaching mindset versus management. When asked about engagement in self-assessment opportunities in preparation for future leadership roles, 94 percent indicated this had been accomplished in the program.

All of these questions were designed to measure participant achievement of objectives and all were over 90 percent favorable. Likewise, in the interviews participants believed that leadership skills were identified and communicated well, self-assessments were beneficial, and coverage of the coaching mindset was the most effective component of the program. The weaknesses identified in achieving program objectives included, opportunities to practice and develop leadership skills with real-world scenarios which could be worked through. Those interviewed indicated that post-program mentoring as well as a second level to the program would be helpful.

Research Question 3. *How were the organizational virtual leadership development program learning objectives effectively implemented by participants from the supervisor's perspective?*

Based on participant supervisor feedback on the follow-up survey to supervisors, the majority, 83 percent, believed that their employee was applying new skills and knowledge attained from participating in the virtual organizational leadership development program. Another 15 percent of supervisors were neutral on the subject, while 2 percent did not believe that the participant was applying skills and knowledge from the program.

Research Question 4. *How did the organizational virtual leadership development program impact participants?*

Based on the data collected and presented in this research study, the program impacted participants in multiple ways. According to the follow-up survey to participants 82 percent indicated they were applying what they learned in the program, 57 percent said they had received the coaching support they needed, 75 percent stated that the program had supported them in their career development. Likewise, in the follow-up survey to supervisors 83 percent indicated their employee was applying what they learned in the program in their current role. In the participant interviews, interviewees indicated that the program was helpful in building their knowledge base of the leadership capabilities ascribed to at the organization and benefitted them with increased self-awareness and an expanded network.

Conclusion

The study results indicated that overall participant and supervisor satisfaction rates with the virtual organizational leadership development program were high. Participants appreciated the advantages of the virtual format of the program and the quality of the instructors. They completed the program with enhanced communication skills, the ability to influence positive change, and increased self-awareness. Based on promotion rates, 31 percent of participants received promotions after completion of the program. Opportunities for program improvement included incorporating real-world projects into the curriculum to give participants the ability to practice the leadership skills taught, the option to be paired with a mentor, and a second part to the program to explore the leadership competencies at a more advanced level. The findings of this study contribute to the existing body of literature with insights into the experiences and perspectives of participants of a virtual organizational leadership development program at a healthcare organization.

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AN INTERDISCIPLINARY APPROACH TO REDUCING ERRORS IN EXTRACTED ELECTRONIC HEALTH RECORD DATA FOR RESEARCH

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ABSTRACT

Erroneous electronic health record (EHR) data capture is a barrier to preserving data integrity. We assessed the impact of an interdisciplinary process in minimizing EHR data loss from prescription orders. We implemented a three-step approach to reduce data loss due to missing medication doses:

- Step 1—A data analyst updated the request code to optimize data capture;
- Step 2—A pharmacist and physician identified variations in EHR prescription workflows; and
- Step 3—The clinician team determined daily doses for patients with multiple prescriptions in the same encounter.

The initial report contained 1421 prescriptions, with 377 (26.5 percent) missing dosages. Missing dosages reduced to 361 (26.3 percent) prescriptions following Step 1, and twenty-three (1.7 percent) records after Step 2. After Step 3, 1210 prescriptions remained, including 16 (1.3 percent) prescriptions missing doses. Prescription data is susceptible to missing values due to multiple data capture workflows. Our approach minimized data loss, improving its validity in retrospective research.

Keywords: Data integrity, electronic health record, data abstraction, prescription.

Background

By 2015 almost 96 percent of all non-federal acute-care hospitals possessed certified health information technology (HIT), and 86 percent of office-based practices had adopted an electronic health record (EHR).[1,2] In addition to its primary function as a documentation tool used to store the clinical narrative, the EHR is a rich source of large amounts of information, including pharmacy, laboratory, financial, and patient demographic data. This gives the EHR utility for public health practitioners and researchers.

This "secondary use" of EHR data[3] is especially powerful when combined with data from other sources, e.g., census tracts, surveys, morbidity and mortality data.[4]

From the technical perspective, data quality in EHR-based studies remains a challenge for investigators with respect to data completeness, standardization and the lack of use of controlled vocabularies.[3-6] The process can be time-intensive, as it involves sifting through raw EHR data that is often disorganized and replete with uncodified variables. Furthermore, data point duplication errors often require specialized personnel with knowledge of the EHR data structure to run meaningful queries.[7] Additionally, limitations include incomplete, inconsistent, or inaccurate data.[5] Other barriers include the presence of multiple disconnected data capture systems, the lack of timely access to EHR data, interoperability issues between EHR vendors,[6-8] and changing data standards and practice guidelines over time.[9]

We had experienced some of these limitations first-hand while evaluating prescribing patterns of second-generation antipsychotic (SGA) medications in children and adolescents. Here we assess the impact of an interdisciplinary, stepwise approach to improve the quality of data by reducing missingness of data during an EHR data abstraction.

Methods

The Institutional Review Board of the primary author's institution approved the study with exempt status. We conducted a retrospective study using EHR data to evaluate SGA prescribing patterns in children and adolescents between June 1, 2017, and December 31, 2018. This included data collected from the Epic EHR (Epic Corp, Verona, WI). We utilized data from three health systems in and around a small Midwestern city in the United States, encompassing a Federally-Qualified Health Center, an academic teaching center, and a private community-based healthcare system. The interdisciplinary team involved a physician, a pharmacist, a biostatistician, and a data analyst who deidentified the data extracted from the EHR.

The requested data included all encounters during the specified time period for all patients under the age of 18 at time of visit who received an SGA prescription at any time during the specified period. The data analyst created a Structured Query Language (SQL) encounter-level report utilizing an abstraction from Epic's Clarity data warehouse. The Clarity database stores hospital-specific data, which analysts query to create complex, data-intensive reports. The analyst masked the patient medical record numbers (MRN) utilizing the community identification number (CID) within the Epic software, which deidentified the data while allowing the research team to group hospital encounters by individual patients. The query design utilized the medication list to pull medication names, frequencies, and doses.

Upon discovering a significant number of encounters with missing medication doses, we were unable to determine if the SGA encounter records without doses were different from the SGA encounter records with doses; we therefore could not rule out the potential of a confounding difference between the two subsets. This was our impetus to design a stepwise approach to minimize missing SGA medication doses:

Step 1: The data analyst updated the data request code to optimize data capture. This was necessary because the first query included all medication orders, including the cancelled and discontinued orders. As researchers, we had incorrectly assumed these orders would not be added. In order to be able to exclude these records from analysis, the analyst edited the query design criteria to only include active and completed medication orders.

Step 2: the pharmacist and physician on the team reviewed the EHR prescription workflows to identify and account for variations in prescribing methods.

Step 3: if there were multiple prescription records for the same patient on the same day, the clinician team determined daily medication doses in one of three ways: (1) duplicative orders were deleted; (2) multiple prescriptions with directions for different times of the day were added; or (3) records of multiple SGA prescriptions were left on multiple rows.

Results

A total of 346 individual patients met the inclusion criteria, representing 1,421 individual SGA prescriptions. The initial query yielded 377 (26.5 percent) entries with missing data. In discussions with the data analyst, we discovered "abandoned" orders in the data set, where a clinician initiated and then discarded a refill or new-prescription order. The data analyst thus required the database to select against "order status = cancelled". This Step 1 intervention reduced the total SGA prescriptions to 1374, with 361 missing dosages (26.3 percent).

Given the continued missing data, we implemented Step 2, with review of clinician orders using the computerized physician order entry (CPOE) system. We found that clinicians were able to use "free text" fields to bypass the discrete dose data field. We then populated medication dose fields utilizing the free-text instructions. The challenges encountered are listed in **Table 1**. This reduced the total number of prescription orders with missing dosage values to 23 (1.7 percent). The remaining unreconciled orders after Step 2 were "blank" free-text fields without dose instructions.

The clinician team then further analyzed data for patients who received multiple SGA prescriptions on the same day, and 373 prescription records met the criteria for Step 3 analysis. The data represented 175 unique encounters (of which 34 encounters had two SGAs prescribed), that contained prescriptions that were interpretable. Once the doses were interpretable, the final dataset contained 1,210 prescriptions, and only 16 (1.3 percent) had a missing dose. The results are summarized in **Figure 1**.

Discussion

Despite utilizing standardized approaches to request specific data points to create an encounter-level report, we discovered a high level of missing data that would have impacted the validity of our intended analysis. Through a systematic, dialectic approach including all members of the team, we initially addressed EHR data request issues of which we were unaware. Even after optimizing the data request code, the persistent missing data required a "manual" review via specific expertise of investigators who were familiar with clinician prescribing workflows to reduce errors to an acceptable, though non-zero, level. We particularly emphasize the amount of variability in prescription ordering workflows within the sample; clinicians often tailor established EHR workflows to their preferences and personalize their approaches to using EHR features.[10] Due to this widespread practice, it is critical to recognize and capture this variation when evaluating data sets for accuracy and validity.

Medication prescribing orders are particularly vulnerable to errors related to the common structure of these orders. CPOE medication fields consist of three main regions: the prescription or “Rx line”, which contains medication name, strength amount and units, and drug form; the patient instructions or “Sig line”, which includes dose units, route of administration, frequency and duration in days; and a “Special Instructions line”, which includes detailed instructions and clarifications. It is the latter that generates the free-text field.[11] In the clinical setting, prescriptions are used essentially as a communication tool between clinicians and pharmacists. Thus, discrepant or unclear instructions are resolved using either the pharmacists’ knowledge or follow-up communication between the two providers, a system that leads to inefficiencies.[11]

We found variable free-text data that led to analysis discrepancy after the first intervention in up to 24.7 percent of the data points, which was less than Palchuk’s study,[11] but still required Step 2 of the intervention. Multiple strategies have been proposed to draw meaningful information from indiscrete data, including using established databases and rule-based systems[12] and machine learning analyses.[13] Instead of retrospective approaches for data extraction and “cleaning”, we stress the importance of proactive approaches that educate clinicians on the importance of following standard CPOE prescription workflows in the EHR. One strategy is to optimize prescribing workflows through a user-centric CPOE system, which includes using drop-down menus for drug dosing options. A system that prioritizes selecting commonly found medication doses and routes could prevent clinicians from bypassing discrete entry in favor of free-text options.[14] Another way is to implement clinical decision support (CDS) processes that can perform checks on free-text orders[11] though there are limits to both the deployment and functioning of CDS.[15] Until such time that a singular or combination of strategies are used to automate mitigation of errors in prescribing input, we believe that research teams should utilize an interdisciplinary approach with content-expert team members to contribute to the process. As evident from our method, although data analysts are integral to the data pull and serve as the “honest broker” for research protocols,[16] they are often unable to account for the nuances in clinical workflows that impact data quality. This underscores the importance of having a clinician on the investigator team who is intimately familiar with the clinical process where the data are generated and collected. Similarly, clinical investigators often have limited knowledge of how data is structured within the EHR, and the analyst is needed to implement changes, as was the case in our Step 1 with the cancelled orders. An interdisciplinary approach has grown in healthcare research[17] and has particular value in EHR-based research involving informaticians and clinicians. However, not every institution has access to a clinical informatician, hence it is critical to build teams with interdisciplinary content expertise.

The limitations of our study included data from a single EHR covering three organizations in a single geographic area, and hence results may not be generalizable to other regions or EHRs. However, replication with larger sets of data points and collating data from multiple sources can extend our model and test its value. This was also a cross sectional approach, looking at a defined set of prescriptions as part of larger project. It would be important to look how pervasive the errors are when expanded over a longer period of time. Furthermore, system workflows change over time, so any follow-up studies must account for practice or guidelines changes.[18] Finally, we did not compare a human review to machine learning or other automated methods.

Conclusions

An interdisciplinary, stepwise approach to reducing EHR-based prescription data loss can be effective. Prescription data is particularly susceptible to missing values given the multiple methods of data entry, including the use of free-text fields, sometimes replete with medical abbreviations and typographical errors. We advocate that EHR developers explore ways to simplify interfaces and options with an eye to reduce human error opportunities, so that clinicians can document in the EHR using the method that best matches their workflow. Multiple methods of data entry can complicate the secondary use of EHR-data for research. On research teams involving EHR data, input from clinicians and other content specialists is critical to optimizing the completeness, accuracy and validity of an EHR-data abstraction, since quality of studies that use EHR data are only as good as the data that is available.

