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A Framework for Artificial Intelligence Applications in the Healthcare Revenue Management Cycle

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A Framework for Artificial Intelligence Applications in
the Healthcare Revenue Management Cycle

by

Leonard J. Pounds

A dissertation submitted in partial fulfillment of the requirements
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We hereby certify that this dissertation, submitted by Leonard J. Pounds conforms to acceptable standards and is fully adequate in scope and quality to fulfill the dissertation requirements for the degree of Doctor of Philosophy.

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There is a lack of understanding of specific risks and benefits associated with AI/RPA implementations in healthcare revenue cycle settings. Healthcare companies are confronted with stricter regulations and billing requirements, underpayments, and more significant delays in receiving payments. Despite the continued interest of practitioners, revenue cycle management has not received much attention in research. Revenue cycle management is defined as the process of identifying, collecting, and managing the practice's revenue from payers based on the services provided.

This dissertation provided contributions to both areas, as mentioned above. To accomplish this, a semi-structured interview was distributed to healthcare executives. The semi-structured interview data obtained from each participant underwent a triangulation process to determine the validity of responses aligned with the extant literature. Data triangulation ensured further that significant themes found in the interview data answered the central research questions. The study focused on how the broader issues related to AI/RPA integration into revenue cycle management will affect individual organizations. These findings also presented multiple views of the technology's potential benefits, limitations, and risk management strategies to address its associative threats. The triangulation of the responses and current literature helped develop a theoretical framework that may be applied to a healthcare organization in an effort to migrate from their current revenue management technique to one that includes the use of AI/ML/RPA as a means of future cost control and revenue boost.

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Chapter 1

Introduction

Background

As healthcare institutions navigate the industry's varied challenges, they increasingly rely on healthcare information technology (HIT) as a means of cultivating solutions to recurrent problems (Bohr & Memarzadeh, 2020, p. 25-60; Stanfill & Marc, 2019). HIT includes diverse systems, hardware, and software that provide varied benefits to selected users across organizational contexts. One specific HIT application includes artificial intelligence (AI): A collection of systems and programs that rely on computer-generated thinking to perform a range of prescriptive and predictive tasks. Current AI applications in healthcare contexts include machine learning platforms that contribute to decision-making in both clinical and administrative areas of operation (Lin et al., 2017). Analysts predict that as technology advances and becomes increasingly manageable from risk mitigation, and cost-effectiveness standpoints, planners across the healthcare sector will likely adopt AI and Machine Language (ML) platforms to assist with multiple functions (Hut, 2019). However, other reports indicate that planners will also need to address a complex set of potential barriers to HIT implementation and use it to implement technology-oriented solutions within their organizations (Christodoulakis et al., 2020). Artificial intelligence (AI) and related technologies are increasingly common in business and are beginning to be applied to healthcare. While these technologies have the ability to transform many aspects of patient care, as well as administrative processes within the provider and payer organizations, researcher recommendations conflict regarding the extent of benefits versus risks offered and posed by using AI in such settings (Christodoulakis et al., 2020; Davenport & Kalakota, 2019). There are already several research studies suggesting that AI can perform as accurately as or more accurately than humans when it comes to essential healthcare tasks, such as diagnosing diseases (Davenport & Kalakota, 2019).

Nonetheless, Christodokulakis et al. (2017) highlight the associated challenges and risks introduced alongside such benefits. Therefore, a need exists for practitioners and researchers in healthcare to understand the advantages as well as the barriers or challenges associated and more comprehensively with AI implementation in clinical settings, especially as such factors relate to organizational financial solvency so that AI technologies can be implemented and used in the most appropriate and beneficial ways. Another contextual factor complicating the consideration and implementation of AI systems and their associated challenges and benefits is the current changing healthcare regulation environment (Forcier et al., 2019; Gerke et al., 2020). Changing healthcare regulations and evolving revenue cycle management lead to immense transformation in the healthcare industry. Along with staying current on updates to the Affordable Care Act (ACA), Medicaid, and other healthcare programs, healthcare providers need efficient billing and tracking procedures in place. Staying up to date with changing regulations is one area in which AI can assist organizations. Utilizing AI in the revenue cycle will assist with some of the essential aspects, such as:

1. Billing and Collections Mistakes - If healthcare establishments do not have an effective billing process, they risk losing money. With complicated insurance plans becoming more common, a billing and collections department's need to continuously review payor receipts is paramount.
2. Untrained Staff – Inaccurate data can cause billing issues in various ways, such as improper medical coding, billing, and insurance claim filing. These errors can add up to a significant amount of bad debt per year. Unpaid bills can easily get lost in the shuffle, even after only 60 to 90 days (DECO, 2019).

Based on the need to better understand associated risks, challenges associated with, and benefits of AI systems in healthcare (Shaw et al., 2019), this research was able to describe both the potential that AI offers to automate aspects of the revenue cycle and some of the barriers to the rapid implementation of AI in healthcare. This research also helped in filling a gap in understanding a conscience theoretical framework for healthcare executives to use during implementation. Therefore, the results of this research contributed to building a framework that administrators may use to leverage the benefits of AI while minimizing the risks to improve organizational operability, productivity, and financial solvency more successfully and appropriately.

Problem Statement

The problem addressed by this study was a lack of understanding regarding the specific risks and benefits associated with AI implementation in healthcare settings. Many administrative tasks are currently completed manually in healthcare, which takes high labor costs and increases human computation error potential. However, it is unknown to what extent AI may improve these administrative tasks and address challenges (CAQH, 2018). To better understand this research was able to analyze the issues affecting the healthcare industry revenue cycles. Despite some automation of claim submission and other transactions, many administrative transactions are still primarily driven by inefficient manual processes (CAQH, 2017). According to the 2017 CAQH Index, an annual report of adopting electronic business transactions, the lack of automation for these transactions costs the healthcare industry more than $11 billion per year. In order to process a patient claim, the patient financial services department is required to employ experts with advanced healthcare knowledge. Experienced professionals are necessary for auditing the claims. The current manual claims auditing methods involve extensive human efforts, time, and money and often result in claims denial. One of the obvious solutions is to adopt automation, which, despite advantages, is accompanied by many uncertainties and consideration of countless variables. Thus, this dissertation analyzed the issues affecting the revenue cycle within the healthcare industry to understand better the financial risks and benefits associated with AI implementation in the healthcare setting and constructed a theoretical framework behind using Artificial Intelligence (AI) and the financial benefits vs. the risks that will be gained by utilizing this technology. The main goal of the study was to estimate the outcome of implementing AI in the revenue cycle.

Furthermore, this study first examined theoretical trends in healthcare revenue cycle processes by researching literature related to the topic. Existing literature was analyzed to identify and address current gaps in understanding. By doing so, a broader set of observations was generated that was applied to the report's follow-up section of designing a lean process theoretical framework for the use of AI within the healthcare revenue cycle process.

Problem Broader Context

Revenue cycle management in modern health systems can be viewed in three ways (Becker & Ellison, 2019). First, the processes represent critical areas of fiscal management and administrative oversight. In brief, a health systems approach to revenue generation requires a systemized and efficient model. The literature defines an efficient model as combining the separate billing, collections, reimbursement, and accounting activities within the same framework (Becker & Ellison, 2019). Second, revenue cycle management ensures a health system's effective ability to operate in immediate and future terms. The revenue cycle must combine billing, collections, reimbursement, and accounting in the immediate present and the future. Third, for the system to continue to be efficient, it must anticipate how these domains will change in the future. Administrative and medical employees focus almost half of their time addressing revenue-oriented issues (Hillman, 2020). The same author additionally noted that healthcare systems spend approximately $266 billion annually on revenue cycle management operations. These same costs can also be compounded as systems seek to reconcile problems generated through human error. Current regulations allow healthcare entities to lower administrative costs and increase the rate of collections. However, applying AI and ML should theoretically increase revenue by reducing the number of timely filling errors and reducing the financial services team's administrative burden. Considering these issues, this dissertation addressed the problem associated with developing a framework for more successfully implementing AI and ML into healthcare organizations' revenue cycle. The literature on this topic was evaluated by examining key performance indicators (KPIs) that provide insight on reimbursements, denials, the price per accession, price per unit, paid units, throughput, and write-offs (XIFIN, 2020).

Justification of the Study

The literature clearly demonstrates a role for AI and ML in the context of the revenue cycle. For example, Blass and Porr (2019) argued that AI and ML could decrease the risk of error within compliance and risk management, ultimately streamlining the revenue cycle. However, this research was general and did not provide a specific framework for integrating AI and ML into a system. Instead, the research stated that it could be helpful. This trend has been present overall in all the research on this topic. Accordingly, there is a significant gap in the literature concerning helping organizations develop the appropriate frameworks and protocols to integrate AI and ML into their revenue cycle systems successfully, thereby justifying this study's need and developing a framework to follow. Current literature findings are not helpful for healthcare system administrators who seek to integrate technology-based solutions within their existing fiscal cycle management operations. According to Hamet & Tremblay (2017), to incorporate AI into the revenue cycle, it is first necessary to identify the barriers to implementation and then develop a framework to implement that addresses those barriers. Hence, this dissertation aided in clarifying how AI and ML can provide tangible solutions for healthcare systems by utilizing the theoretical framework. Understanding the development of such a tangible solution requires research that presents solutions that can universally apply to diverse healthcare operations.

Dissertation Goals

The dissertation's primary research goals that were addressed and detailed in future chapters are summarized as follows:

1) To expand on the current literature surrounding the use of AI in the health care revenue cycle and provide a framework to allow health care executives to quickly visualize the benefits or drawbacks of such a technology in their specific healthcare revenue cycle departments.
2) To create a framework that may be applied to a healthcare organization in an effort to migrate from their current revenue management technique to one that includes the use of AI/ML/RPA as a means of future cost control and revenue boost.

Research Questions

This dissertation explored an increasingly critical issue affecting healthcare organizations related to the use of AI software systems as a means to improve financial operability and solvency. This study used a mixed-methods approach involving a meta-analysis of the literature and semi-structured interviews to inform the following research questions:

R1. What prospective benefits can be generated by using AI revenue cycle applications for healthcare organizations?

R2. What are the risk factors associated with AI implementation in healthcare?

R3. What outcomes are derived by using a Lean Six Sigma (LSS) designed framework for healthcare executives deciding to implement AI/RPA in the healthcare revenue cycle?

Relevance and Significance

The research questions hypothesized in this study have high significance for the field of healthcare. Discussions regarding the need for better fiscal management have grown as the healthcare industry has matured. Before the 1950s, hospitals were mainly non-profit, and financing was handled mainly through charitable campaigns (Cleverly & Cleverley, 2018). When Medicare financing of many services delivered by hospitals caused a significant growth in hospital revenues, this opened the door for a heightened interest in healthcare accounting and finances. Hospitals started making the shift from charities to big business. Both cost accounting and management control became essential tools for managing finances in hospitals.

The most recent seismic shock to the system came in the 1980s when the federal government started feeling pressure from hospital billings that seemed to be spiraling out of control (Cleverly & Cleverley, 2018). At this point, the push began to have more patients treated on an outpatient basis to control costs. With this, the federal government created the Prospective Payment System, which created an opportunity for the creation of other types of medical providers other than hospitals, such as ambulatory surgery centers and other providers.

With more recent developments, such as the passage of the Patient Protection and Affordable Care Act [ACA] (2010), healthcare providers have been put under increasing pressure to find ways to achieve the "triple aim" of healthcare. The triple aim calls on healthcare organizations to (1) improve patient care experiences, (2) improve the health of populations, and (3) reduce the cost of healthcare per capita (J. Evans, 2017). The latter component of the triple aim, the thrust to reduce healthcare costs, is at the heart of financial management. Healthcare organizations must be run professionally and efficiently to be able to deliver high-quality healthcare for diminishing payments. This has required those in the healthcare industry to seriously rethink their business structures and find ways within those structures to maximize the payments that they already receive so that they can benefit the organization to the most significant degree possible.

That is why the consideration of using AI to improve fiscal management is so relevant and significant for the healthcare industry today. Successful financial management of modern healthcare organizations, which are becoming increasingly complex, requires timely, relevant information to make better business decisions (Cleverly & Cleverley, 2018). Because the existing systems are still overly dependent on humans to do the processing, they are inefficient. This leads to delays in the reimbursement for services delivered and delays in delivering an up-to-date look at the healthcare organization's financial situation. As a result, healthcare executives often find themselves in a position to make critical business decisions based on information that is out of date and often of questionable accuracy. If the use of AI can improve that situation, then healthcare managers could move to a position where they have information that is timely and accurate, enabling them to make better business decisions that will enable them to improve the profitability and feasibility of the services provided to the public.

Barriers and Issues

Several barriers and issues were faced when doing this type of research. The field of medicine has been primarily dominated by research that follows the scientific method. As a result, literature reviews that are conducted regarding many healthcare topics include discussions about levels of evidence used to support the study's assertions, foundation, and findings. As Fineout-Overholt and Melnyk (2015) outline, levels of evidence can be categorized in seven levels, with systematic reviews of randomized controlled trials (RCTs) being the "best" evidence, or categorized as level I, and evidence from opinions expressed by either authorities or expert committees as being the "lowest" form of evidence, which is categorized as level VII. The distinction between levels of evidence is important because the level of evidence that is used to support an argument or assertion is often used as a basis for determining if the research applies to healthcare decision-making.

The Agency for Healthcare Research and Quality, as cited in Fineout-Overholt & Melnyk, 2015 defines levels of evidence by three criteria: quality, quantity, and consistency. In this context, quality speaks to how the study was designed and if approaches were used that ensured that the findings were accurately measured and that measurement, selection, and confounding biases were avoided. This is in part why systematic analyses of RCTs are generally considered the highest level of evidence. Within the AHRQ definition, quantity refers to the number of studies, the participants involved, the magnitude of the treatment, the strength from causality assessments on the outcomes, such as odds ratios or relative risk. Consistency refers to whether or not multiple researchers are reporting similar findings using the same basic study criteria. High-level evidence has a lower risk of bias in addition to greater generalizability. The latter refers to whether the findings can be generalized to a more significant population (Fineout-Overholt & Melnyk, 2015).

As Frączek (2016) discusses, the financial field has started to put more emphasis on using evidence-informed practices (EIP), which are analogous to evidence-based practices (EBP), which are used heavily in healthcare delivery practices. Applying EIP to financial questions permits the practitioner to analyze the information that they are receiving against the levels of evidence to determine the strength of the recommendations and the applicability of the information to a wide range of financial situations. It is precisely in this context where performing studies regarding healthcare finance becomes somewhat difficult. The majority of literature considered in this study in the literature review is from level VII evidence or opinions expressed by either authorities or expert committees. As such, it is difficult to assign a weight to such studies, given that the opinion primarily informs them of experts in the field. However, these opinions are not necessarily backed by any evidence that would be considered empirical, at least not from a scientific standpoint.

The fact is, due to the newness of AI, ML, and RPA, the key concepts under discussion in this study, there is a lack of actual research studies of any type applying these topics to the field of healthcare finance. A cursory look at Google Scholar with the search terms +" artificial intelligence" +finance AND +" randomized controlled trial" revealed zero studies regarding the combined topics in 5 pages of searches (the top 50 results). This search range was delimited to the past ten years (only articles since 2012). As expected, removing the time limitation did not reveal any new articles on the topics.

Assumptions, Limitations, and Delimitations

Assumptions

This study assumed that the findings presented in the literature are accurate and a true reflection of the current state of affairs regarding using AI, ML, and RPA in healthcare finance situations. This has to be an assumption because the "evidence" presented and reviewed in the literature review is Level VII evidence. There are no empirical means to identify the presence of biases or the accuracy of statements in the articles. It is also assumed that the information collected during the semi-structured interviews from select subject matter experts indicates and represents the current state of affairs in the healthcare industry, similar to the assumptions made regarding articles in the literature review.

Limitations

The design of this mixed methods research study presents certain limitations. For example, the selection of participants for the semi-structured interviews is a non-randomized convenience sample. It may be indicative of circumstances or feelings specific to certain healthcare organizations or the attitudes and approaches used in a specific region of the country. Due to this limitation, the findings may or may not be generalizable to the population of healthcare finance professionals in the United States, let alone the approaches used in other countries that use an entirely different approach to healthcare financing and funding.

Delimitations

Certain delimitations have been selected that may also impact the generalizability of this study. In order to keep the study manageable, an arbitrary number of 10 participants for the semi-structured interviews were selected. As Creswell and Creswell (2018) noted, a phenomenology study generally involves a range of 3-10 participants, so the number selected for this component of the study is not inappropriately small. Another aspect that could impact the study is historical contamination. Unfortunately, this study was conducted during the coronavirus pandemic. While participants' responses in this study are expected to be as accurate as possible, there is a possibility that internal validity could be compromised due to the impact of the coronavirus and related financial strains that would not be present during other periods when a pandemic is not in process.

Definition of Terms

Analytical-oriented approaches – Analytical-oriented approaches utilize the ability of a machine to perform sentiment analysis at the document and sentence levels as well as based on the aspect. Through such approaches, insights that would ordinarily not be extracted are identified and converted into decisions that can be acted upon (Gandomi & Haider, 2015).

Artificial intelligence (AI) – Artificial intelligence is defined as a theory and creation of computerized systems designed to perform actions that typically would be done using human intelligence and senses such as hearing, vision, language translation, and decision-making (McGrow, 2019).

Data mining - is a process that utilizes algorithms to comb through large data sets (big data) to extract usable activity patterns or outcomes (Bautista et al., 2016).

Healthcare information technology (HIT) - is a blanket term used to delineate the diverse systems, programs, and mechanisms of technology that collect, store, process, and manipulate the information contained within them for various healthcare-related purposes (Wager et al., 2017).

Lean Six Sigma (LSS) – This is a fact-based, data-driven philosophy of improvement that values defect prevention over defect detection. It drives customer satisfaction and bottom-line results by reducing variation, waste, and cycle time while promoting the use of work standardization and flow, thereby creating a competitive advantage. (ASQ, 2020).

Machine learning (ML) – This is the process of a computerized system advancing "knowledge" of a selected phenomenon through testing and adaptation, using observed patterns and trends to improve decision-making capabilities (McGrow, 2019).

Predictive modeling – This occurs when an analysis of past patterns of activity can be used to accurately predict future events, such as analyzing past payments based on a particular CPT code to predict when a current claim will be paid (Nilsson, 2019).

Revenue cycle management – This refers to the process of streamlining and optimizing processes throughout the revenue cycle to achieve the best possible cash flow outcome for the organization (LaPointe, 2020).

Robotic process automation (RPA) – This is a process whereby tasks previously engaged in by humans are automated to be performed by computers. In the context of this study, an analog would be a case where a human used to collect information from a variety of inputs such as email, spreadsheets, and other sources, interpret and collate the data, then transfer it to a business system like an enterprise resource planning (ERP) or customer relations (CR) system (Lacity & Willcocks, 2016).

Summary

As this review has considered, healthcare organizations deal with tremendous amounts of information that must be processed and handled. Current approaches to financial management are primarily manual, and this requires a significant investment in human resources at a considerable cost. Research suggests that many of the manual processes that are currently being used in financial management could be replaced by a combination of AI, ML, and RPA. With a switch to these technologies, the speed of submitting claims, the accuracy of those claims, and predictions of when claims will be paid can improve exponentially. This benefits healthcare organizations because the faster claims are submitted and paid, the less strain this exerts on cash flow demands.

The following section will consider the current state of knowledge in the areas of AI, ML, and RPA. These topics will be considered with a particular interest in how they are currently utilized in connection with revenue cycle management. The following literature review will also discuss gaps in the literature and areas where more information is needed.