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AN EXPLORATION OF GLOBAL LEADERSHIP BEHAVIOR AND JOB SATISFACTION IN HEALTH INFORMATION MANAGEMENT

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Abstract

Health information management (HIM) professionals are a vital component of a global network of healthcare specialists who assure quality documentation, data governance, analysis of data, and medical coding of vital healthcare statistics.[1] These healthcare professionals make up a globally diverse community[2] which demands leaders with globally transferable leadership skills.

The goal of this study was to explore the application of Servant Leadership Theory[3] to job satisfaction through globally applicable and transferable leadership behavior. A case study approach of semi-structured interviews and blog posting entries were examined through the principles of a global mindset.[4] Results of this study are applicable to the community of practicing HIM professionals through the identification and examples of the application of effective and globally transferable leadership behavior.

Keywords: Health information management, global leadership, global mindset, servant leadership

Introduction

HIM professionals are a vital component of a global healthcare workforce who apply their expertise in governing and analyzing healthcare data for security, accuracy, and integrity. There are more than 200,000 HIM professionals in the United States[5] and over 32,000 in Canada.[6] Due to the globalization of healthcare, the outsourcing of HIM tasks has increased by 31 percent from 2011 to 2016[7] and international companies based in the United States are hiring HIM professionals from around the world. This has spawned a mosaic of ethnicities in HIM[8] who are at the forefront of a digital healthcare industry which has transformed from regional to global and consumed more than or $3.5 trillion, or 18 percent of GDP in 2017.[9]

It's projected the United States will see an increase of more than 6,000 HIM positions per year, yet foresee only 2,000 annual graduates from accredited HIM programs.[10] In Canada, an additional 12,330 will be needed within the next few years.[11] The shift to a global workforce and the projected shortage of HIM professionals presents the importance of providing an organizational climate which promotes job satisfaction. When professionals compare the aspects of a job, allowances for pay and working conditions will be made, but recognition of personal and professional value won't be sacrificed.[12] Identifying globally transferable leadership skills which recognize and nurture the value of the employee is vital to the recruitment and retainment of qualified employees.

Job satisfaction is dependent on the communication and relationship[13] between an ethical leader[14] and follower. This provided the motivation to explore servant leadership theory through the application of a global leadership approach. Servant leadership behavior is comprised of conduct which “seeks to involve others in decision making, is strongly based in ethical and caring behavior and enhances the growth of workers while improving the quality of the organizational climate"[15] and exhibits the behavioral traits and characteristics of serving first and leading second. Yet, within the global society of HIM professionals, exhibiting these leadership traits are not enough; leaders must be able to apply global leadership skills in an environment of global diversity.

An effective leader of HIM professionals must have the ability to motivate a group of people, constructively seek a clear vision and foster growth while working within a globally complex frame of reference.[16] The ability to learn and understand at a global level (intellectual capital), the self-confidence to function in a cultural environment different from their own (psychological capital) and the ability to cultivate new relationships with individuals from diverse cultures (social capital) is crucial to serving first and leading second in global diversity.[17]

Due to the crucial need of globally effective leaders, this research explored the effect of servant leadership theory on job satisfaction as applied through a global mindset of leadership behaviors. Canadian participants were included due to both the United States and Canada experiencing a shortage of HIM professionals and to give the research a global perspective. The context of this qualitative research was framed within the thematic description of 10 servant leadership characteristics[18] and the original servant leadership definition of, "The best test is: Do those served grow as persons; do they, while being served, become healthier, wiser, freer, more autonomous, more likely themselves to be servants?"[19] and the merger of global mindset characteristics[20] demonstrated in **Table 1**.

The servant leadership traits of conceptualization, persuasion, building community, commitment to growth and foresight of the future[23] were also explored through a definition of global leadership[23] shown in **Table 2**. Please note the original theory of servant leadership was developed in 1970, and the bulk of research following took place within the first quarter century of development. Hence, you will find research and references within this research predominately from the time period of 1970s to the mid-1990s.

Methodology

The multiple-case study and blog entry format utilized was based on a constructivist approach[26] and utilized the Interactive Model of Research Design[27] to explore the following questions:

1. How do HIM professionals describe the experience of job satisfaction in the United States and in

Canada?

2. How do HIM professionals describe their job satisfaction experiences with leaders who exhibit servant leader and global mindset behavior?

3. How do leaders describe the role they play in the job satisfaction of HIM professionals?

As seen in **Figure 1**, the Interactive Model of Research Design[28] intertwines the goal, conceptual framework, method, and validity with the research questions which allows continual assessment and comparison between each investigative component.

Similarities and differences were explored between participant responses from semi-structured interviews with currently employed HIM professionals in the United States and Canada and an additional cyber-artifact obtained from open forum blog entries. The use of blog entries provided a forum for anonymous participant participation and provided extensive data within a naturalistic context.[30] Blog entries also represented the "symbols" of the group and were used to "understand their beliefs, values, and behaviors."[31]

Blog entries further allowed a view of the everyday life of the blogger[32] with the additional ability of continuous access to data. Both participant interviews and blog entries were focused on the leader/follower perception of servant leadership, global mindset, and job satisfaction.

United States interview participants were procured from the eastern United States, while the interview participants from Canada were procured from both the eastern and western sections of northern Canada. Interview participants were chosen randomly from a request for participation from the website of three different professional organizations for HIM professionals.

Due to not knowing the number of interview participants and blog entries needed prior to beginning this qualitative/case study research, a prediction of ten participant interviews and cyber-artifacts was made. The exploration of data continued until saturation (each new unit of analysis produces very little new data) was reached[33] which resulted in conducting 11 extensive interviews. Blog entries of three HIM professional organizations were chosen for their focus population of health information professionals. Blogs were seeded (an initial post regarding general leadership behavior was posted to begin a conversation) and open forum blogs were monitored for 14 days.

Data analysis focused on coding and analyzing for the thematic presence of job satisfaction, servant leadership behavior and an attitude of global awareness within two recognized qualitative strategies- a categorizing strategy (coding) which disaggregated the data into substantive categories and an additional analysis of data by theoretical categories which allowed a comparison with previous leadership theory.[34] Substantive categories allowed "open coding" to be performed which permitted an exploration of general, overall concepts within the data while "theoretical propositions"[35] of Servant Leadership Theory[36] and a global attitude were analyzed. All interview participant and blog participant entries were coded utilizing the 54 codes listed in **Table 3**.

Due to the large scope of acquired data, in addition to manual coding, the qualitative cross-platform QDAS (qualitative data analysis software) system Dedoose™ was employed to code professionally transcribed interviews and blog entries. This provided the opportunity to "learn about the rich, complex and contextualized ways in which our research participants experience their lives"[37] which coincided with the qualitative focus of the study.

Findings

Each research question was analyzed for thematic presence of servant leadership behavior and included both interview and blog participant data. Job satisfaction task codes were used to determine the thematic presence of job satisfaction. (See **Table 4**, **Table 5**, and **Table 6**).

The use of case description[38] was used in the interpretation of data to find the thematic presence of servant leadership behavioral characteristics and five characteristics of job satisfaction.[39] **Figure 2** shows a summation of thematic presence by listing the major themes found throughout the data by frequency of both interview and blog participant data.

Table 7 depicts the analysis of the 19 functional attributes of servant leadership,[40] with data disaggregated by interview and blog participants and was singled out for analysis due to its servant leadership inclusivity.[41] **Figure 3** shows 91 percent (10 of the 11 participant interviews) and 100 percent of blog participant entries were coded for stewardship.

Analysis of job satisfaction data included comparing coded results between interview and blog participant data for application of the five job characteristics of job satisfaction[42] and the servant leadership categorical, parent and sub-codes developed from the ten-servant leadership characteristics[43] are found in 100 percent of all participants. (**Figure 4**)

Throughout the data, servant leadership themes are dominant and perfectly associated with the presence of job satisfaction in both interview and blog participants.

Discussion

Unlike quantitative research which has specific statistical calculations, "Theoretical generalization is the domain of case study as what statistical generalization is to the true experiment."[45] This allowed the gleaning of conclusions from the application of "theoretical generalizations."[46] Triangulation of data[47-49] was performed through the inclusion of the additional artifact of blog entries,[50] obtaining rich data through interviews and blog entries and performing respondent validation through comparison of both blog entries and participant interviews.[51]

This study broke new ground within two areas of previously unexplored territory of global research through the exploration of servant leadership behavior and job satisfaction within a global mindset and via both interview and blog participant data. The comparison of interview and blog data is a relatively new area of research and provides an endless opportunity of global studies to occur from anywhere around the world via virtual interviews and blog posts.

Due to the non-existence of previous research on servant leadership through a global mindset and job satisfaction via the use of participant and blog data within the health information management community a limitation to this study is an inability to compare results with previous research for enrichment[52] or to determine replication for authenticity.[53] Currently, the only available comparison is research within other areas of servant leadership and job satisfaction. A systematic literature review of servant leadership and job satisfaction through both qualitative and quantitative means found a direct correlation between servant leadership behavior and increased job satisfaction[54-58] yet none of the previous results were attained from the diverse community of HIM professionals.

Conclusion

This research has shown an association of job satisfaction and servant leadership behavior within a global mindset of leadership which is applicable to the diverse community of HIM professionals. There are implications for immediate application within the global leadership and training of HIM professionals by the addition of servant leadership skills applied within a globally focused mental attitude. This research is also provides the stimulus for health information management education to include servant leadership training and application at both the associate degree and bachelor degree level.

This research provides a basis for further research:

- A quantitative study on global leadership/servant leadership and health information management professionals
- A quantitative/qualitative study on leadership behavior and job satisfaction of remote leaders of health information management professionals in the United States and globally
- A mixed-methods study on global leadership mindset and job satisfaction within health information management professionals
- A quantitative study using/comparing/obtaining data from blogs on job satisfaction in health information management professionals

“Leadership is the process of influencing others and a great organization consists of all leaders.”[59] To meet the demands of the growing and diverse community of HIM professionals, the future agenda of global leadership research must include the continuation and formalization of the application of globally transferable leadership skills which include the seven constructs of love, humility, altruism, vision, trust, empowerment, and service[60] and designates a globally aware servant leader as someone who "has an innate desire to lead by serving, serves to align own beliefs, and strives to meet the highest priorities of others."[61]

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EXAMINING INDIVIDUAL TRANSITION FROM HEALTHCARE TO INFORMATION TECHNOLOGY ROLES USING THE THEORY OF PLANNED BEHAVIOR

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Category: Spring 2021

By Rebecca Johnston, MHIM, RHIA; Barbara Hewitt, PhD; Alexander McLeod, PhD; and Jackie Moczygemba, MBA, RHIA, CCS, FAHIMA

Abstract

Many health information management (HIM) positions, including coders and transcriptionists, are evolving due to the widespread adoption of electronic health records (EHR) and other automated entry systems.

Thus, focus for roles associated with those positions are changing and new positions to manage and manipulate the data collected in the new systems. This study seeks to identify which factors influence HIM professionals' decision to transition from a traditional HIM role to an information technology (IT) position.

An online survey was sent to these individuals to determine which factors influenced their decision to consider a transition from healthcare roles to information technology using the theory of planned behavior. In other words, this study explored whether these individuals were influenced by attitudes, normative beliefs, and self-efficacy to consider transitioning from healthcare roles to information technology positions. In order to better understand whether education played a role in this behavior, an additional element, education efficacy was added. The findings revealed that these health information management professionals are not considering a transition from healthcare positions to IT roles.

Keywords: Theory of Planned Behavior, education, health information management, career choices, information technology

Introduction

The Health Information Technology for Economic and Clinical Health (HITECH) Act, signed into law on February 17, 2009 as part of the American Recovery and Reinvestment Act (ARRA) of 2009, promoted EHRs adoption and meaningful use of health IT.[1] The wide spread adoption of EHRs is changing the roles of healthcare professionals, particularly those in health information management (HIM).[2] Many of the traditional roles that HIM professionals hold are shifting from traditional clinical, operational, and administrative settings to the technical side of managing health information.[3] Health IT is an integral part of patient care delivery used to reduce errors and improve patient outcomes and safety.[4] According to Cascio and Montealegre, "The goal is to create an optimized space that links people, computers, networks, and objects, thereby overcoming the limitations of both the physical world and the electronic space."[5]

The American Health Information Management Association's (AHIMA) Board of Directors created a task force consisting of representatives from all levels of the HIM industry to identify "HIM

Reimagined Recommendations" based on changes in healthcare, technology, and education. The recommendations include new educational strategies to ensure current and future professionals are prepared for the future HIM roles in this rapidly changing environment.[2]

Many positions are slowly evolving as the work formerly performed by employees is automated, captured by technology, or generated by software. For example, the medical coder role is changing as computer-assisted coding software automatically generates medical codes using the transcribed clinical documentation, thus, replacing many aspects of their job.[6] Medical transcriptionists are also affected as physicians utilize natural language processing, which uses voice-recognition software to automatically convert patient care notes dictated by the physician directly into the medical record.[7] Structured Data Entry Systems allow the physician to customize patient-record templates for quicker data entry into the EHR, allowing maximized data completeness and a standardized structure.[8] While the need for coders and transcriptionists still exists, these positions will transition into auditing roles managing automated processes and resolving technical software issues.[9] These advances will force some HIM employees to transition into non-traditional positions,[10] including more technological roles.

As healthcare roles evolve, the demand for a more focused IT workforce will increase. The United States Department of Labor, Bureau of Labor Statitics[11] predicts that by 2024, IT roles will have grown 12 percent as emphasis is placed on cloud computing, data collection and storage, analytics, and information security.

According to the United States Department of Labor, Bureau of Labor Statistics[12] women make up 75 percent of healthcare practitioner and technical occupations, but only 25.6 percent of the IT field. While most women are capable of attaining the skills necessary to fill IT positions, the industry is failing to attract and/or retain them. Ashcraft and Blithe[13] found that half of the women working in science, engineering, or technical (SET) jobs left the fields within two years of graduation, whereas, most men were still employed in these types of positions two years after graduation. Therefore, this research study assesses the factors influencing individuals, particularly women, who may have or are planning to transition from a healthcare role to an information technology role.

Background

According to Abrams, et al.[2], "One doesn't need to look too far into the past to see what happens to industries and professions that fail to maintain relevance in a changing environment." As previously mentioned, technology advancements are evolving in the healthcare industry. The purpose of HIM Reimagined is to provide recommendations to help move forward and to prepare for the rapid changes that are changing and evolving in the industry.

The Theory of Reasoned Action (TRA) was created to understand the relationships between attitudes, intentions, and behaviors; distinguishing between attitude toward the object and attitude toward a behavior.[14] TRA's constructs included attitudes and social norm as influencers for decisions about human behavior including health behaviors, adoption of technology, and other adoption decisions. Ajzen[15] derived its successor, the Theory of Planned Behavior (TPB) framework from TRA. TPB proposes that behavior is influenced by specific personality traits and environmental factors. The constructs of TPB (attitude, subjective norm, and perceived behavioral control) have been beneficial in understanding the relationship between behavior and beliefs, attitudes, and intentions; which could potentially be influenced by social and psychological determinants.[16, 17] The definitions for the constructs are shown in **Table 1**. TRA and TPB are often used to explore human behavior, particularly to examine career choices.[18] TPB has also been used to predict intentions related to career behaviors in various situations including decision to major in computing degree programs.[18-22]

Research Questions

Using the validated survey items from the prior study and adding the items for IT education efficacy, the authors seek to answer the following questions:

1. Do health information management workers have a positive attitude about transitioning from a traditional healthcare position to an IT role?

2. Do health information management workers receive support from referent others about transitioning from a traditional healthcare position to an IT role?

3. Do health information management workers possess self-efficacy that would support their transition from a traditional healthcare position to an IT role?

4. Does IT education efficacy play a role in the health information management professional's self-efficacy about their decision to transition from a healthcare position to an IT role?

5. Do health information management professionals intend to transfer to IT roles from their more traditional healthcare roles?

Methods

The purpose of this exploratory research was to analyze the attitudes of healthcare professionals. A survey was developed to test an individual's decision to change careers or career paths. The descriptive statistics from the survey responses were computed using Microsoft Excel.

Participants. Participants responded to questions designed to reveal factors that influence their intent to transition from healthcare to IT roles. The survey included previously validated items to measure attitude, subjective norms, and perceived behavioral control. In order to determine if education requirements were detrimental to someone considering a career in IT, items were added to measure IT education efficacy.

Instrument. While this study focused on theory and items previously validated, a new construct was added to measure IT education efficacy. Thus, to validate the reliability of the research items prior to collecting data from healthcare professionals, approximately 1,000 undergraduate and graduate students majoring in various healthcare degrees at a central Texas university were invited to participate in a pilot study via email. To increase the response rate, two reminders were sent to the students at one-week intervals following the original email. Three hundred fifty-seven students responded. However, 157 responses were removed due to incomplete responses, brevity of response time, or no variance in responses. To ensure that the items adequately represented the constructs, SPSS was used to perform a confirmatory factor analysis with varimax rotation. Items that did not load properly on factor were modified slightly or removed from the survey.

Study Variables. To gather demographic information about the respondents, the survey captured information about current employment, industry, role, and whether participants have considered IT as a career. Following the demographic information, the instrument contained 27 questions related to attitudes, self-efficacy, normative beliefs, and IT education efficacy. The survey consisted of seven-point Likert questions where the first radio button represented strongly disagree and the seventh radio button represented strongly agree. The survey items were randomly presented to the respondents.

Data Collection. The researchers received approval to conduct the study from the Institutional Review Board. The researchers first recruited students to complete the pilot study. The target population included health information management professionals currently in healthcare roles and those who may have transitioned or intend to transition to IT roles. The researchers invited 617 individuals from a Health Information Management (HIM) department's alumnus in Texas via an email message to complete the survey. Two follow-up reminders were sent to the alumnus group at one-week intervals following the original invitation. While one hundred thirty individuals started the survey, 24 responses were eliminated for incomplete responses. Thus, 106 responses were analyzed for the research study. This yielded a 17 percent response rate.

Analysis

Respondents replied to questions that used a seven-point Likert scale to assess their attitudes toward changing from a healthcare role to an IT position. Results were generated using descriptive statistical analysis including frequencies and percentages. Microsoft Excel was used to compute descriptive statics.

Demographics. Subjects of all gender, racial, and ethnic background, and age range (23-65) that graduated with an HIM degree from one university regardless of where they worked were invited to participate in the survey. With regard to gender, 91 percent of the participants were female and 9 percent were male. The sample was comprised of 95 percent White/Caucasian; 14 percent Black/African-American; 5 percent Asian; 5 percent from multiple races; 4 percent from other races; and 2 percent of the participants preferred not to respond.

One percent of the survey respondents reported having a high school diploma; 10 percent completed some college; 5 percent had an associate's degree; 65 percent had a bachelor's degree; 8 percent of participants completed some post-graduate work; 34 percent had a master's degree; and 2 percent had a Ph.D., law, or medical degree. **Table 2** shows the demographics of the individuals to summarize the results.

Results

Question 1 explored whether an individual's attitude impacted their intent to transition from a traditional healthcare role to an IT role was supported. While most individuals (63 percent) indicated that there is more potential to work in IT for growth opportunities, less than one-quarter or 23 percent of the respondents in the current study either strongly agreed or agreed that they would not have greater opportunity if they transitioned to an IT role than a traditional healthcare role. These results can be seen in **Table 3**.

In the current study, 64 percent of the female respondents and 60 percent of the males agreed or strongly agreed that "Working in IT would offer potential for growth opportunities." These results indicate that most respondents believe that transitioning from healthcare roles to an IT role will provide more potential; however, only one-fifth or 21 percent of our female respondents and 40 percent of our male respondents strongly agreed or agreed that they would have great opportunity transitioning to an IT role from their traditional healthcare role.

In response to Question 2, when asked whether referent others are encouraging the individuals to consider transitioning from a healthcare position to an IT role, only 11 percent of the respondents indicated that people who were important suggested that they work in IT. Referent others, including only 7 percent of employers, 7.5 percent of mentors, and 8.5 percent of coworkers, have suggested that these HIM professionals' transition to an IT role. Only 7 percent of females and 10 percent of males were influenced to work in the IT field. Other social norm questions showed similar results. While roughly 20 percent of males were being told that they should transition to IT jobs by people they valued, employers, and mentors, only 6 percent of females received suggestions to consider a transition from employers, mentors, and 8 percent from coworkers as indicated in **Table 4**.

Question 3 explored whether individuals had the self-efficacy to make the transition to IT. Forty-six percent of the respondents felt that they had the knowledge, 43 percent felt that they had the resources, and 52 percent felt that they have the ability and the aptitude as shown in **Table 5**. As indicated, self-efficacy was strong for males with 70 percent indicating that they had the knowledge, 60 percent indicated that they had the ability and advanced computer skills, and 90 percent believed they had the aptitude. Less than half of the female respondents felt that they had the knowledge (44 percent), resources (44 percent), or computer skills (25 percent). On a positive note, over half of the females (51 percent) felt they had the ability to pursue a career in IT.

To determine if the individuals thought trying to complete an IT concentration would be hard, Question 4 explored whether individuals had IT education efficacy. Roughly half of the respondents indicated that IT courses would be challenging (49 percent); however, most respondents did not feel that an IT concentration would be difficult (18 percent) or required long hours of study (38 percent). Additionally, the respondents did not feel that IT courses are demanding (38 percent). Very few of the respondents felt that an IT concentration would take a long time to complete (8 percent). These results are shown in **Table 6**. Half of the males (50 percent) and females (49 percent) agreed that IT courses would be challenging. Males believed that they would have to study many hours (60 percent) and the courses would be demanding (70 percent). Females were less concerned with needing to study many hours (35 percent) and only 34 percent felt that the courses were demanding.

In response to Question 5, roughly13 percent of our respondents stated they would transfer to an IT role and only 12 to 14 percent were considering a transfer to an IT role as shown in **Table 7**. Males were more likely to consider the transition, but that number was only 40 percent. Only 6 percent of the females indicated that they plan to transition to an IT role.

These results are shown in **Figure 1**. The items used in Figure 1 were selected from the results above. This shows that while most individuals believe that they could transition to IT, they do not intend to actual transition.

Discussion

This research explored whether factors as identified in the TPB factors model influenced an individual working in healthcare to consider transitioning to an IT role. The proposed model included IT education efficacy and different attitude questions to test opportunity, whether it was gender-based, and whether individuals felt the geek/nerd stereotype kept them from considering it as a role. When comparing the results of this study with other career choice studies that used the TPB model, this study further confirms the suitability of the model for evaluating career choices. Furthermore, TPB improves our understanding of attitude, self-efficacy, and normative beliefs for these individuals as they consider career choices and changes to those decisions.

Question 1 explored whether an individual's attitude impacted their intent to transition from a traditional HIM role to an IT role was supported. The majority indicated that IT jobs offered great job opportunity, but only 23 percent either strongly agreed or agreed that transitioning to an IT role would give them a better opportunity than a traditional HIM role. These results were similar to previous research. For example, Croasdell, McLeod, and Simkin[23] determined the difficulty of an IS major and curriculum[23]. While "difficulty of major" and "aptitude" were not significant determinants in choosing an IS major, the study did find that a "genuine interest in Information Systems (IS) and the "influence of family" strongly influenced a woman's decision to major in IS. Amani and Mkumbo[19] used TPB to evaluate the determinants of career intentions among undergraduate students in Tanzania.[19] Attitude was found to be the strongest predictor of career intentions, followed by subjective norms, career knowledge, and career self-efficacy. Joshi, Kvasny, McPherson, Trauth, Kulturel-Konak, and Mahar[21] surveyed university students to explore how self-efficacy and perceived IT skills affected IT career choice.[21] While the study found positive results pertaining to intentions, self-efficacy did not have direct effects on IT career intention. Although AHIMA created the HIM Reimagined initiative, which provides job growth strategies as technology evolves the industry, HIM professionals are not making it a personal mission to equip themselves both academically and professionally to keep up with the changes that are occurring.[24]

To explore whether the responses were gender differences, results for males were compared to females. While 40 percent of males indicated that there were greater opportunities to transition from the HIM field to the IT field, only 21 percent of the females agreed with them. Basically, neither males nor females feel the need to position themselves for the possibility of needing to transition to a more technical role.

Question 2 tested whether individuals were influenced by others to transition from a traditional HIM role to an IT role. The results indicate that few individuals felt influenced by referent others (10 percent), employers (8 percent), coworkers (9 percent), mentors (8 percent), and professors (7 percent). The current research found that normative beliefs were significant in that referent others, including professors, coworkers, mentors, employers, and other individuals of importance, played an influential role in an HIM professional's intent to work in an IT role; however, only a few referent others encouraged the HIM professionals to consider a transition to an IT role.