Chapter 2

Review of the Literature

Literature Review

The themes explored by academic and healthcare industry journals surround discussions of technology and applications, the benefits delivered through analytical-oriented approaches to revenue cycle management, and the barriers to these same innovations. A final set of discussions entailed assessments of likely risk variables and viable risk management approaches to address these challenges. Analyses that explored background themes related to the dissertation's topic focused on three areas of discussion: the concept of artificial intelligence (AI) and machine learning (ML), process definitions of revenue cycle management, and the broader assessment of ML's potential for managing these same processes.

A large group of research in the areas of AI and ML that is specific to healthcare finance revolves around the processing of claim requests and payments from third-party payers. The research has indicated that a significant amount of money is lost due to the complexity of claims and inaccurately completed claims. When a claim is inaccurately completed, it must be returned to the institution filing the claim, and this must be rectified. This creates additional time in reworking the claim and extends the time between claim submission and payment, which negatively reflects on the organization's financial health. Numerous studies have used novel approaches combining AI and ML to automatically detect such errors and annotate them with reasons why they are being flagged. Some of these systems boast a 25% improvement over any current claim analysis software or methods.

This literature review identified several specific aspects of machine learning and artificial intelligence related to the healthcare revenue cycle. Of importance, the revenue cycle and the processes associated with it often have very repetitive tasks performed by humans. However, many of these tasks would benefit from using machine learning or artificial intelligence to automate them. In implementing these strategies, healthcare organizations could likely reduce costs and improve accuracies related to payments and other similar factors, thus increasing revenue from existing claims by reducing denials.

Justification for Inclusion and Exclusion

Inclusion

This literature review pursued studies that covered issues about AI, ML, and RPA. Also, articles regarding process definitions for revenue cycle management were sought. Finally, articles applying AI, ML, and RPA to financial processes in healthcare were sought. Articles that focused on AI, ML, and RPA, especially how they applied to the healthcare field, were selected. Articles published within the past ten years, available in full text, and the English language were considered for inclusion. The full text was required because, while abstracts provide a general overview, they do not provide details that were needed for this report. Articles featuring expert opinion were included because of a lack of research in this field, although research studies were preferred.

Exclusion

Studies were excluded from this literature review if they were published more than ten years ago. Studies that were not published in English were not considered. The reason for these exclusions is that studies older than ten years would likely not reflect current practice or thinking about the use of technology in financial issues.

Previous Work and Strengths and Weaknesses

As noted in the introduction to this study, most of the articles regarding AI, ML, and RPA were based on an accumulation of research (secondary research) and expert opinion (primarily interviews). For example, several studies were explorations of the knowledge about AI and ML, with an attempt to explain how these could be applied to various aspects of healthcare, but mainly focusing on the clinical side of things (Clancy, 2020; Davenport & Kalakota, 2019; McGrow, 2019; Shaw et al., 2019). Some articles researched the application of AI and ML from entirely different applications and industries, such as using them for automation in the supply chain (Dash et al., 2019), for making general business decisions (J. R. Evans, 2015), generic applications of AI and ML (Kühl et al., 2019), order processing in the telecommunications industry (Lacity & Willcocks, 2016), the manufacturing and construction industry (Lee et al., 2019), and financial management in the hospitality industry (Millauer & Vellekoop, 2019).

The literature review contained many articles from *Healthcare Financial Review (HFR)*, a respected peer-reviewed journal. Unfortunately, many of the articles were interview pieces that relied upon experts in the field recounting different ways that they were already or were planning shortly to utilize AI and ML in their financial operations (Baxter et al., 2019; Hegwer, 2018; Hut, 2019). Other HFR articles were secondary research articles, using other research to quantify the use and intents of AI and ML in the healthcare finance industry (Hillman, 2020; Navigant Consulting, 2019; Nilsson, 2019; Schouten, 2013).

The use of secondary research was not limited to HFM. Several other articles from peer-reviewed journals mainly were, if not entirely, secondary research, compiling information about AI and ML from other sources (Blass & Porr, 2019; Cheatham et al., 2019; Christodoulakis et al., 2020). In a search to create a sufficient research foundation to work from, some non-peer-reviewed sources, including interviews and quotes from industry professionals, were included in the literature review (Becker & Ellison, 2019; LaPointe, 2020).

There were a few research papers that looked to apply AI and ML to specific healthcare financial issues. One paper resulted from the authors analyzing a healthcare financial situation, using attributional tools to predict future discrepancies to reduce billing rejections, then testing them on a group of claims to evaluate whether the method would be successful (Wojtusiak et al., 2011). This study only tested a small group of claims, which could cause questions about the generalizability of the research to other real-world situations with far greater claim diversity. Several research studies addressed using an AI/ML approach to identifying and rectifying medical claim errors as a component of risk prevention (Chimmad et al., 2017; Kim et al., 2020; Wojtusiak et al., 2011). A few research studies focused on ways to use AI and ML to promote deep learning in several areas of medicine, including finance (Kumar et al., 2010; Rajkomar et al., 2018; Wojtusiak, 2014). Other studies focused on using various techniques associated with AI and ML to "scrub" medical claims or improve medical claims prediction (Abdullah et al., 2009; Che & Janusz, 2013).

The lack of high-quality research studies in this area presents a challenge. It makes it difficult to make a compelling case for or against a particular AI, ML, or RPA practice, absent quantifiable evidence to support the practice. While several research studies were found, they almost all were oriented at creating and testing means to improve aspects of finance that have proven to be tricky, such as claim denial by third-party payers. No studies were identified that identified specific performance improvements as a result of applying AI principles. Therefore, there is no empirical foundation to quantify the benefits of AI, ML, and RPA on the healthcare industry other than "expert" reports and secondary research.

Gaps in the Literature

The especially glaring gap in the research that was identified in this literature review is the lack of rigorous research studies in this area. While several authors created algorithms and approaches to common problems experienced by healthcare finance professionals, backing their effectiveness up through a scientific method of testing, the broader picture appears not to be addressed in the literature. It would be most helpful if one of the many organizations who have put AI/ML/RPA into practice in their organizations would perform a retrospective review that could provide numbers of differences between using this approach compared with the previous state of affairs.

Analysis of Research Methods Used

There were several research methods used in this study. Several of the articles were "expert opinion" articles and focused on interviews and reports from several healthcare finance professionals (Becker & Ellison, 2019; LaPointe, 2020). The large majority of the other articles were secondary research articles, and the data for these studies were accumulated mainly through reviews of the current literature, although not systematic (Blass & Porr, 2019; Cheatham et al., 2019; Christodoulakis et al., 2020).

The proper "research studies" in this literature review used many approaches to generate their findings. For example, in the article on deep learning for medical predictions, Rajkomar et al. (2018) used predictive modeling. They reported the accuracy of such predictions using an area under the receiver operator curve [AUROC] across sites. In the study by Kim et al. (2020), the authors studied the accuracy of a new Deep Claim system to identify potential payment rejections and found that using the new system resulted in a 22.21% relative recall gain (95% precision). Wojtusiak et al. (2011) was the only study that measured the performance of their model to use rule-based prediction of medical claims payment in a before and after a fashion, providing actual numbers on the increase in effectiveness in using the new approach over previous performance.

Concept of Artificial Intelligence, Machine Learning, and Robotic Process Automation

Kuhl et al.'s (2019) analysis provided an in-depth discussion of both AI and ML. Their work specifically noted that while AI can be defined as an overarching conceptual category that references a diverse set of computer intelligence-driven technologies, machine learning represents a particular application. The authors noted that machine learning could be understood as a program's ability to perform routine tasks, become increasingly proficient in completing these same tasks, and utilize and apply known information towards advanced problem-solving forms. Kuhl et al. (2013) also contended that optimal approaches to machine learning involve base-level operations in which programs perform repetitive tasks that gradually increase in their complexity (Kuhl et al., 2013).

An anonymous report from the publication *Healthcare Financial Management* noted that healthcare operations' revenue cycle management process often provides unique machine learning applications opportunities. These tasks include these same traits (Baxter et al., 2019). In the same publication, a follow-up report also noted that healthcare systems increasingly rely on automated and analytics-driven revenue cycle management approaches even as they outsource these processes to third-party specialist firms (Navigant Consulting, 2019). Dash et al. (2019) demonstrated how increasing complexity is helpful in the context of supply chain management. Much of their analysis can be applied to the context of an automatic revenue cycle, specifically, to help provide a framework for how artificial intelligence can adapt to increasingly complex tasks. Robotic process automation (RPA) is an industrial response to the vast amount of manual work that individuals perform daily, weekly, or monthly to support a broad array of high-volume business processing (Lacity & Willcocks, 2016).

RPA is mainly associated with the task level. The application areas include finance and accounting, IT infrastructure maintenance, and front-office processing. The so-called robots are software programs that interact with enterprise resource planning and customer relationship management systems. The robots can gather data from systems and update them by imitating manual screen-based manipulations. RPA solutions are appealing from a business perspective because they automate repetitive tasks while minimally invasive into the overall processing they support.

Process Definitions of Revenue Cycle Management

Literature analyses describe the healthcare sector's current strategies and other industries to implement automated revenue cycle management approaches. Millauer and Vellekoop's (2019) healthcare industry discussion noted that firms frequently utilize these approaches for three main reasons. These models streamline the repetitive nature of fiscal cycle operations by applying machine learning models and algorithms to these tasks. This same approach additionally serves to mitigate the risks stemming from human error within these processes. McGrow (2019) highlighted the importance of removing human error from processes when it is possible to do so. However, currently, these processes are still being completed by humans because there is not currently a sufficiently sophisticated machine learning system to replace the human element with an automated system completely. Analysis conducted by Becker and Ellison noted that the same models' current healthcare industry applications include a multilayered set of strategies. Among these entail using machine learning-based models to structure routine billing operations efficiently, complete complex coding tasks, and generate predictive data that can be used for risk assessment and management purposes (Becker & Ellison, 2019). Blass and Porr similarly noted that automated approaches to revenue management typically include the ability of programs and their applied algorithms to gradually identify patterns associated with payers and contracting groups (Blass & Porr). Over time, these applications can detect risk variables that might indicate the client's inability to deliver payment on time (Blass & Porr, 2019).

Evans cited automated forms of revenue cycle management as a valuable instrument in helping firms in diverse industries achieve higher efficiency and optimization levels in their internal areas of financial operations (J. R. Evans, 2015). Similarly, Davenport and Kalakota identified revenue management as one specific benefit derived from AI and ML learning applications across health systems (2019).

Based on all of these studies, if machine learning were implemented correctly in the future, it would be possible to replace most, if not all, of the billing processes with machines rather than humans.

Potential of Machine Learning for these Processes

Discussions of the benefits generated through ML-driven revenue cycle management processes in healthcare include assessments of current and likely or predictive benefits. Simultaneously, these collective assessments emphasize technology's role as drivers in achieving current and future term benefits. Hut's discussions noted that current generation AI and ML platforms could process and structure complex and recurrent tasks within health systems (Hut, 2019). Revenue management represents one specific example in this same context. Hegwer similarly noted that current ML applications help firms achieve excellence in fiscal cycle management processes. The author provided several discussions of cases of large systems that applied these technologies and yielded notable improvements in their ability to process patient data, predict reimbursement patterns, and predictively assess the likelihood of nonpayment among specific groups or clients (Hegwer, 2018).

Nilsson (2019) also noted that the same applications can predict payer behaviors and indicate the times in which they will likely remit payment and if they are at risk for nonpayment or default. Schouten (2013) contributed to these same discussions by assessing machine learning platforms' capabilities to examine recurrent payment loss patterns by investigating multiple channels of revenue and reimbursement. While the author's discussions referenced the current technologies currently utilized by health systems, his analysis also identifies these technologies' ability to complete increasingly complex and predictive-based assessments. In implementing these more complex processes, errors would likely continue to be reduced, and organizations would have a more efficient billing process. Schouten's commentary parallels Rosenfield's discussions of future term machine learning applications and roles (Schouten, 2013). The latter author noted that advanced machine learning benefits could include these platforms' ability to conduct complex operations that subdivide payment systems according to billed procedures and specialized coding (Schouten, 2013).

In both cases, the analyses cited ML-based algorithms' ability to conduct increasingly complex operations as they engage in many of the same procedures over the longer term. On a more global scale, Lee et al. (2019) found that artificial intelligence has significant potential for automation in many industries and automation of non-robotic tasks. This is important in understanding how organizations can implement artificial intelligence to automate revenue cycle management. While Nilsson's analysis identified the potential and prospective benefits generated through machine learning applications, his report implicitly located one of these systems' critical risks (Nilsson, 2019). The author specifically identified the necessity of cultivating a strategic plan to implement and incorporate ML-based technologies in a healthcare firm's operations.

This approach represents a vital aspect of technology management as it will better ensure that an implemented strategy will achieve positive returns from a cost/benefit perspective. The issue of cost represents another critical factor frequently identified by related literature. Fundamentally, these applications represent a methodology for achieving savings-based returns (Hillman, 2020). Accordingly, healthcare organizations typically integrate and apply these innovations to avoid waste, identify redundant expenses, and locate ways of optimizing fiscal cycle operations. However, achieving these outcomes often requires an organization's ability to mitigate short-term risks that accompany implementation strategies. Accordingly, the costs associated with purchasing technology and integrating it into existing networks can present firms with a combined set of fiscal and technical challenges that they will have to address as they develop change management plans. For example, Clancy (2020) made a point of describing the importance of organizations using artificial intelligence to automate certain aspects of the revenue cycle, particularly those aspects that are repetitive and are an inappropriate use of human resources.

The risks encountered during these initial stages can additionally affect organizations in the longer term in cases where firms do not explicitly identify the specific functions that integrated ML platforms will achieve in the context of a firm's fiscal cycle management processes. For example, issues related to a platform's immediate use, its prospective future term value, and the role that human agents will have in monitoring the applications represent core issues that decision-makers need to address during planning sessions (LaPointe, 2020). Similarly, analysts identify the need for carefully value mapping a proposed model before its implementation: a methodology that can evaluate the specific departments and stakeholders that will benefit from the applications. In cases where departments or individual employees exhibit a reluctance to accept the proposal, the same strategies can be used to identify the role these stakeholders will play in managing the applications (Christodokulakis et al., 2017).

A final set of recommendations includes the need for cultivating a set of measurable objectives that clearly define the role, purpose, and strategy of the integrated systems across the technology's prospective lifecycle. Cheatham et al. conducted an in-depth analysis explaining some of the risks associated with artificial intelligence (Cheatham et al., 2019). Organizations, including hospitals that implement artificial intelligence, must also use specific protocols to mitigate its risks. Specifically, they must have a clear structure that pinpoints the specific risks associated with AI. The structures must also have institution-wide controls rather than limited controls.

Lastly, there must be a nuance in analyzing the risk in light of the risk's nature. This is important because organizations must understand the risks and how to mitigate them before implementing new protocols when they plan to implement artificial intelligence.

Application of Machine Learning/Artificial Intelligence to Healthcare Issues

The fact that vast amounts of money are lost due to inaccurate claim processing is well established in the literature (Kim et al., 2020; Wojtusiak et al., 2011). One of the problems that frequently occur that causes claims to be rejected is the inclusion of an incorrect ICD code for diagnosis or CPT code for diagnostic tests (Abdullah et al., 2009; Chimmad et al., 2017). This is the reason that multiple researchers have looked for ways to use AI and ML to automatically analyze massive bodies of medical claims to detect and, in some cases, repair information that was incorrectly entered (Abdullah et al., 2009; Chimmad et al., 2017; Kim et al., 2020; Zhong et al., 2019). Improving the information on medical claims can reduce lag time between claim submission and payment, which is a critical financial measurement indicating the financial health of a healthcare organization (Cleverly & Cleverley, 2018).

Kim et al. (2020) proposed a novel implementation of AI/ML that they call Deep Claim. The Deep Claim approach uses a three-step process to improve the accuracy of predicting the exact amount that third-party payers will present. The first step is the development of clinical contextual interrelations at the high level of claims, which uses ML against raw claims data, avoiding the need for expert knowledge or extensive preparation of the data before processing. The next stage is deploying Deep Claim in real deployment scenarios. The third step is where Deep Claim flags questionable fields in the claim based on what it learned in the ML process. This gives it high prediction interpretability, along with data presented that explains why the fields were flagged so they can be double-checked and rectified. This novel approach asserts that it can identify 22.21% more denials than the best system that is currently in place.

In research by Wojtusiak et al. (2011), the researchers developed an ML application that would permit the AI system to combine rules that were already known for claim rejection and combine these with new rules that were detected by the AI algorithms. The ability of the AI to generate new rules was particularly important because healthcare is continually changing, and this architecture permits the system to adapt as new changes in the healthcare system occur. The system effectively identified new errors that had slipped through the system, with 60% of Medicaid, 50% of DRG 371, 55% of

DRG 372, and 44% of DRG 373 abnormalities detected. The false-positive rates were relatively low, ranging from 5% to 30% for the same groups.

In the study by Kumar et al. (2010), the researchers used data mining, which could then be used for an ML process to improve the prediction of claims that need reworking. They noted that 30% of the administrative staff in health insurers are dedicated to reworking incorrect claims, which be rectified using AI. The researchers developed a method of detection based on ML, then deployed that model at one of the nation's largest health insurers. Because the new system was much more precise, it generated a substantial increase in hit rates, identifying faulty claims. The improved accuracy provided by this novel application of AI and ML could potentially generate cost savings of between $15-25 million for each standard insurer using the system.

Other researchers explored ways to label data or develop concept representations from existing data sets using combinations of AI and ML (Bai et al., 2019; Che & Janusz, 2013; Lu et al., 2020; Zhong et al., 2019). Being able to generate rules and label data or categorize it in a way that ML systems can easily interpret is a crucial stepping stone to practically using such data to apply to numerous healthcare applications, such as financial management (Che & Janusz, 2013; Wojtusiak, 2014).

Summary and Thematic Analysis

This literature review has considered numerous aspects of how the healthcare finance industry has considered and implemented ML, AI, and RPA into their business frameworks. The financial process, especially that of submitting claims, is complex and regularly involves touching tens of thousands of documents. The potential for errors is high, and as the research has indicated, some organizations have up to 30% of their staff dedicated to "reworking" claims that were incorrectly submitted. With the constant pressure on healthcare organizations to decrease costs, finding ways to use AI, ML, and RPA to streamline finance department processes and make them more efficient is highly attractive. Even more so, the potential cost savings, which are projected into the tens of millions, are sufficient to get the attention of healthcare finance professionals. This review has explained how AI, ML, and RPA can be applied to the healthcare finance field. It has also demonstrated that systems currently in use generate considerable savings for many healthcare organizations.

These findings are especially significant to healthcare finance professionals who are under considerable pressure to find ways to reduce costs in their departments and improve cash flow through efficient claims processing and payment turnaround. The findings are also relevant to the healthcare finance field because the application of certain aspects of the research has been demonstrated to generate considerable cost savings. Healthcare finance departments are also responsible for maintaining the organization's financial health. The potential of AI and ML technologies to improve payment turnarounds is highly relevant, as this is a key financial performance metric for all hospitals.

The literature review presents valuable information. Specifically, these analyses identify analytics-based approaches to revenue cycle management as an increasingly utilized strategy among diverse healthcare systems. The findings indicate that sector decision-makers identify vital benefits that can be derived from these applications as fundamental savings and risk-management tools. While discussions of the model's current and prospective capabilities differ in terms of their understanding of the benefits derived from their application, they are interconnected by their mutual contention that these outcomes are directly correlated with the platform's existing and emerging technological features and capabilities. In brief, these views suggest that as AI and ML systems advance, healthcare organizations will be able to apply them in increasingly sophisticated ways. Assessments of risk identify the challenges related to initial and start-up processes as being the most significant. Recommended risk management approaches include applying detailed and precise technology strategies that identify an implemented model's specific role within the organization and outline the specific objectives that the platform will help the company achieve.