To delve further into these responses were also supported indicating that normative beliefs influence both female's and male's intent to transition from a traditional HIM position to an IT role. Surprisingly, 7 percent of females and 10 percent of their male counterparts indicated that they were influenced by referent others.

Question 3 tested whether self-efficacy influenced a HIM professional's motivation to transition to an IT role. More than half of the respondents either strongly agreed or agreed to having the capability and more than 50 percent but less (46 percent) had the knowledge to transition. These results are quite interesting and signify that HIM professionals are not influenced to change their careers to an IT role by others in the profession including their bosses and colleagues. These results are similar to those found by Brinkley and Joshi, who determined that males had a higher self-efficacy than females regarding hard IT skills[20]. Govender and Khumalo[25] found that female respondents showed that they need to have a high computer self-efficacy for them to consider a major in IS.[25]

Question 4 explored whether these individuals felt IT courses were challenging. The results indicated that IT education efficacy influenced one's attitude. While half (49 percent) felt the courses would be challenging, overwhelmingly, they indicated that the courses would not be challenging (82 percent). Only one-third indicated that the courses would require many hours to study. Because HIM roles are very different when compared to IT roles, many HIM professionals may feel that education requirements may be too challenging; thus, preventing them from transitioning from their present position to one in IT. The results indicated that the degree of difficulty perceived in the IT curriculum negatively affected the attitudes toward choosing an IT major. Males and females agreed upon the amount of difficulty of IT concentrations, but males were more concerned about studying and the demand of the courses compared to their female counterparts.

This study also measured the individual's intention to transition to answer Question 5. While 40 percent of the males stated they plan to transition, but only 6 percent of the females planned to transition from a more traditional HIM role to an IT position. These results are alarming as they are contrary to the current state of the field, with electronic health records changing the roles of these professionals.

The goal of this study was to investigate and evaluate influencing factors for individuals, particularly women, who may be considering a transition from an HIM role to an information technology role. The results suggest that attitude, normative beliefs, self-efficacy, and IT education efficacy all statistically play a positive role in determining such factors. However, males were not impacted by self-efficacy and IT education efficacy.

The shortage of individuals, particularly women, in IT roles is evident as discussed in previous studies. As HIM roles evolve and become more technology-oriented, education programs should introduce more IT-oriented subjects into the classroom. IT subjects can be integrated across the HIM curriculum to promote a greater sense of self-efficacy and potentially attract more individuals into the IT field. Concern needs to be expressed since the majority of our respondents did not consider a transition to an IT role (90 percent).

Conclusion

In summary, the study presented in this paper refined the Theory of Planned Behavior, providing a more representative model for analyzing factors that influence HIM professional's intention to transition into information technology roles. IT education efficacy was added to the TPB model to explore whether an individual was influenced by how challenging they perceived an education in IT and how it would affect their self-efficacy. The study also explored how gender affected individual intentions to transition into an IT role within the TPB framework.

While the combined population provided homogenous responses towards attitude, social norms, and self-efficacy, self-efficacy and IT education efficacy results varied by gender. The results indicated that while almost 50 percent of males surveyed indicated that they had the ability to transition to an IT to (self-efficacy) than their female counterparts, only 18.5 percent of the males intended to transition into an IT role. Fewer females intended on transitioning to an IT role compared to the males who responded to the survey. In these efforts, the study contributed to a deeper understanding by identifying important factors within the framework. By adding an additional element, the results provided a better understanding regarding one's efficacy in IT education. Furthermore, the research identified gender differences pertaining to the intent to transition into an IT role exist.

According to Eramo[26], "technology has transformed almost every industry, and health information management (HIM) is no exception.[26] AHIMA's HIM Reimagined taskforce has been charged with initiating recommendations to ensure that HIM professionals are prepared for the rapidly changing environment resulting from changes in healthcare, technology, and education.[27]

Limitations

While the data in our research study provided positive feedback to support TPB, the present study is not without its own limitations. The first limitation that should be noted is the small sample size. While we invited over 800 individuals to participate and sent at least one follow-up invitation, only 125 of the 155 responses were analyzed due to incomplete surveys.

In addition to the small population size, the survey lacked diversity, with females making up 84.8 percent of the participants and only 15.2 percent males. The lack of a diverse population participating in the survey made it difficult to generalize from this study. The majority of the respondents were white/Caucasian (76 percent). Future research should aim at including a more representative group of people, including more male respondents and a more diverse population.

Another consideration is related to the survey. The instrument should focus on other variables such as age, education level, and various professions in order to assess the generalizability of the scale to a more heterogeneous population[28]. Thus, providing a more comprehensive assessment of the subject.

Contributions and Implications for Future Research

The results provide several contributions for researchers and organizations. By continuing to refine and evaluate the reasons that males and females choose certain careers, researchers will have the ability to better assess and determine one's motivation for behaving in a certain way. The model for this study added an IT education efficacy construct to TPB. This element adds a better understanding of whether individuals believe obtaining an education in IT is challenging. IT education efficacy might affect one's level of self-efficacy; subsequently influencing one's decision to transition from healthcare to IT.

Organizations can benefit from these results, because the model provides a framework for understanding what factors influence individuals making the choice to transition from their current role, in this case, healthcare, to an IT role. The study may also provide additional information on how recruiters from academic institutions can encourage more females to pursue majors in an IT discipline. University HIM departments should consider including more computer-based subjects in their degree programs.

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ELECTRONIC HEALTH RECORD (EHR) ABSTRACTION

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Abstract

The purpose of electronic health record (EHR) abstraction includes collection of data related to administrative coding functions, quality improvement, clinical registry functions and clinical research. This article examines the different abstraction methods, such as manual abstraction, simple query, and natural language processing (NLP). It also discusses the advantages and disadvantages of each of those methods. The process used for successful EHR abstraction is also discussed and includes the scope and resources needed (time, budget, type of healthcare professionals RHIA, RHIT, etc.). The relationship between EHRs and the clinical registry is also examined with a focus on validity of the data extracted. Future research in this area to examine abstraction methods across hospitals who do data abstraction are being finalized for a future publication.

Keywords: Electronic health record, EHR, abstraction, natural language processing, NLP, query, quality improvement, patient safety.

Introduction

The widespread adoption of electronic health record (EHR) systems makes it possible to retrieve patient records digitally and to extract useful clinical data. Therefore, several secondary applications have become accessible such as quality management, health management and translational research.[1] All of these secondary applications aim to improve patient care.[2,3] The overall quality of healthcare and patient treatment depends heavily on the quality of data. Therefore, having inaccurate, incomplete, and inconsistent data and documentation can result in errors and adverse events[4] that may affect patient safety[5], limit health information exchange (HIE), and hinder clinical research.[6]

In the remainder of this article, we discuss the methods of data abstraction. Advantage and disadvantages of data abstraction, the key factors for successful abstraction within EHRs and registries will also be discussed. We also discuss the importance of having a health information management professional at the forefront of clinical data abstraction methods.

Background

The Centers for Medicare & Medicaid Services (CMS) developed the Meaningful Use program, now called Promoting Interoperability, to help healthcare professionals and hospitals improve quality, efficiency, and safety of patient health through the use of certified EHRs.[7,8] Thus, it is increasingly important to get meaningful and efficient methods for data collection, sharing and reporting. Furthermore, it is important to have efficient methods for abstracting the needed clinical data from

EHR systems and other clinical documents. Three methods that can be used for data abstraction include, manual abstraction, search engines, and abstraction using natural language processing (NLP). Several measures can be used to evaluate the quality of each one of these methods, including, completeness, correctness, concordance, currency, and plausibility.[9]

Abstraction Methods

Manual Record Abstraction. Manual abstraction is the process of collecting important information from a medical record and transcribing it into discrete fields within the new EHR. Structured data parts (coded data) in the EHR such as, medications, diagnoses, and an active medication allergy list, helps to abstract the needed information from EHR systems.[10] Manual abstraction can be performed by health information management professionals, nurses, physicians, or other individuals who have training in data abstraction. The review of the entire medical record allows one to collect more specific clinical details, especially for the information that is not readily coded using the existing coding systems.[11]

Manual abstraction helps to integrate discrete patient data into the EHR and make them readily available for healthcare providers. It also allows for triggering some decision support alerts that are related to information integrated into the EHR.[12]

Although the manual abstraction method is convenient and easy to understand, it has several limitations:

1. Some outcome measures, such as those related to cancer recurrence, are usually documented in unstructured notes and reports. Thus, it will be hard to extract all the required information since there are limited structured parts.[13,14]

2. Manual abstraction can be time consuming and expensive.

3. Manual abstraction methods threaten the privacy of patient information.[15]

4. Manual abstraction may increase errors. For compliance with CMS regulations, clinical data abstractors need to review patient records to identify the ones that meet the guidelines.[16] Reviewing this large volume of data increases the risk of making errors. The situation will be worse when dealing with narrative information that lacks standardization. Therefore, data abstractors may get unreliable results.

Search Engines (Simple query). Several studies have shown that physicians prefer to enter their comments in some unstructured free-text entries even if there are options for structured coding elements in the system.[17,18] Additionally, unstructured free text entries are always required for some complex tasks such as, clinical trial recruitment.[19] Extracting some useful clinical data from such unstructured free-text entries is a complex task that face several challenges[20] including; the physician tendency to use some acronyms, abbreviations[21], negation[22,23], and hedge phrases.[24] Lack of standard grammar and punctuation may lead to ambiguity and misunderstanding.[21] The difficulty in automatically processing some context-sensitive meanings[25] and temporal relationships[26] is another challenge. There is a significant need for searching full text medical records.[27] Having some simple SQL queries[28] and search engine tools can help in conducting this full-text search.

In order to solve the problem with abstraction and obtain useful information from the unstructured clinical notes, researchers at the University of Michigan have developed the Electronic Medical Record Search Engine (EMERSE).[1] This is a full-text search engine that is mainly designed to extract useful information from the narrative clinical notes in the EHR systems. CISearch is another tool for searching free-text reports within EHR systems.[29]

Abstraction Using NLP

NLP can be defined as computation algorithms for analyzing machine readable unstructured text.[15] NLP can conclude the meaning behind the words. Automated data abstraction using NLP has the potential to convert the unstructured text-free notes into structured and codified format.[14] Thus, NLP is an efficient alternative for manual abstraction.[30] NLP-based systems can reduce the time and efforts of manual abstraction in large-scale population-based studies.

NLP has the potential to extract all the needed information and perform some complex multivariable queries.[31] It tags every word and puts it into a discrete format that can be used for reporting. Additionally, NLP can recognize related words and phrases. For example, high blood pressure and hypertensive can be considered as fitting in the overall description of the term hypertension. Experts agree that meaningful use/promoting interoperability may be the largest driving factor behind NLP adoption.[31] This is due to the ability of the NLP system to search through a large volume of documents and extract information that are related to meaningful use data elements, such as, a problem list, procedures, medications, allergies, vital signs, social history, and quality measure information.

NLP has been successfully used to abstract useful information in several applications including; emergency medicine physician visit notes[32], pathology reports[33,34], identifying individuals based on cancer screening[35], abstracting findings from imaging[36], conducting pharmacogenomics research[37], extracting cancer stage information from narrative EHR data[38], and identification of breast and prostate malignancies described in pathology reports.[39]

Advantages and Disadvantages of Abstraction

Advantages of the abstraction process include:[40]

1. Ensure correct placement of data into their intended field in the EHR.

2. Speed up the go-live process for physicians since the abstraction can help to provide easy and rapid access to patient data.

3. Save electronic storage space since abstracting only the needed information requires less storage space than whole clinical documents.

4. Abstraction is a source of supplemental information that supports claims information, which in turn provides more specific evidence for clinical care.[41] For example, for some measures, claims information is incomplete. So, information from the abstraction process can be used to supplement evidence of the service provided, to verify the population that is being measured.

5. Abstraction supports key processes such as coding and reimbursement, quality improvement, billing audits, and clinical research.[42]

Also, abstraction can have some disadvantages since it may take extra time and resources in order to enter all the patient information into the EHR. **Table 1** provides a summary of the advantages and disadvantages for each type of clinical data abstraction method.

Discussion

Successful Abstraction Process: One example of successful data abstraction was provided by Care Communications, Inc. which was a leader in providing data abstraction services and is now a part of Ciox Health. Based on their experience in data abstraction it is important to satisfy some key factors including[43]: Increasing the medical records procurement rate, enhancing data integrity using an inter-rater approach and working with specialists in the field of health information management who are familiar with HIPAA, ongoing status reporting, and personalized project management.