The implications derived from the preliminary literature review relate to the following themes: 1) the current state of the use of AI/ML/RPA and 2) the continuing gaps in the healthcare revenue cycle areas that could benefit from this technology. As the review indicated, the current field provides prospective decision-makers with an in-depth set of data that explains the concept of analytics-driven approaches to revenue management. It generally outlines the types of benefits derived from its application. Analyses that reference individual health systems as case studies provide contextual information that identifies how single organizations apply these innovations. While informative and descriptive, this information lacks a level of specificity that could otherwise help planners make targeted decisions. Accordingly, these preset gaps require follow-up studies that assess common thematic issues from an organizational perspective. Evaluating the variables of benefits, drawbacks, risks, and appropriate risk management strategies from a healthcare organization's strategic perspective can aid in balancing the current tendency for associative literature to focus on macro-level themes related to these same issues.

Chapter 3

Methodology

Approach

The purpose of this study was to identify the potential risks and benefits of using AI-based applications in the revenue cycles of large healthcare organizations. Specifically, the study closed the research gaps by identifying and analyzing the perspectives of key stakeholders responsible for managing revenue cycles. As mentioned in Chapter 1, the study followed a qualitative methodological approach when the researcher conducts semi-structured interviews with recruited participants. Semi-structured interviews provide researchers with opportunities to identify significant themes across participants and establish an appropriate context for developing theoretical explanations of emerging themes found in coded data. In many ways, the selected approach provided a solid basis for identifying broader issues noted in earlier published studies. Conducting semi-structured interviews with participants also provided the researcher's opportunities to discuss how systems thinking concepts and risk management strategies apply in different healthcare settings (Alam, 2016; Anderson, 2016). By including interview data in this study, its overarching goal was to determine how researchers may perform similar investigations using qualitative, quantitative, or mixed methods approaches.

Justification for the Methodology

Following Hissong et al. (2015), a qualitative methodological framework applies to this study proposed when it guides how researchers understand the meaning derived from lived experience. Accordingly, qualitative research involves studying individuals as they behave in different social, organizational, or institutional contexts. Given that few currently published studies address how key stakeholders manage revenue cycles in healthcare, the decision to apply a qualitative framework involved accounting for differences between individual experiences, meanings placed on individual experiences, how individuals respond to different environments, and developing models whereby researchers performing future investigations may design empirically verifiable instruments.

For example, qualitative researchers may apply a phenomenological design when investigating the relationship between professional development and barriers to accessing consistent healthcare (Creswell & Creswell, 2018; Hissong et al., 2015). Phenomenological study designs typically involve researchers performing semi-structured interviews with a sample size of no more than ten (n = 10) participants. While quantitative researchers may perceive that such a small number of participants cannot produce generalizable results, they may provide an in-depth analysis of how significant themes coded in the interview data can inform future investigations. The lack of generalizability will constitute a significant limitation that influences how researchers performing future investigations may attempt to replicate the study design across other settings (Creswell & Creswell, 2018). Instead, the selected methodology refers to an inductive process from which data inform theory development.

Theoretical Framework and Development

The theoretical framework developed for this study included three key areas of analysis. First, the proposed framework will draw from key concepts impacting healthcare administration. Examples of concepts included in this framework are systems thinking and risk management strategies. Whereas systems thinking spans multiple disciplines and apply to various organizational contexts, its applications to the healthcare industry are such that researchers often explain why relationships between different components are more complex than others (Anderson, 2016). Given that the healthcare industry is complex, its relationship to systems thinking indicates further where researchers can detect patterns and failure probability. In relation, risk management strategies involve healthcare professionals emphasizing financial and business viability from an organizational perspective.

Healthcare professionals must follow specific steps when addressing risks, which entail identifying the context, explaining known risks, analyzing these risks, evaluating the risks, and managing the risks properly (Alam, 2016). By combining elements of systems thinking and risk management strategies, the researcher applied specific concepts to technology management practice in artificial intelligence (AI) applications. The emerging theoretical framework then aligned with significant themes identified in the current planning and risk management literature. More specifically, the theoretical framework developed from an analysis of themes coded from the interview data aligned with how researchers previously utilized AI models for revenue management practices in healthcare. As the interview portion of the study will receive attention, the researcher will apply systems thinking concepts and risk management strategies to indicate the presence of significant themes.

Next, concepts found in the research on risk management strategies were applied to identify themes like AI risk and risk mitigation. An informed view of principles guiding risk management strategies will likely improve how the researcher interprets the interview data and accordingly builds a theoretical framework. From there, the ADDIE model used to evaluate practice among e-learning designers and developers will guide theory development. Researchers note further how the ADDIE model supports a process of analyzing, designing, developing, implementing, and evaluating AI designs in complex healthcare environments when their implications for revenue generation along cyclical lines are vast (Anderson, 2016; Gawlik-Kobylinska, 2018). While the ADDIE model also supports improvements to healthcare decision-making, it corresponds more closely to risk identification. Subsequently, the theoretical framework developed from the findings will inform problem-solving approaches significant stakeholders in healthcare may use when measuring the risks and benefits associated with integrating AI technologies into revenue cycle management.

Interview Structure and Design

The researcher used a set of 12 interview questions (see Appendix A) that each participant received. All participants received both a standard email invitation and NSU’s standard informed consent (see Appendix C and D). All responses provided by the participants will provide keywords that the researcher may use to ask further questions. Following this design provided a rich context for analyzing the interview data as they coincide with this study's three central research questions. As detailed below, a set of four interview questions addressed themes related to how AI-based technologies will benefit the healthcare revenue cycle management processes. Three interview questions involved asking the participants to address risk factors that negatively impact the healthcare revenue cycle management processes. A final set of five interview questions invited the participants to discuss risk management and problem-solving strategies that guide decision-making processes in the organizational context.

First, the interview questions addressing themes related to how AI-based technologies will benefit healthcare revenue cycle management processes are as follows:

1. What types of patterns or processes have you seen as a healthcare administrator, accounting/financial management officer, or information technology (IT) staff member who influenced your healthcare revenue cycle management perceptions?
2. Which of these patterns or processes left the most significant impact on organizational performance? Why do you believe these patterns or processes play such an essential role?
3. How do you believe that AI-based technologies can inform the triple aim of healthcare when financial and related schemes appear challenging to manage?
4. How do you believe AI-based technologies may contribute to improvements in administrative, financial, or other forms of professional decision-making?

Responses to these questions will guide how the researcher steers each interview and links major themes to those found in the extant research literature. The exact process will apply to the two remaining sets of interview questions on risk factors that negatively impact healthcare revenue cycle management processes and risk management strategies that also guide decision-making processes in the organizational context.

The second set of questions will involve the researcher asking participants the following:

1. Which risks specific to your organization left the most significant impacts on decision-making after integrating AI-based or other types of technologies into healthcare revenue cycle management?
2. How have these risks driven past performance and shaped decision-making? Which risks still demand critical attention in the present?
3. What do you believe will mitigate future risks when some issues impacting healthcare revenue cycle management remain?

While this set of questions will initially lead the participants to provide closed-ended responses, its relation to the specific findings discussed in Chapter 2 will provide an appropriate context for developing theory from the interview data and answering the three central research questions.

Lastly, the third set of questions will involve the researcher asking participants the following:

1. Which risk management strategies, if any, did you apply in the past to ensure that your organization could integrate AI-based technologies effectively?
2. How did you apply these strategies to mitigate current and future risks?
3. Which strategies do you believe are still effective and why?
4. Which strategies do you wish the organization would eliminate? What examples can you provide to support any changes in administrative or other types of decision-making in the organizational environment?

5. How have the past and current strategies impacted your ability to develop yourself professionally while gaining knowledge of how revenue cycle management functions?

As with the first two sets of semi-structured interview questions, this third set will ensure that each participant will provide rich insights into how AI-based technologies inform a lived experience among staff members at different levels within the same organization.

Data Collection and Research Questions

The study followed a qualitative design to generate three distinct datasets. Next, the datasets produced in this study were aligned with the responses to interview questions. From there, the artifacts produced contributed to the discussion and answered all three research questions (Hissong et al., 2015; Regnault et al., 2018). After the researcher combined all three datasets, a triangulation process followed to ensure that all responses provided by each participant establish an appropriate context allowing for comparisons against previous research findings (Creswell & Creswell, 2018). To reiterate from Chapter 1, three central research questions guide this study as follows:

R1: What prospective benefits are possible from using AI revenue cycle applications in the healthcare industry?

R2: What are the risk factors associated with implementing AI-based technologies in the healthcare industry?

R3: What outcomes are derived by using a Lean Six Sigma (LSS) designed framework for healthcare executives deciding to implement AI/RPA in the healthcare revenue cycle?

All three research questions contributed to theoretical development in the following ways. First, the research questions encouraged the researcher to focus on specific sub-topics related to the broader issue. Second, the research questions provided a set of discussion points applicable to all three datasets emerging from the study design. Third, the research questions provided the basis for exploring AI-based technology in health systems.

Sampling

The study included semi-structured interview data provided by at least five (n = 5) participants with experience managing AI-based technologies while managing healthcare revenues. For this study, a quota sampling strategy works best to ensure that all recruited participants meet specific characteristics (Creswell & Creswell, 2018; Hissong et al., 2015). The selected strategy allows qualitative researchers to focus their attention on which recruited individuals will demonstrate the highest possible degree of knowledge or expertise in their field. From there, the researcher will use recruitment strategies appropriate to location, culture, and population until achieving a specific quota.

Quota sampling is a nonprobability strategy that resembles purposive sampling in selecting participants according to criteria relevant to answering one or more research questions. While the sample size depends mainly on the time, resources, and study objectives, they may differ when an investigator approximates how many participants will provide interview data (Creswell & Creswell, 2018). However, the quota sampling strategy applies when researchers evaluate populations with characteristics that correspond to set properties.