Several decisions should be taken in order to guarantee a successful abstraction process, such as[12]:

1. Determine the scope of the abstraction, which means deciding what data should be abstracted and when and whether there are some special abstraction needs for sub-specialists.

2. Determine the time required to do the abstraction.

3. Determine the budget for the abstraction process based on the scope of the abstraction.

4. Determine who will do the real abstraction of data and how the abstractors will be trained.

Scope of Abstraction: Examples of abstracted data include:[12,44] demographics, scheduled appointments, active orders, allergies, medications, immunizations, chronic conditions, problem lists, hospital discharge summaries, special studies (echocardiograms, pulmonary function tests, etc.), and patient history (medical, surgical, social and family). The chart abstraction process may also include the identification of key paper clinical documents that need to be included in the new EHR by scanning those records into the electronic chart prior to bringing the new EHR live.

Six important categories should be recorded when doing abstraction including:[45]

1. Impact on clinical outcomes (length of stay, morbidity, mortality, validated measure of health-related quality of life (HRQOL) or functional status, adverse events).

2. Impact on health care process outcomes (preventative care ordered/completed, clinical study ordered/completed, treatment ordered/prescribed, impact on user knowledge).

3. Impact on workload, efficiency, and organization of health care delivery (number of patients seen/unit time, clinician workload, efficiency).

4. Impact on relationship-centered outcomes (patient satisfaction).

5. Impact on economic outcomes (cost).

6. Impact on health care providers (HCP) use and implementation (HCP acceptance and satisfaction, implementation of clinical decision support system (CDSS).

In general, coders abstract Present on Admission (POA), Hospital-Acquired conditions (HAC), some patient safety indicators (PSI) and the Core Measures.[46] Additionally, many facilities require their coders to check the charges for services or enter charges altogether based on the type of record they code. Based on a survey done by Himagine solutions (www.himaginesolutions.com) on their field coders[47], the coders reported that there are many more elements that are currently being abstracted in an effort to capture data, streamline the process, and assure the accuracy of input.

Time of Abstraction. The time required to complete the abstraction depends on the clinical practice[48] (NextGen Healthcare[49]). Generally, patients see their physician three to five times per year. Thus, the abstraction volume will decrease in the first two months. However, the abstraction volume will keep increasing when having new patients, and thus the time will also increase.

Budget. Generally, the data abstraction process is labor intensive and requires solid data validation and quality control mechanisms.[50] The budget for abstraction and the needed information varies depending on the scope, size, and the needs of the clinical practice.[12] Thus, the budget can range from very little to very high.

Who Will Do the Abstraction? Based on the NextGen Healthcare experience, the abstraction process needs to be delegated to either; nurses or medical abstractors which can include health information management professionals. Some of the NextGen Healthcare clients have used their current health information staff to do the abstraction. One benefit of using the current HIM staff as data abstractors is to reduce the time required to do abstraction since they will be familiar with the practice and the EHR. NextGen Healthcare clients have suggested that there might be a need to hire some temporary abstractors for the first two to three months. Through time, the amount of information that needs to be abstracted will decrease. Additionally, HIM staff, physicians, nurses will become more proficient with the abstraction process, and thus, they will be able to keep up with the abstraction.

Using credentialed HIM professionals (RHIAs and RHITs) and Registered Nurses (RNs) to do the data abstraction will be better than assigning the abstraction task to clinical coders.[51] The reason for this claim is that health information management professionals (RHIAs and RHITs) and RNs are consistently focused on clinical data integrity in their day-to-day tasks. Thus, they will be able to provide the most valuable details about the continuity of patient care. Furthermore, RHIAs, RHITs, and RNs can understand patient data in a broader way and they will be able to extract the critical details since they understand all the different clinical components that shape the picture of the individual's whole health.[51]

Organizations can use their health information management professionals, internal nurses, and physicians to do the abstraction, or they can outsource the abstraction to other organizations that have some clinical experts who can do the abstraction.[51] Although it seems that doing the abstraction internally can be feasible and cost effective it may reduce the productivity of the internal staff.

The ideal clinical abstraction team can include:[52]

1. Project manager who can monitor all the abstraction project components such as budget and timeframe.

2. Research manager who can monitor the quality of the abstracted data. He/she needs to have a high clinical and technical expertise.

3. Lead abstractor who can monitor the daily details of the abstraction process and supervise the abstractors.

4. Abstractors who will conduct the actual abstraction and they should have experience in clinical data abstraction and familiarity with the EHR.

Ideally, data abstractors need to have the following qualifications:[53]

1. Experience with retrospective data collection from the EHR
2. Clinical and research experience relevant to the study being conducted
3. Advanced educational preparation in a health information and health care profession.

It is important to identify the required resources, budget, and time constraints ahead and before the real abstraction process. Some studies are resource intensive that need high-level planning for all the steps of the abstraction process. For example, the abstraction of charts in the study of screening lung cancer that was performed by Care Communications is very complex and challenging[54] and requires high level project management and clinical experience. This study requires screening thousands of medical records within more than twenty hospitals in the nation.

EHRs and Registries

A registry can be defined as an organized system that uses observational study methods to collect uniform clinical data to evaluate specified outcomes for a population defined by a particular disease, condition, or exposure, and that serves one or more predetermined scientific, clinical, or policy purposes. Registries are focused on populations and are designed to fulfill specific purposes defined before the data are collected and analyzed.[55] On the other hand, EHRs are focused on the collection and use of individual patient health-related information. Although, it seems that both registries and EHRs overlap in functionality, their roles are different. According to the Institute of Medicine (IOM), (which is now called the National Academy of Medicine), an EHR has four core functionalities: health information and data, results management, order entry and support, and decision support.[56] There are several obstacles to achieve the meaningful communication between systems such as, EHRs and registries. These obstacles are related to confidentiality, security, privacy and data access.[55]

Currently, there is an increasing demand for physicians to participate in the registries in order to manage safety, evaluate effectiveness, and measure and improve the quality of patient care. Therefore, it is becoming increasingly important that EHRs should serve as an interface for several registries with different purposes at the same time. EHRs can enable health care information to be available and accessible to registries. Additionally, EHRs can provide some relevant information from the registry to the physicians such as, information about natural history of disease, safety[57], effectiveness, and quality.[58] **Figure 1** demonstrates the relationship between the EHR and the registry.

Navaneethan et al.[59] have described the development of a registry for patients with chronic kidney disease (CKD) that is derived from EHR data. The benefits of this kind of patient registry can range from allowing better aggregation of patient data for practice assessment or quality improvement, to facilitating clinical research. The study shows that the quality of data in this registry is comparable to that of the data from a much more labor-intensive and expensive process of human abstraction. This registry can be used for quality improvement, clinical research, and other important tasks.

Conclusion

Abstraction Validity. Medical record abstraction is a primary mode of data collection in secondary data use. Abstraction is associated with high error rates.[60] It is important to validate the abstracted data and ensure that the data are abstracted correctly and consistently. There are several benefits of the validation process[41] including:

1. Enhance the clarity of specification through the identification of specification ambiguities that are related to the abstraction process.

2. Help to ensure abstractor consistency through the ongoing monitoring.

3. Reveal quality of care opportunities.

4. Provide some information for future internal quality improvement. Strategies for improving the validity of data abstracted from medical records include[61] training abstractors, masking abstractors to study hypotheses, assessing interrater reliability and agreement, and the re-abstraction of records.[62]

There are three components of validation[41] including:

1. Validating the currently used tools from different vendors and updating the existing tools.

2. Validating the abstraction process and this can be done during the data collection by taking a convenience sample of records and ensure that all measures are abstracted consistently by different vendors to uncover any specific ambiguities.

3. Validating at the end of data collection in order to ensure the integrity and accuracy of the abstracted data.

Future Research

We have conducted a study to examine abstraction methods across hospitals using interviews of managers of abstraction within their healthcare organizations as well as a survey of clients of a large consulting company (Ciox Health) who do data abstraction. Those results are being finalized and will be provided in Part II of a future publication.

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COMPARISON OF ICD-9-CM TO ICD-10-CM CROSSWALKS DERIVED BY PHYSICIAN AND CLINICAL CODER VS. AUTOMATED METHODS

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Abstract

Purpose: To evaluate whether automated methods are sufficient for deriving ICD-10-CM algorithms by comparing ICD-9-CM to ICD-10-CM crosswalks from general equivalence mappings (GEMs) with physician/clinical coder-derived crosswalks.

Patients and methods: Forward mapping was used to derive ICD-10-CM crosswalks for 10 conditions. As a sensitivity analysis, forward-backward mapping (FBM) was also conducted for three clinical conditions. The physician/coder independently developed crosswalks for the same conditions. Differences between the crosswalks were summarized using the Jaccard similarity coefficient (JSC).

Results: Physician/coder crosswalks were typically far more inclusive than GEMs crosswalks. Crosswalks for peripheral artery disease were most dissimilar (JSC: 0.06), while crosswalks for mild cognitive impairment (JSC: 1) and congestive heart failure (0.85) were most similar. FBM added ICD-10-CM codes for all three conditions but did not consistently increase similarity between crosswalks.

Conclusion: The GEMs and physician/coder algorithms rarely aligned fully; human review is still required for ICD-9-CM to ICD-10-CM crosswalk development.

Keywords: Coding algorithms, diagnosis codes, healthcare research, general equivalence mappings, ICD-10 transition.

Introduction

Observational studies of administrative claims or electronic medical record (EMR) data frequently require the use of coding algorithms to identify patients with a particular comorbidity or outcome of interest.1 The coding algorithms developed in the *International Classification of Diseases, Ninth Revision, Clinical Modification* (ICD-9-CM) coding system are now obsolete when analyzing contemporary data.

The United States Department of Health & Human Services required providers to switch from diagnosing medical conditions with the ICD-9-CM to the ICD-10th Revision, Clinical Modification (ICD-10-CM) by October 1, 2015.2 This transition necessitated a "crosswalk" of existing ICD-9-CM coding algorithms to the ICD-10-CM system. The Centers for Medicare & Medicaid Services (CMS) published the GEMs as a software tool to facilitate this process, with the goal of allowing medical professionals, researchers, and others to identify ICD-9-CM to ICD-10-CM coding crosswalks.3

The GEMs are a comprehensive translation tool used to convert diagnosis and procedure codes from one ICD coding system to the other.4 These crosswalks assist healthcare professionals, researchers, and administrative staff by linking codes for data used for billing, tracking quality, recording morbidity/mortality, calculating reimbursement, and converting any ICD-9-CM-based application to ICD-10-CM/Procedural Classification System.4

There are two types of GEMs tools, which are directional. The forward mappings convert ICD-9-CM codes into ICD-10-CM, and the backward mappings convert ICD-10-CM codes into ICD-9-CM. The forward and backward GEMs tools are not exact duplicates of one another; they are independent mappings that differ in coverage.

The accuracy of GEMs and similar tools, however, is not well established. The CMS published the GEMs crosswalk tool to test and convert ICD-9-CM codes to ICD-10-CM, develop application specific-mappings, and link and analyze data in long-term clinical studies. There are few direct matches that exist between coding systems, as some ICD-9-CM codes are represented by several ICD-10-CM codes, and vice versa. Approximate matches, therefore, may not necessarily identify the most clinically appropriate ICD-10-CM coding algorithm for a given condition. This study compared ICD-9-CM to ICD-10-CM crosswalks from GEMs with those derived by a physician and clinical coder and evaluated whether automated methods are sufficient for deriving ICD-10-CM algorithms.

Methods

This was a coding algorithm development and comparison study; no patient selection or analysis of patient data was performed.

Existing ICD-9-CM algorithms were compiled and evaluated by the study authors for the following 10 clinical conditions: acute myocardial infarction (AMI), cardiac arrhythmia, chronic kidney disease (CKD), congestive heart failure (CHF), diabetes, diabetic neuropathy, hypertension, hypoglycemia, mild cognitive impairment (MCI), and peripheral artery disease (PAD). The GEMs crosswalk software tool was used to identify the corresponding ICD-10-CM codes from each ICD-9-CM code in the existing algorithms for each clinical condition via forward mapping. As a sensitivity analysis, forward-backward mapping (FBM) was conducted on three of the clinical conditions: AMI, arrhythmia, and hypoglycemia. In FBM, both forward and backward dictionaries were used to search for ICD-10-CM codes corresponding to the ICD-9-CM codes in the algorithms.

A physician and a clinical coding expert also independently identified an appropriate ICD-10-CM algorithm for each clinical condition; no specifications or restrictions were placed on the means they used to identify those codes. A questionnaire (see **Supplemental Table 1**) was pre-filled with each clinical condition and corresponding ICD-9-CM algorithm and was provided to the physician and coder to guide their development of ICD-10-CM algorithms. The physician and clinical coder were asked to evaluate the differences and exercise their judgment to determine which ICD-10-CM codes were required for inclusion or exclusion from each algorithm.

The differences between the GEMs and the physician/coder crosswalks for each selected condition were then quantitatively summarized using descriptive statistics, including means, medians, and ranges. The analysis unit of the differences was billable codes. The Jaccard similarity coefficient (JSC), a measure ranging from 0 (completely dissimilar) to 1 (completely similar), was also used to identify the degree to which GEMs-derived crosswalks were similar to the physician/coder crosswalks. The JSC was calculated as JSC(A,B) = |AB| / |AB|, with A representing the elements in set A (i.e., codes from the GEMs-derived crosswalk), B representing the elements in set B (i.e., codes from the physician/coder-derived crosswalk), representing the number of elements shared in both sets, and representing the total number of unique elements in both sets. The theoretical impact of differences between algorithms on sensitivity and specificity was assessed qualitatively.

Results

The full ICD-10-CM crosswalks from the GEMs and the physician/coder algorithms are located in **Supplemental Table 2**.

As shown in **Figure 1** and **Figure 2**, the crosswalks for diabetes and PAD had the most differences (>240 after comparing those from GEMs forward matching with those identified by the physician/coder), while the crosswalks for MCI, CHF, and hypoglycemia had the fewest differences (<7) between the two sets. The JSC ranged from 0.06 for the PAD crosswalks to 1.00 for the MCI crosswalk. In general, the crosswalks identified by the physician/coder were far more inclusive than those identified by the GEMs system. When compared with crosswalks identified by the physician/coder, the crosswalks from GEMs were missing a mean of 61.2 individual billing level ICD-10-CM codes (median: 9.0; range: 0–294). Alternatively, the GEMs crosswalks sometimes contained codes that were not identified by the physician and coder. The algorithms identified by the physician/coder were missing a mean of 4.0 codes after comparison with the GEMs crosswalks (median: 3.0 codes; range: 0–15).

AMI**.** Interestingly, GEMs did not identify some codes that appeared to be clearly indicative of myocardial infarction, such as ICD-10-CM I21.01 (ST elevation myocardial infarction involving left main coronary artery). The JSC for the GEMs and physician/coder crosswalks was 0.53.

Arrhythmia**.** The physician/coder algorithm identified codes that appear to indicate a diagnosis of arrhythmia, even when the term did not appear in the description (including ICD-10-CM code 148.4 - atypical atrial flutter). In general, the crosswalk developed by the physician/coder should have a higher sensitivity, but perhaps lower specificity, than the crosswalk identified by GEMs (JSC: 0.40).

CKD. Broad differences were identified across the GEMs and clinician/coder crosswalks (JSC: 0.29), and the physician/coder crosswalk likely has a higher sensitivity than the GEMs crosswalk. For instance, some ICD-10-CM codes for diabetes mellitus with diabetic CKD or kidney complications were included in the physician/coder crosswalk, but not in the crosswalk identified by GEMs.

CHF. The two sets of crosswalks were largely similar (JSC: 0.85), although the physician/coder algorithm is more inclusive than the GEMs algorithm. For example, ICD-10-CM I11.0 (hypertensive heart disease with heart failure) and P29.0 (neonatal cardiac failure) were found in the physician/coder algorithm but not in the GEMs algorithm.

Diabetes. Only one-third of codes were similar across the two sets of crosswalks (JSC: 0.33); due to the large number of codes identified for this condition by each approach, this level of dissimilarity resulted in 298 differences between the GEMs and physician/coder crosswalks. The physician/coder crosswalk included 294 codes that the GEMS crosswalk did not identify.

In some of those cases, GEMs did not include relevant codes, such as ICD-10-CM E10.32 (type 1 diabetes mellitus with mild non-proliferative diabetic retinopathy). Other GEMs omissions were related to the etiology of the disease, e.g., the physician/coder included ICD-10-CM codes for drug/chemical-induced diabetes and gestational diabetes.

Diabetic neuropathy**.** Again, the physician/coder crosswalk for diabetic neuropathy had higher sensitivity; just over half of the codes identified from both crosswalks were similar (JSC: 0.56). For example, codes E10.41 and E10.42 (type 1 diabetes mellitus with diabetic mononeuropathy and polyneuropathy, respectively) were included by the physician and coder only. The physician/coder also omitted some codes included by GEMs, including related conditions that could play a role in the development of diabetic neuropathy (such as E11.65/E10.65–type 2/1 diabetes mellitus with hyperglycemia).

Hypertension. Some codes included by the physician and coder but not GEMs identify medical conditions that specify hypertension, such as ICD-10-CM I15.1 (hypertension secondary to other renal disorders) and I15.9 (secondary hypertension, unspecified). Over half of the codes (JSC: 0.60) were similar across sets.

Hypoglycemia. Only half of the codes identified for hypoglycemia by each approach were similar (JSC: 0.50). The codes identified by the physician and coder specifically mention hypoglycemia (for example, ICD-10-CM code E11.641; type 2 diabetes mellitus with hypoglycemia with coma), while those identified only in the GEMs search did not (E71.0; maple-syrup-urine disease).

MCI. The ICD-9-CM algorithm for MCI included only one code (331.83: mild cognitive impairment), and both the GEMs and the physician/coder algorithms included only the analogous ICD-10-CM code, G31.84 (JSC: 1.00).

PAD. The crosswalks derived for PAD by each approach were most dissimilar among all conditions included in the study (JSC: 0.06). Nearly all (n = 243/249, or 97.6%) differences identified from the crosswalks for PAD were codes that were identified by the physician and coder but not the GEMs algorithms. Most of those codes were for diagnoses that should improve the identification of PAD, such as ICD-10-CM I70.2 (atherosclerosis of native arteries of the extremities).

Sensitivity analysis. Three conditions—AMI, arrhythmias, and hypoglycemia—were included in the sensitivity analysis to assess differences between the GEMs forward matching and FBM approaches. Overall, FBM reduced the number of differences between the GEMs-derived algorithms and the physician/coder algorithms for two conditions, although it added five differences (codes now identified by GEMs FBM that were not identified by the physician/coder) for one condition. Eight differences between the GEMs and physician/coder approaches were identified for AMI after forward mapping (all were codes identified by the physician/coder but not by GEMs); all eight of those codes were identified by FBM, so no differences remained between the two approaches after FBM (JSC increased from 0.53 to 1.00). One additional ICD-10-CM code was added by FBM for the arrhythmia algorithm, but this code was not present in the physician/coder crosswalk, so similarity between the crosswalks decreased (JSC decreased from 0.40 to 0.38). FBM identified six additional ICD-10-CM codes for hypoglycemia, but only one of these matched with the codes in the physician/coder crosswalk, leaving five additional unmatched codes; therefore, the crosswalks were more dissimilar after FBM (JSC decreased from 0.50 to 0.42).

Discussion

This study used two distinct methods to identify ICD-9-CM to ICD-10-CM crosswalks for 10 selected clinical conditions — an automated system (GEMs), and a process by which a physician and clinical coder applied their expertise (with the aid of a questionnaire) to assess the selected conditions. The similarity of crosswalks derived from each approach varied considerably, and results demonstrated that the crosswalks developed by the physician/coder were more inclusive than those identified via GEMs, except for hypoglycemia (three vs. four) and MCI (no differences). The general inclusiveness of the algorithms identified by the physician and clinical coder likely increased the sensitivity of the algorithms, while potentially decreasing the specificity, in comparison with those identified via GEMs.

The ability of a physician/coder to consider various clinical factors related to individual conditions made it possible to identify a larger number of potential codes. The GEMs method, on the other hand, struggled to identify clinical conditions with a broad scope and/or various etiologies (e.g., diabetes), those where the definition may vary somewhat between physicians (e.g., PAD), and conditions that may be a side effect of some therapeutic classes of medications (e.g., hypoglycemia).

Fung et al have summarized the performance of various methods for using GEMs to generate ICD-9-CM to ICD-10-CM crosswalks and determined that FBM had better performance than conventional forward mapping.[5] The forward and backward GEMs are not mirror images, and the FBM approach permits the user to identify codes that would not otherwise be identified through either forward or backward matching alone. In the present study, our comparison of the AMI crosswalks from GEMs and the physician/coder yielded eight differences; the use of FBM eliminated all eight, resulting in fully similar crosswalks across both approaches. However, the use of FBM decreased the similarity of crosswalks derived for two other conditions (arrhythmia and hypoglycemia) included in the sensitivity analysis. While the use of FBM was an improvement compared with conventional forward mapping for the crosswalk developed for one condition (AMI), it was not a full substitute for physician and coder involvement in developing ICD-10-CM crosswalks in the present study.

Although the human element provided a clear advantage for creating crosswalks for existing algorithms, algorithms derived from any method should be reviewed and refined by researchers to ensure that they are appropriate for the study objectives. A retrospective analysis of claims data with a chart review could provide valuable information for validation of selected algorithms. The "gold standard" for identifying whether a patient did or did not have a condition of interest would involve a review of the medical charts or other approach to confirm the diagnosis, and the sensitivity, specificity, and other performance metrics of the algorithms identified by GEMs and by a physician and coder could be calculated against the extracted data from the validation. As no patient data was used in this study, such a validation was not possible.

Limitations

The conclusions of this study may have differed if a larger, or alternate, set of conditions was used to evaluate the algorithm crosswalks. The algorithms were identified by one physician and one clinical coding expert; variations in expertise and resources could impact the review process — and ultimately, the results — of other physician/coding experts. Finally, only qualitative statements about the likely effect of differences between crosswalks on performance metrics, such as specificity, sensitivity, positive predictive value, and negative predictive value, could be made due to the lack of patient data/chart review.

Conclusion

The use of GEMs alone is likely insufficient for identifying appropriate ICD-10-CM crosswalks from ICD-9-CM algorithms; physicians and clinical coders use their expertise and other resources to identify additional codes required in the development of more accurate algorithms. Neither method is comprehensive, however, and algorithms should be thoroughly reviewed and validated, if possible, prior to implementation by researchers.

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CLINICAL DATA ABSTRACTION: A RESEARCH STUDY

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By Valerie J. M. Watzlaf, PhD, MPH, RHIA, FAHIMA; Patty T. Sheridan, MBA, RHIA, FAHIMA; Amal A. Alzu'bi, PhD; and Laura Chau, BS in HIM

Abstract

This is the second part in a two-part research study on clinical data abstraction.[1] Clinical data abstraction is the process of capturing key administrative and clinical data elements from a medical record. Very little is known about how the abstraction function is organized and managed today. A research study to gather data on how the clinical data abstraction function is managed in healthcare organizations across the country was performed. Results show that the majority of the healthcare organizations surveyed have a decentralized system, still perform the abstraction in-house as part of the coding workflow, and use manual abstraction followed by natural language processing (NLP) and simple query. The qualifications and training of abstractors varied across abstraction functions, however coders followed by nurses and health information management (HIM) professionals were the three top performers in abstraction. While, in general, abstraction is decentralized in most enterprises, two enterprise-wide abstraction models emerged from our study. In Model 1, the HIM department is responsible for coding, as well as all of the abstraction functions except the cancer registry and trauma registry abstraction. In Model 2, the quality department is responsible for all of the abstraction functions except the cancer registry, trauma registry, and coding function.

Keywords: Abstraction, electronic health record, clinical, descriptive research study, natural language processing, query, models

Introduction

Clinical data abstraction is the process of identifying and capturing key administrative and clinical data elements. The purpose of abstraction includes the collection of data related to administrative coding functions, quality improvement, patient registry functions and clinical research. A previous review of the literature which includes the abstraction methods, advantages and disadvantages of those methods, the abstraction process, and the connection between EHR abstraction and patient registries have been summarized in a previous manuscript.[1] From this review, we found very little on how the enterprise-wide clinical data abstraction function is managed. Therefore, we have conducted a descriptive study that includes multiple methods of data collection such as qualitative interviews and quantitative surveys of healthcare professionals on how the abstraction function is managed in their organizations today. The results of this study will be shared as well as best practice models that can be used in the organization and management of the abstraction function.