The researcher selected participants from the quota sampling strategy, including healthcare administrators, accounting/financial management officers, and information technology (IT) staff members employed within the same organization. The selected group of participants represents a collective of internal stakeholders capable of providing in-depth feedback to semi-structured interview questions regarding their experience using AI-based technologies in revenue cycle management. Specific inclusion criteria that apply here include 1) employment in one area of healthcare administration that reflects professional responsibilities and experience in revenue cycle management; 2) employment within the same organization; and 3) two to three years of experience with the same organization. Each of the recruited participants will receive an informed consent letter explaining this study. All responses to semi-structured interview questions will remain confidential to maintain the anonymity of each participant.

Data Analysis Procedures

As previously mentioned, the semi-structured interview data obtained from each participant underwent a triangulation process to determine the validity of responses in alignment with the extant literature. Following Creswell and Creswell (2018), triangulation entails a process of comparing outcomes and evaluating whether lived experiences described by participants match those observed in previous studies. Since the study involved performing semi-structured interviews with recruited participants, data triangulation is an optimal strategy for comparing how individuals responded to each question. Data triangulation ensured further that significant themes found in the interview data answered the central research questions. While investigator triangulation that involves the use of different evaluators ensured the interview data was feasible in answering the central research questions, time and resource constraints limit opportunities to make closer comparisons between closer observations. Despite how participants may view their experiences of AI-based technologies and healthcare revenue cycle management differently, their responses to each interview question produced outcomes that researchers should consider when performing future investigations.

Further, the data analysis procedure invited the researcher to address how AI-based technologies impacted healthcare revenue cycle management by addressing potential outcomes like associated benefits, associated weaknesses, risk mitigation, and effective strategies. Each outcome reflected how the recruited participants described their lived experience of using technology to improve revenue cycle management. The use of an NVivo-based application was applied here when interview data initially appeared unstructured in a raw format. By using NVivo, the researcher coded and segmented data according to patterns recorded in the interview data. The coded data then informed the theoretical framework development to indicate where participants offered similar and different perspectives on their experience using AI-based technologies.

Trustworthiness and Reliability

Ensuring trustworthiness in this qualitative study required attention to factors like credibility, transferability, dependability, and confirmability. As Nowell et al. (2017) explained, credibility occurs whenever qualitative researchers account for participants' lived experiences and align them with the extant literature. Researchers may use procedures like data triangulation as an external check to increase credibility (Creswell & Creswell, 2018; Nowell et al., 2017). However, most cases involve researchers checking preliminary findings and comparing them to raw interview data obtained from participants. Member checking and the use of external auditors may inform this process. However, time and resource constraints limit how many individuals will participate in the data analysis process.

Second, transferability establishes that findings analyzed from the interview data should generalize across populations in some way. While smaller samples rarely make the findings of qualitative studies generalizable, researchers must still provide thick descriptions to account for where gaps in theory development remain (Creswell & Creswell, 2018; Hissong et al., 2015; Nowell et al., 2017). Along these lines, dependability allows qualitative researchers to trace and document the sources of interview data logically. Researchers may better judge the dependability of investigations by examining data collection and analysis procedures as informed how accurately they interpret the findings (Nowell et al., 2017). Here, researchers may achieve confirmability by explaining how the findings answer specific questions and inform theoretical development. Confirmability entails further that researchers performing future investigations may replicate study designs and understand how some decisions were made.

Considering how this study aimed to include three datasets, ensuring the validity of each will require an application of reliability-oriented approaches reflecting potential outcomes in future investigations. Accordingly, the researcher double-checked that each dataset corresponded to significant themes found in the interview data by performing an audit trail (Nowell et al., 2017). Documenting an audit trail will also inform the confirmability of study findings when the lived experiences described by each participant match a defined research context. However, increasing familiarity with the data will remain necessary to explain similarities and differences in perceptions regarding how AI-based technologies produce benefits or risks within a specific organizational context. Especially as qualitative studies increase in popularity, researchers will need to familiarize themselves with various tools for ensuring the data collected from participants have more extensive applications. Aligned with the purpose of this study, a qualitative methodology will support theory development when each data source provides evidence of which strategies work and where decision-making can improve.

Summary

The goal of this chapter was to outline the research method used to answer the research questions. A discussion of the procedure, study participants, data collection, and interview questions outlined the specifics of how the study was conducted and who participated in the study. The methodology overview detailed the steps for creating the interview structure and how that data would flow into a triangulation to ensure the validity of the responses. This chapter outlined a listing of required resources that were needed to support data collections, analysis, and suggested sampling. The instrument development and validation process provided insight into combining interview data and performing the triangulation to form the questions for the theoretical framework. The goal of Chapter 4 is to provide the study results and demonstrate that the methodology described in Chapter 3 was followed and supported.

Chapter 4

Results

Data Analysis

There was a total of twelve interview questions conducted from a sample size of ten participants that included healthcare administrators, accounting/financial management officers, and information technology (IT) staff members employed within the same organization.

Thematic Analysis Approach

The researcher recorded the interviews via a Microsoft Forms engine and transcribed into text, then arranged and sorted them in NVivo 12 computer-assisted qualitative data analysis software (CAQDAS) (see Appendix B).

The sixth stage process of thematic analysis by Braun and Clarke (2006) (i.e., familiarizing yourself with your data, generating initial codes, searching for themes, reviewing themes, defining and naming themes, and producing the report) was followed to analyze the transcribed information. Appendix E details the coding process that was used.

Table 1

Research Questions with Relevant Themes Hierarchy

Research Question	Themes
R1: What prospective benefits are possible from using AI revenue cycle applications in the healthcare industry?	1. Benefits of AI in HRCMP 1.1 Cost reduction and revenue growth 1.2 Improved data quality 1.3 Organizational benefits 1.3.1 Decrease or reduce workforce 1.3.2 Enhances teamwork 1.3.3 Make better and quick decisions 1.4 Patients benefits 1.4.1 Help in early diagnosis 1.4.2 Improved patients' experience 1.4.3 Reduces patients' denial rate
R2: What are the risk factors associated with implementing AI-based technologies in the healthcare industry?	2. Negative impact of risk factors on HRCMP 2.1 Impact of the human component 2.2 Increase in cost 2.3 Need to retrain employees 2.4 Security and privacy concerns 2.5. Technological complexity
R3: What outcomes are derived by using a Lean Six Sigma (LSS) designed framework for healthcare executives deciding to implement AI/RPA in the healthcare revenue cycle?	3. Risk management and problem-solving strategies 3.1 Data security 3.2 Identification of risks 3.3 Implementing NLP 3.4 Properly trained staff 3.5 Review and audit of Processes 3.6 Transparency of processes

Details of Interviews

A total of ten interviews were conducted with recruited participants. Table 2 exhibits an overview of each participant (interviewee) with the interview duration.

Table 2

Interview Overview with the Duration of Interviews

Interviewee Number	**Duration (In minutes)**
Participant -1	2 hrs 23 min
Participant -2	14 min
Participant -3	3 hrs 22min
Participant -4	43 min
Participant -5	45 min
Participant -6	1 hr 48 min
Participant -7	1 hr 12 min
Participant -8	10 min
Participant -9	59 min
Participant -10	1 hr

Word Frequency

Word frequency query of fifty most repeating words having a length of 4 (four alphabets) was run to get the initial familiarity of the data/document. The following figure or word cloud exhibits a list of the most frequently occurring words or concepts in responses of the ten participants.

Figure 1

Word Frequency

Analysis Process in NVivo

A total of fifteen axial codes were grouped into three broad categories labelled based on the research objective and research questions: the categories were defined based on already developed questions in the semi-structured interviews (see Appendix E). The data in each category was further mined, and various concepts (themes) and sub-concepts (sub-themes) were identified and interpreted.

Findings

Benefits of AI in HRCMP (Healthcare Revenue Cycle Management Process)

To define HRCMP stands for Healthcare Revenue Cycle Management Process. The first research question, “What prospective benefits are possible from using AI revenue cycle applications in the healthcare industry?" was answered by formulating a level-3 theme of "Benefit of AI in HRCMP." This theme was made up of four sub-themes 1). Patients benefits, 2) Organizational benefits, 3) Improved data quality, and 4) Cost reduction and revenue growth. The themes of patient benefits were further categorized as 1) Reduces patients' denial rates, 2) Improved patients experience, and 4) Help in early diagnosis. The theme organizational benefits were further categorized as enhancing teamwork, decreasing or reducing the workforce, and making better decisions.

Figure 2

Theme Hierarchy of Benefits of AI in HRCMP

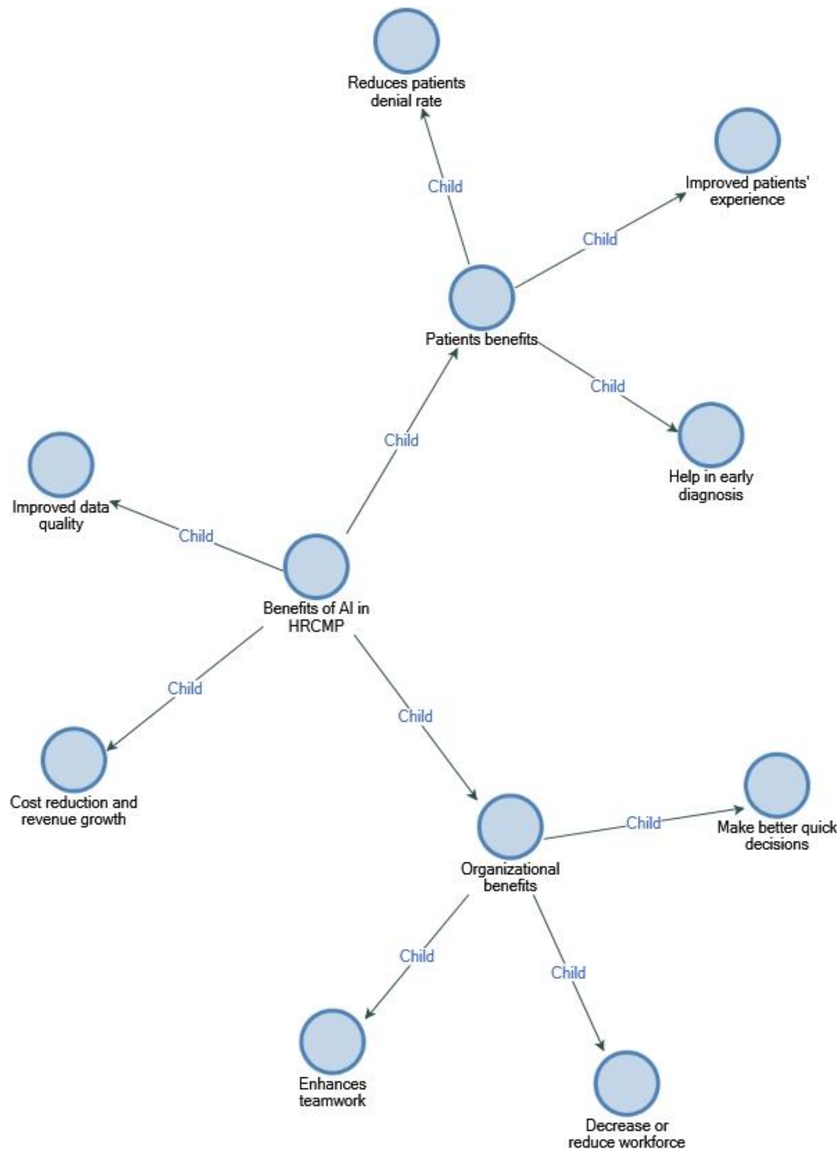
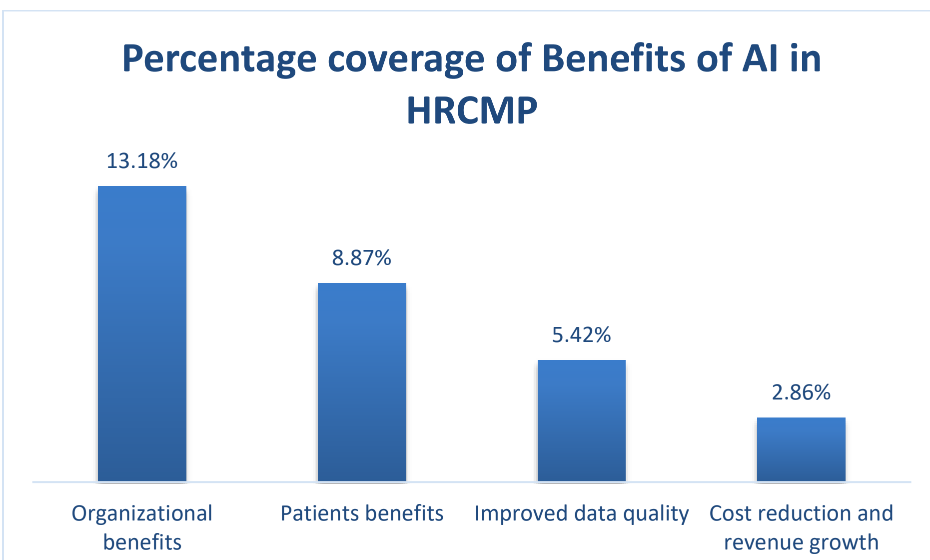


Figure 3 below represents the top beneficial themes from the collected interview data. The data is presented based on the percentage of text coded at each theme (node), and it is calculated by NVIVO based on how many times and the amount of text referenced at each node for the source document. The top benefit identified by the participants is the organizational benefits of using automation within the healthcare revenue cycle, as cited below:

> *"AI would allow for more efficient processes in every department throughout the revenue cycle, which would produce better data creation, which would create better data reporting, which will allow the management team to better pinpoint and address issues affecting both patient health and organizational health."*
>
> *"As AI is based on data, visa Data warehouse, Data lakes, and data marts, essentially data stored from all facets of technology systems and integrations, the possibilities of data aggregations combined with logic, yields to timely and accurate reports or dashboards."*

Figure 1

Percentage Coverage of Benefits of AI in HRCMP

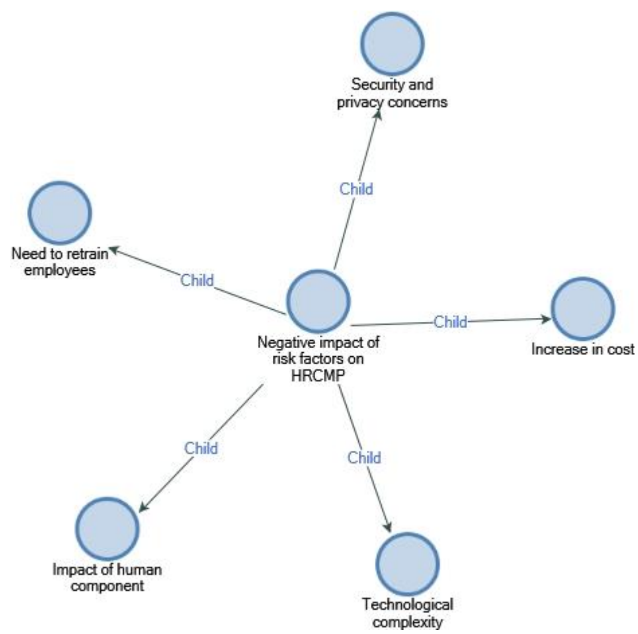


Negative Impact of Risk Factors on HRCMP

The second research question, “What are the risk factors associated with implementing AI-based technologies in the healthcare industry?” was answered by formulating a level-3 theme of “Negative impact of risk factors on HRCMP.” This theme was made up of five sub-themes of Need to retrain employees, Security, and privacy concerns, increase in cost, technological complexity, and Impact of the human component

Figure 2

Theme Hierarchy of Negative Impact of Risk Factors on HRCMP

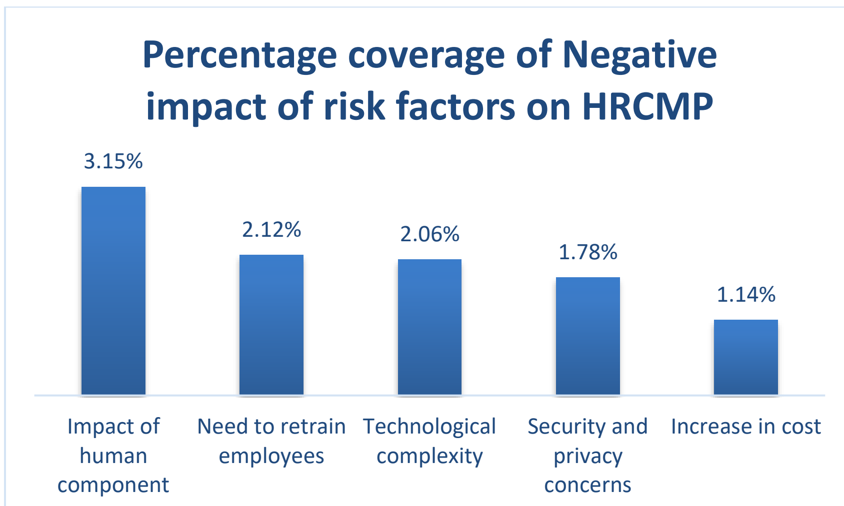


The chart below displays how much of the respondents in percentages are talking about the theme related to the negative impact of risk factors on HRCMP. The highest one is the “impact of the human component,” which means the risk of human error will still exist even after software implementation.

> *“If the data that we are generating through staff creation is poor, even the best reporting will still be inaccurate, leading to inaccurate, and possibly incorrect decisions by management.”*

Figure ***3***

Percentage Coverage of the Negative Impact of Risk Factors on HRCMP

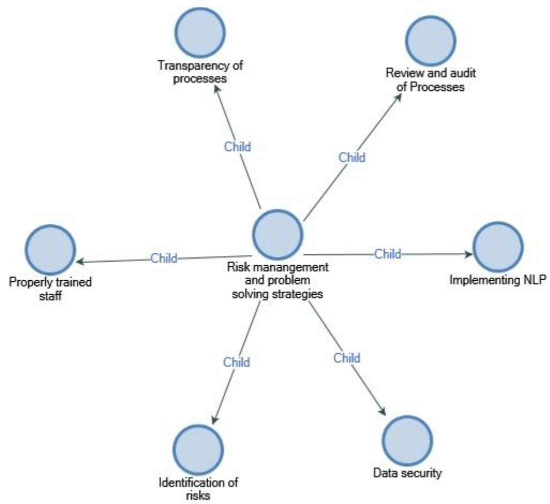


Risk Management and Problem-Solving Strategies

The third research question, “What outcomes are derived by using a Lean Six Sigma (LSS) designed framework for healthcare executives deciding to implement AI/RPA in the healthcare revenue cycle?” was answered by formulating a level-3 theme of “Risk management and problem-solving strategies.” This theme comprised six sub-themes of implementing NLP, Transparency of processes, Data security, Identification of risks, adequately trained staff, and review and audit of processes.

Figure 6

Theme Hierarchy of Risk Management and Problem-Solving Strategies



The review and audit of the processes is the highest coded theme among the codes in risk management and problem-solving strategies.

> *"Having proper dedicated reviewers of all information and processes is incredibly important."*
>
> *"Six Sigma strategies, standardization, and process improvement will pave the way for AI."*

Figure 7

Percentage Coverage of Risk Management and Problem-Solving Strategies

Triangulation of Data

The themes obtained from semi-structured interviews went through a triangulation process to determine the validity of responses aligned with the extant literature. A total of four research articles were selected on the keywords of AI optimizing hospital revenue cycle management. This triangulation tested the validity by converging information from the interview questions and the research articles to ensure that the data gathered was consistent. The results of the triangulation process are represented via table format in Appendix F.