Specific Aims

The goals or specific aims of this research study include the following:

1. Examine how the abstraction function is organized and managed today.

2. Examine the differences in quality and efficiency between manual and automated abstraction.

3. Provide best practices on how healthcare systems are organizing the abstraction function.

Methodology

A descriptive research design was conducted and included multiple methods of data collection to include qualitative interviews with healthcare professionals responsible for the abstraction function. This was followed up with a quantitative-based questionnaire to a larger sample of healthcare professionals.

Participants for the interviews were gleaned from the AHIMA Engage Community, AHIMA Component State Associations (CSAs), coding and quality communities, LinkedIn, and emails to colleagues of the authors who were managers of clinical data abstraction. Twenty-one responses were received, and eight healthcare organizations were interviewed in depth. Appendix A provides the questions asked during the interview.

All interviews were conducted by the primary researchers and were recorded and transcribed. Content analysis was performed on the transcripts by searching for patterns and themes and then summarizing the findings by discussing them with the research team. The quantitative section of the study included building a survey that collected responses from 50 Ciox Health clients on how they manage the abstraction function. The questions for the survey are listed in Appendix B. IRB approval through the University of Pittsburgh at the exempt level was obtained and the IRB number is PRO15110055. The survey was administered through Qualtrics and initial analysis was done through Qualtrics and more specific graphs and tables were conducted by the researchers using Excel.

Results

Qualitative Interview Results:

Demographic Information of Interview Participants

Participants of the interviews were from large healthcare organizations with complex medical systems and employed a range of abstractors from five to 15 full-time employees (FTEs). The range of years of experience of the leaders of the clinical abstraction function ranged from 10 to 36 years and were primarily in senior level positions.

Management of Clinical Data Abstraction

Management of the clinical data abstraction varied from centralized and decentralized abstraction that were separate from the medical record coding and some that were not separated from coding. The breakdown is displayed below in Figure 1 and shows that 38 percent (3/8) implemented a centralized abstraction function but the leader of that function did not oversee coding. Twenty five percent (2/8) did not have the abstraction function separated from coding but did oversee the coding function and 38 percent (3/8) did separate abstraction from coding and did oversee the coding function.

Advantages and disadvantages for separating abstraction from the coding function were discussed during the interview and included increased productivity and data quality, process standardization, leveraging electronic data sources, a focus on skill sets and not on a multidisciplinary person that can do it all. Disadvantages include that abstractors find things that the coder may miss (and vice-versa) so that a second check is not there, multiple people are handling the record multiple times, leveraging structured fields in the EHR to reduce manual abstraction means potentially eliminating abstractor FTEs, which can be seen as a disadvantage since the abstractor could lose their job.

Qualifications and Training

The qualifications and training of the clinical data abstractors varies across abstraction functions. Registries tend to hire credentialed and educated professionals in the field, e.g. cancer registry (CTR), trauma registry (CSTR), cardiac and vascular registry (RN, LPN, RHIA) etc. Quality management departments hire educated and/or experienced abstractors with credentials, such as the RHIA, RHIT, RN, LPN. All abstractors should have an expertise in computer skills, be detail oriented, and have medical record knowledge (data sources, medical terminology, anatomy and physiology, pharmacology, pathophysiology).

Data Elements Abstracted:

The data elements that are most commonly abstracted that are separate from the coding function include:

1. CMS quality reporting measures

2. National Quality Forum (NQF) quality measures

3. The Joint Commission quality measures

4. Patient registry functions (trauma, stroke, cancer, thoracic surgery, general surgery, cardiac etc.)

5. Clinical research studies

The common data elements that are abstracted as part of the coding process include:

1. Any providers involved in the patient's care

2. Date, time of procedure, surgical suite, time of anesthesia, results

3. CDI recommendations

4. Date of POA indicators

5. Admission/Discharge Dates

6. Discharge Disposition

Clinical Data Abstraction Methods Used

The clinical data abstraction methods used by the eight interviewees included five used manual abstraction, two used simple query, and one used NLP. One of the comments by the participants stated, "We tried to do some NLP selection, optical character recognition, discrete data point download, but we found that the medical record is so varied in responses and we have very specific data definitions that the error rate was higher than what we were willing to tolerate, and we have a much better success rate with the visual validation and abstraction."

Data Validation Methods

There can be multiple methods of data validation in the abstraction process. The most common methods used were inter-rater reliability and most of the organizations do this concurrently and as well as retrospectively. The gold standard for the accuracy rate is 95 percent and was made part of the abstractor's job description and is a quality metric for performance evaluations.

Quantitative Survey Results

A variety of healthcare professionals from a number of different healthcare facilities gave valuable information on how the abstraction function is managed in their organization. The majority of the respondents (58 percent) hold the position of HIM director. Seventy percent are from large comprehensive healthcare systems ranging from 100 to 500+ beds. The majority (58 percent) of participants reported that they employed a range of abstractors from zero to nine FTEs with some reporting as high as 30 or more (8 percent). Also, 41 percent of those that performed the abstraction function were coders, followed by nurses (27 percent) and then HIM professionals (8 percent). (**Table 1**).

Other findings (**Figure 2**) show that manual abstraction (58 percent) is the primary abstraction method while NLP was 18 percent; simple query 12 percent; and another 12 percent said that they used their EHR systems/encoder to run reports.

Results also showed that the way the abstraction function is organized across an organization is fairly split evenly between centralized and decentralized (48 percent answered that abstraction is decentralized across the organization and takes place in different departments and 44 percent said that abstraction is primarily centralized with some decentralization). The other 8 percent had varied answers on the topic (**Figure 3**).

Seventy percent of the respondents said that abstraction is performed in-house and 78 percent said that it is performed as a part of the coding workflow process (**Figure 4** and **Figure 5**).

Additionally, retrospective validation using a convenience sample is the most popular validation tool to ensure the abstraction data quality (50 percent).

The results showed that most of the healthcare organizations have fragmented abstraction functions. Based on the results, it seems that there is inconsistency among healthcare organizations on how best to manage abstraction. Furthermore, while centralized abstraction services are prevalent, more (48 percent) of the health systems surveyed have decentralized abstraction functions.

Discussion

Results from this descriptive study that incorporated both qualitative and quantitative data about clinical data abstraction, found that most of the healthcare organizations interviewed and surveyed have a decentralized system but some said they were moving toward a centralized system. The majority of healthcare organizations still perform the abstraction as part of the coding workflow, and 70 percent of those surveyed do it in-house. The majority of those healthcare organizations use manual abstraction followed by NLP and simple query.

The qualifications and training of clinical data abstractors varies across abstraction functions as registries and quality reporting tend to hire credentialed and educated professionals, whereas abstraction for coding related data need less education and skills. Most common data elements collected include required quality reporting measures, patient registry functions, clinical research studies and data collected as part of the coding process such as POA indicators, discharge disposition etc.

Two enterprise-wide abstraction models emerged from our study. In Model 1 (**Figure 6**), the HIM department is responsible for coding, as well as all of the abstraction functions except the cancer registry abstraction which is normally housed under the oncology department. In Model 2 (**Figure 7**), the quality department is responsible for all of the abstraction functions except the cancer registry abstraction and is not responsible for the coding function. Model 1 is centralized under HIM and still includes coding, administrative data elements abstracted, quality measures, special study data abstraction, and registry data abstraction. Model 2 is centralized under the quality department and includes everything in the first model except coding.

Limitations

There were some limitations to our descriptive study as listed below:

1. Even though we received 21 responses for our interviews, we were only able to interview 8 individuals and therefore their responses could be different than what we may have received if we were able to connect with the entire group that responded.

2. The quantitative responses from the survey we developed was limited to just 50 Ciox clients who responded to that survey. This sample may not be a good representation of the entire population of clients who oversee clinical data abstraction and therefore their views may then be different than the entire population.

3. Due to our limited sample size, it was difficult to do more than basic descriptive statistics with the

data received.

Future Research

Future research in this area is needed to focus more on the technologies that may now be used and how they compare to human abstraction in relation to efficiency, accuracy, and cost. There is still limited information in this area, so more research is needed to determine the best methods for abstraction as well as the best organizational and management methods around the abstraction function since it varied across organizations. Also, more research is needed on the best qualifications and training that are needed for abstractors since those performing this function varied across organizations and new technologies could lead to more thorough and extensive training methods. Clinical data abstraction is such a vital function that more research in this area world-wide could determine high quality methods of implementation that can then be used by healthcare organizations across the globe to improve the workflow and the quality of the data collected which in turn will lead to better health outcomes for patients.

Conclusion

There is room for improving the quality of healthcare data abstracted and centralizing the abstraction services. This could possibly be tackled by creating and implementing policies and procedures that can outline how to and who performs the abstraction function. Ensuring that the staff follow the abstraction policy might lead to a more consistent process among healthcare organizations which will result in better healthcare reporting and documentation. **Figure 8** shows our root cause analysis regarding the problem of fragmented abstraction functions. Furthermore, the advances in technology have also improved the clinical data abstraction function. NLP and machine learning systems are able to understand the language of the textual variables within the medical record and produce them so that the abstractor can audit them for inclusion, if appropriate. Over time the accuracy of machine learning systems improves as larger sets of data are reviewed. There have been several studies that have found that the use of NLP and machine learning enhance clinical data abstraction.[2-5] As more healthcare organizations use NLP, the efficiency and quality of clinical data abstraction will increase and the need for health information management professionals in this area at an analyst or auditor level will be needed as well. Education and training in the areas of artificial intelligence and machine learning is important to provide to healthcare and health information professionals so that they understand and use these tools to enhance the clinical data abstraction function within their healthcare organizations.

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best practices that when adopted can improve the efficiency and effectiveness of the U.S. healthcare system.

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ASSESSING THE PREVALENCE OF AHIMA-IDENTIFIED HEALTH INFORMATICS AND INFORMATION MANAGEMENT CAREERS AND RELATED SKILLS: A CROSS-SECTIONAL STUDY

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By Charisse R. Madlock-Brown, PhD, MLS; Marcia Y. Sharp, EdD, RHIA; and Rebecca B. Reynolds EdD, RHIA, CHPS, FAHIMA

Abstract

This study's objective was to identify the prevalence of the American Health Information Management Association (AHIMA) career map jobs and determine which job categories, degrees, and skills are associated with higher pay. We extracted data from SimplyHired, a major employment website, from December 2018 to December 2019. We retrieved 12,688 career posts. We found differences in average salary by career category (p-value 0.00). Most jobs were in coding and revenue cycle (CRC) and information governance (IG) categories. The highest average salaries were in data analytics (DA) and informatics (IN). Each career category had a unique set of skills associated with the highest paying jobs. Eighty-two percent of CRC, 67 percent of IG, 65 percent of IN, and 83 percent of DA jobs listed in the AHIMA career map were present in the extracted dataset. These results can help employees, academics, and industry leaders understand the health informatics and information management (HIM) workforce landscape.

Keywords: HIIM workforce, job skills, informatics, job salaries, higher education

Introduction

The health informatics and information management (HIM) field has changed dramatically with new jobs, knowledge, and skills required. This makes identification of current jobs challenging.[1]

With increased technology and advances in medicine, the necessary skills of managing patient information on paper now require managing patient information electronically. Identifying the skills required of HIM professionals is challenging, as the needs are impacted by a quickly changing healthcare system driven by regulations, standards, guidelines, and compliance with various federal and state mandates.

However, the Bureau of Labor Statistics estimates that HIM professionals' demand will grow 8 percent between 2019 and 2029.[2] Therefore, as the job market changes and the healthcare industry moves toward more automation and increased use information technology to drive decisions and reimbursement, there is a need to continuously evaluate the HIM workforce skillset, job requirements, and job titles.

AHIMA addressed these concerns by re-evaluating its educational strategy, revamping its career map[3], and charting a new course for the HIM workforce. Bold educational directives were made to ensure the continued vitality of the HIM profession.[4]

The AHIMA career map groups jobs into four domains: coding and revenue cycle, information governance, informatics, and data analytics.

The career map comprises HIM job titles, roles, expected salary, related skills, job descriptions, and domains. AHIMA used AHIMA members, subject-matter experts, and staff to guide the career map development. The map was last updated in 2016.

When studying the job market and identifying current jobs, there are limitations to using the AHIMA career map. These include that existing positions are determined only from jobs and roles of the AHIMA membership and do not include members of the current workforce working in these jobs or related fields. It also does not have frequencies of job titles. Another issue with the AHIMA career map data is the emerging roles in the career map were developed by focus groups and did not reflect actual jobs that may or may not exist in the industry.

As the authors began exploring the origins of the data in the career map, it became apparent that a job-market analysis was required to identify the current jobs available in the healthcare market in the HIM scope of work.

Previous research on the HIM workforce highlights emerging skills and current health information technology (HIT) trends. AHIMA completed a workforce study in 2014 to assess workforce demand, challenges, and needs. Among the top skills reported were analytical, coding, and critical thinking.[5] Furthermore, the future's principle skills would include electronic health record management and privacy and security skills.

Another workforce study outlined the overlap of HIM and HIT roles, which included project management, and privacy and security[6]; while DeAlmeida et al. used data from AHIMA membership profiles to link jobs to STEM technology job titles.[7] Marc et al. studied the U.S. and global trends in HIM job announcements using relevant HIM keywords and identified current job domains.[8,9]

The purpose of our study was to obtain empirical data on current AHIMA job titles listed in SimplyHired. Our study sought to analyze salary trends, top skills, and career prevalence. Our review is the first to map AHIMA job titles to current announcements and report specific job titles. The specific research questions which guided our study are as follows:

1. How prevalent are AHIMA career map jobs, and are there emerging and current positions not represented?

2. Which job categories/degrees and skills are associated with higher pay?

3. What are the differences in skills required by job category?

Methods

The AHIMA career map is divided into four broad categories of HIM jobs: Coding and revenue cycle, information governance, informatics, and data analytics.

In addition, each position is categorized as either “current” or “emerging” to reflect anticipated changes in the workforce. We collected all career data from the AHIMA career map (accessed April 2019) using a Python application. Python is a programing language, and the Python package selenium was used to copy information from the AHIMA website. The following job attributes were retrieved: career category, title, responsibilities, description, skills, responsibilities, training, work experience, and alternate job titles.

We wrote an application in the Scala programming language to run nightly to crawl the SimplyHired website for jobs using "health information management" as a search term. The following job attributes were retrieved from this data extraction, including title, location, company, date posted, minimum salary, maximum salary, responsibilities, description, required/preferred education, benefits, and skills.

References to education-level, benefits, and skills were extracted from job descriptions by SimplyHired. We stored the information retrieved in a PostgreSQL database. SimplyHired aggregates job postings from thousands of other employment websites and job boards and is a good representation of publicly advertised employment opportunities. We accessed jobs from December 12, 2018, to December 16, 2019.

We mapped SimplyHired titles to the AHIMA career map titles by converting the latter into a bag-of-words and matching the former. If a SimplyHired title contained all the words from an AHIMA career map title, it was considered a successful match even if the words were not in the same order, or the SimplyHired job had additional terms. If the AHIMA career map titles had added abbreviations, we removed them (e.g., we removed the abbreviation EHR from electronic health record implementation specialist). In two cases, the title listed alternative words (e.g., director/chief). In that case, we created two separate titles, each with one of the terms.

We aggregated all SimplyHired jobs by AHIMA career category. We displayed the average maximum salary with confidence intervals for job categories, education level, job titles within job categories, and top skills within job categories. We performed the Kolmogorov-Smirnov[10] normality test on all salary distributions by category. We tested for normality to decide if statistical tests designed for normal distributions could be used. Normality tests, such as Kolmogorov-Smirnov, compare the z-score of the sample (in our case, salary values) to the z-scores of normal distributions with the same mean and standard deviation as the sample. The Kolmogorov-Smirnov test is appropriate for sample sizes >=2000. The null hypothesis for this test is that the distribution is normally distributed. So, a p-value >0.05 would indicate a normal distribution. We used the one-way analysis of means[11], which does not assume equal variance, to assess differences in average minimum/maximum salary by category. The one-way analysis of means is a non-parametric test appropriate for non-normal distributions. We provided confidence intervals on proportions for job counts by degree, career category, and job titles within career categories. All visualizations and statistical tests were performed in R using the following packages: tidyverse, DescTools and rcompanion.

Results

Our application retrieved 12,688 postings from SimplyHired that match AHIMA career map HIM careers. The results of our Kolmogorov-Smirnov test indicated that the average maximum salaries by career categories are not normally distributed with p-values <0.05. Our one-way analysis of means for maximum salary by job category showed differences in average salary with a p-value of 0.00. Distribution of jobs from our data into the AHIMA career map categories found 4,943 jobs in coding and revenue cycle; 3,373 jobs in information governance; 2,202 in data analytics; and 2,170 in informatics.

Of the job listings that mention education required/preferred, the distribution showed that 4,482 needed a Bachelor's degree; 1,964 required a high school diploma or GED; 1,456 required an Associate's degree; 1,004 required a Master's degree; and 96 required a Doctoral degree. Eighty-two percent of CRC, 67 percent of I.G., 65 percent of IN, and 83 percent of DA jobs were present in the extracted dataset. The majority of AHIMA jobs not present in the SimplyHired dataset were in the information governance domain, though each category had at least one title not present in our dataset. These job titles can be viewed in **Appendix 1**.

As seen in **Figure 1a**, jobs in the DA and IN categories have the highest average salaries. The error bars between these two categories show overlap, indicating that their average salaries in the population may not be different. The error bars for those categories do not overlap with the CRC or IG categories, indicating that the true population averages between DA-IN and CRC-IG are different.

Figure 1b shows that SimplyHired jobs referencing master's degrees have the highest average maximum and minimum salaries. Error bars for the Doctoral degree are the only category that overlap with other jobs. The differences in averages between all other jobs are likely to represent the true population averages. It is important to note that the jobs requiring doctoral degrees are few, which may impact the representativeness of this to the population averages.

As seen in **Figure 2a**, the most frequent CRC jobs are revenue cycle manager, coding professional, clinical documentation specialist, and medical biller. Medical biller is an entry-level job, and the other two are advanced jobs according to the AHIMA career map. Each of these jobs was listed as current on the AHIMA map as well. The three least frequent jobs are mid-level or advanced jobs, according to the AHIMA map. Each of these jobs is listed as current.

The three most frequent jobs in the DA category are all in the advanced category, and the least frequent job, mapping specialist, is in the mid-level category. The most frequent job in the Information Governance domain, patient registrar, is an entry-level job.

Among the next three top jobs, health information technician and information security officer are mid-level, and compliance officer is advanced. All these top jobs are listed as current in the career map. Of the top four most frequent jobs in the informatics career category, data application analyst and implementation support analyst are mid-level. Release of information specialist is an entry-level job, and quality improvement analyst is an advanced job. All these jobs are current.

As seen in **Figure 3a**, **Figure 3b**, **Figure 3c**, and **Figure 3d,** several of the job categories have a significant distribution of average salaries. Average salaries range from below $50,000 to above $150,000 for average maximum salaries.

For CRC jobs, the director of coding (master level) job has the highest average salary and is the only job in this domain with an average max salary above $100,000. Though the error bars are wide, they do not overlap with any other job. These next two jobs with the highest average salaries in that AHIMA category are also frequent jobs, with revenue cycle manager (advanced level) being the most frequent and second highest paying job. Data quality manager (advanced level) is the highest paying and the second most frequent job in the DA domain. The chief technology officer (master level) has the highest salary across all career categories in the informatics category.

However, the wide error bars have overlap with the top jobs in CRC and G The top three informatics jobs have average maximum salaries above 100,000. Though IG had the second-lowest average salary according to **Figure 1a** and **Figure 1b**, it is the only category with four jobs with average maximum salaries at or above $100,000. These jobs' error bars do not cross over the $100,000 mark, indicating that the true population average for these jobs is above that threshold.

Figure 4a, **Figure 4b**, **Figure 4c**, and **Figure 4d** show the skills associated with top-paying careers in each category. Each category has a unique set of top skills. The top skill in Data Analytics is Hadoop, a big data framework for storage and computing. Software Development Life Cycle (SDLC), is a framework for efficient software development and is the second-highest paying career in that category. Business Intelligence, Python programming language, quality management, and Current Good Manufacturing Practice CGMP are also top skills indicating a preference for workers who have experience with analytics and management of resources and the application of analytics for improved business operations. Other desired skills in this category are related to project and data management and other data analytics skills (XML, data mining, relational databases, etc.). There is an overlap in the top skills between the informatics category and data analytics. The top skill for informatics is business intelligence--which is included in the data analytics list. The next three skills, Oracle, data management, and data warehouse- all relate to databases' management. Other skills in this category relate to project management (PMP, leadership experience), basic computer science skills (Microsoft Project, I.T. Experience), business administration, visualization(Tableau), specific analytic skills(SQL, Visio, etc.), and particular certifications (Project Management Professional (PMP), and Epic Certification).

The Information Governance (IG) and Clinical Revenue Cycle (CRC) categories' skillsets only reference analysis skills and Microsoft products. The top skill for I.G. is COBIT (Control Objectives for Information and Related Technologies) which is a framework for I.T. management and information governance.

Other I.G. top skills include those related to national standards and information security (national institute of standards and technology), CISSP (Certified Information Systems Security Professional), information security, and SANS- GIAC (Global Information Assurance Certification). The rest of the skills in IG reference government legislation such as SOX (Sarbanes-Oxley Act for compliance related to financial reporting), management (risk and project management, organizational skills, public speaking, and leadership experience, etc.), and business management (audits and budgeting). The top skills in **Figure 4d** for CRC are in management (project management, leadership, conflict management, and negotiation) as well as managed care. Clinical documentation certification and medical insurance are HIM specific skills mentioned.

Although the RHIA and RHIT were not in the list of top 20 skills for any of the categories, RHIA was mentioned in 7 percent (n=876) of career announcements, and RHIT was mentioned in 7 percent (n=843).

Discussion

This study indicates that earning potential increases as educational level increases (**Figure 1b**). The average salary increases with references to advanced degrees (the Master's degree average salaries are higher than the baccalaureate degree). Our findings are consistent with other studies, which indicate that learning more yields to earning more.[12]

Job titles show that there are many jobs available for entry-level professionals in those categories that allow for entry into the HIM workforce. The jobs with higher proportions show there are opportunities for career advancement in the HIM field.

The proportion of jobs for each job title within the four AHIMA categories is critical to investigate future job opportunities or target career advancement. It is important to note that the informatics job category pays more than the other AHIMA job categories. Additionally, we see that many of the jobs listed as emerging the AHIMA Career Map were found in the job search we conducted. Further work is necessary to know whether some of the jobs we did not see in our job search might be there with other job titles.

Our results show that information governance and informatics skills lead to higher-paying average salaries (**Figure 4b** and **Figure 4c**). Future students must realize these are the top skills in the respective areas, and from a curriculum standpoint, these skills should be included. Quality management, a skill identified in data analytics, is a core competency within the HIM domain. Data governance skills are essential for jobs in the health informatics and data analytics category. Coding and revenue cycle skills demonstrate a consistent progression from entry to higher critical thinking skills.

Overall, the job categories of data analytics and informatics yielded the highest average salaries. Among the degree requirements, the master's degree holders have the highest average salaries. Concerning job skills, project management, leadership, data management, oracle, and business intelligence expertise showed the highest average salaries. Several specialized certifications like Hadoop, COBIT, SAP, Tableau, and Python also had high average salaries. Throughout all job categories and domains, project management and leadership skills were prevalent.

An interesting observation is the number of jobs held by AHIMA members, as reflected on the AHIMA career map, not in the Simply Hired jobs search. Perhaps the job titles are changing and may reflect other job titles found in our investigation of open positions. Some of the job titles are shifting as there are more postings for analysts that might have been more specific titles in the past. It appears that many of the jobs that were not found in our search were jobs with specific titles such as Enterprise Master Patient Index Health Information Exchange Coordinator. These jobs may not exist because the master patient index terminology has changed to patient identity management so that those jobs may exist with different job titles. Another job that did not emerge, the Meaningful Use Specialist, was a very-specific job title based on a federal mandate that has since been changed.

One of the limitations of studying the HIM job market is the variety of job titles in the HIM domain that may not be included in the AHIMA career map. The educational requirements for these positions vary from medical coders to chief information officers. There is also a plethora of credentials available and skills required for the jobs which vary widely over the domain areas. Our future work will include mapping the HIM curriculum skills using the curriculum standards in the AHIMA and AMIA competencies.

Conclusion

The HIM workforce is ever-changing, and HIM professionals play a critical role in and impact the healthcare industry's success. This study's roles and domains demonstrate the variety of skills and job titles represented within the HIM field and their associated pay scales. With such a diversity of jobs and skills, it is essential to stay abreast and aware of industry workforce needs. The need to adapt to changing job demands is critical as there is a wide range of knowledge and skills required. Now is the time for HIM professionals, educators, and other stakeholders to commit to including more specialized resources and expertise in their educational programs to meet the workforce needs today and in the future.

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