Framework Design

Development

The development of the framework presented below was in conjunction with one of the goals of this research:

> *To create a framework that may be applied to a healthcare organization in an effort to migrate from their current revenue management technique to one that includes the use of AI/ML/RPA as a means of future cost control and revenue boost.*

The researcher was able to construct a framework to provide guidance to healthcare executives on selecting appropriate tasks for artificial intelligence (AI)/robotic process automation (RPA) by using the data gathered from the literature review as well as the responses from the interview data. The framework represents the main areas of opportunities and concerns that were expressed in the various interviews. The themes and various subthemes of the benefits of AI in HRCMP and the negative impact of risk factors on HRCMP were used to create the questions and rankings within the framework.

These themes were aligned with the previous research, such as Deloitte's study of the Smart use of artificial intelligence in health care, Seizing opportunities in patient care, and business activities (Chebrolu et al., 2020). In this article, the main areas of benefit were increasing efficiencies and minimizing risks, and the largest area of concern was ensuring that the technology complied with regulations. By using articles such as these, the researcher was able to complete a data triangulation to validate the interview responses.   The validation was done by utilizing NVivo to mine the interview data and align the responses to the sub-themes and existing literature. The researcher was able to construct the below framework using the results.

Framework Example

Step 1:

Answer the question below for each task the company is considering automating. If the answer is “no,” then the task is not appropriate for automation, and you do not need to continue with steps 2 and 3.

1. Can automation be used for the task under consideration?
    a. Bots may not be allowed because of government regulation or company policies.

Step 2:

Fill out the below tables for each revenue cycle task the company is considering automating. Once finished answering the questions, create an overall final evaluation score by considering the responses to the individual questions. Additional information for each category or question is included after each table. If unable to answer a specific question, leave it blank.

Table 3

Risk Viability Framework

Risk Viability	Lower Viability			Higher Viability	
Activity Type	1 Judgment Based	2	3	4	5
Process Structure and Risk	1 Low	2	3	4	5 High
Data Risk	1 Unstructured	2	3	4	5 Structured
Custom Development Required	1 High	2	3	4	5 Low
Automation as Preferred Solution	1 No	2	3	4	5 Definitely

Final Risk Viability Evaluation	1 Low Viability	2	3	4	5 High Viability

Additional information about "Risk Viability" categories:

- **Activity Type** refers to the extent to which the audit activity requires human judgment or learning.
- **Process Structure and Risk** refer to the frequency with which the underlying process changes. Some processes remain the same over time, whereas other processes are constantly fluctuating. Frequent changes to the underlying process will require constant updates to the bot or advanced programming.
- **Data Risk** refers to the extent to which bot technology will be processing data that has a high-risk category.

- **Custom Development Required** refers to the amount of time, money, and expertise needed to create the bot. Development requirements tend to increase with the complexity of the process.
- **Automation as Preferred Solution** refers to the that not every process should be automated.

Table 4

Benefits Framework

Benefits of Automation	**Less Beneficial**			**More Beneficial**	
Effort Required for Manual function	1 Low	2	3	4	5 High
Frequency of the Function	1 Low	2	3	4	5 High
Staffing Concerns (Turnover/Overtime)	1 High	2	3	4	5 Low
Data Accuracy Concerns	1 High	2	3	4	5 Low
Compliance Concerns	1 High	2	3	4	5 Low

Final Evaluation of Benefits	1 Low Benefit	2	3	4	5 High Benefit

Additional information about Benefits of Bot categories:

- **Effort Required for Manual function** refers to the amount of time and mental energy needed to perform the Revenue Cycle activity (and not the creation of the automation).
- **Frequency of the Function** refers to the number of times the activity occurs within a given time period. Activities that occur more often are more beneficial to automate.

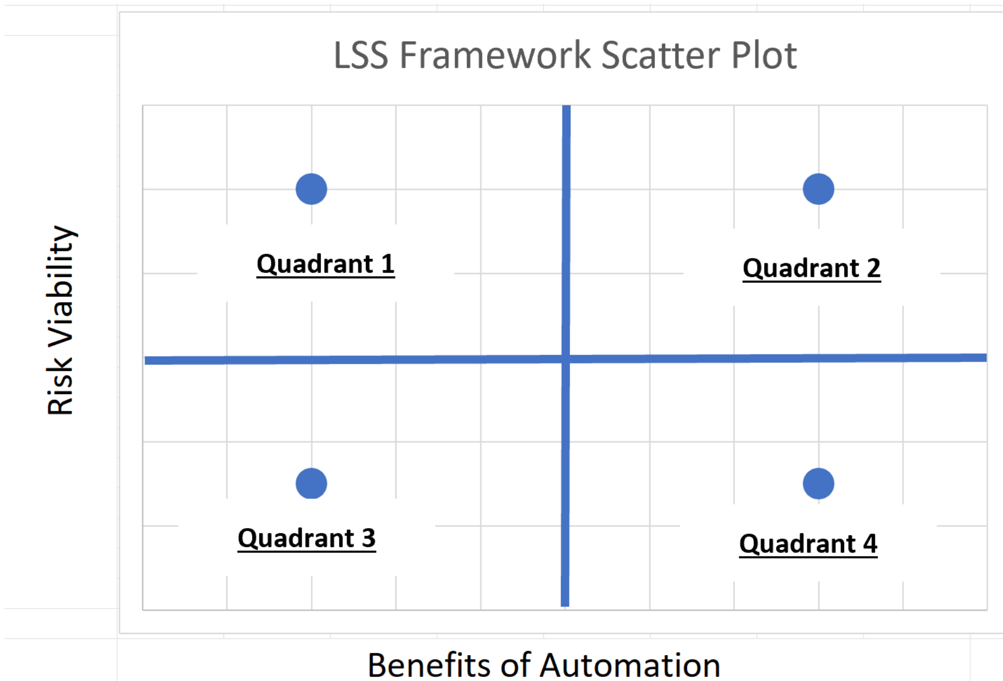
- **Staffing Concerns (Turnover/Overtime)** refers to the amount of staffing issues your department faces. By creating automation, companies should be able to redeploy staff to perform more complex tasks, increasing employee engagement thus creating a 24x7 workforce.
- **Data Accuracy Concerns** refers to the amount of human error and variations from the standard.
- **Compliance Concerns** refer to the amount of concern an organization has with possible data errors resulting in a reportable offense.

Step 3:

Plot the scores for each potential bot activity on the matrix below. Automation activities that are in Quadrant 2 should be prioritized for immediate development. Once all Quadrant 2 activities are developed, Quadrant 1 activities should be developed, and activities in Quadrant 3 and 4 should not be developed.

Figure 8

Framework Scatterplot



Summary

This chapter revealed the study findings. First, the subject matter expert's results were outlined. Second, the custom coding via NVIVO was described along with its results and ended with ten qualified employees. Third, data triangulation was done to validate the interview responses against current literature. Utilizing this data, the researcher was able to answer the three research questions and construct a theoretical framework for healthcare executives to use when deciding to implement AI/RPA within their organizations.

Chapter 5

Conclusion

The conclusion begins by exploring the results of the three research questions. Limitations of the study are then described, noting how they may have had an impact on the results. Next, implications and recommendations are theorized to offer a context for further evolution of the concept of the use of AI/RPA in the healthcare revenue management cycle. A summary of the research study concludes the chapter.

Research Questions

Research Question 1: What prospective benefits can be generated by using AI revenue cycle applications for healthcare organizations?

As noted in the literature review, many studies have been done in relation to the use of AI/RPA in other industries. This study attempted to incorporate these studies as well as the interview data to answer the first research question. Similar to the other studies, the researchers noted a core group of proposed benefits: 1) Patient benefits, 2) Organizational benefits, 3) Improved data quality, and 4) Cost reduction and revenue growth.

Research Question 2: What are the risk factors associated with AI implementation in healthcare?

Most healthcare organizations are forced to assess risk levels prior to implementing any innovative technologies. Similarly noted in other research studies that were targeted to healthcare implementations, this study noted the following strategies that need to addressed potential high risks in the use of AI/RPA in the revenue cycle, including external, physical, and digital, as well as maintaining a governance framework to assure patient privacy and other HIPAA requirements. Utilizing the proposed framework developed in research question 3, healthcare companies should assess whether the potential benefits sufficiently outweigh the associated risks.

Research Question 3: What outcomes are derived by using a Lean Six Sigma (LSS) designed framework for healthcare executives deciding to implement AI/RPA in the healthcare revenue cycle?

This research study provides a theoretical framework for using AI/RPA in the healthcare revenue cycle, which will allow for waste reduction and elimination of non-value-added activities along with variability reduction. Lean tools reduce waste and non-value-adding activity and enhance the effectiveness of equipment, tools, and machines. For this research question, a theoretical framework was constructed, the Lean Six Sigma framework should be implemented to reduce the defects which occurred during the revenue cycle. The theoretical framework combines the interview data and literature as well as Lean Six Sigma methods to mitigate the errors and defects and increase patient satisfaction while reducing overhead costs.

Limitations

Upon retrospective review, multiple study limitations were identified. Firstly, a relatively small sample size was utilized to accomplish this study. Due to this limitation, the findings may or may not be generalizable to the population of healthcare executives in the United States or healthcare revenue cycle strategies used in other countries.

Secondly, a limitation was due to conducting this research during the COVID-19 pandemic. This limitation caused the researcher to adapt from a typical face-to-face interview. Face-to-face interviews have been considered the gold standard in qualitative interviewing, especially for their potential to elicit honest views on sensitive topics by building trust with research participants. At present, this is not feasible, and remote methods were required to conduct this study. This caused the researcher to possibly miss valuable data and insights due to a lack of an unstructured conversation. These conversations may have led to other topic areas that might have influenced the outcomes of the study.

Implications

The theoretical framework constructed in this research is subject to several limitations that suggest several opportunities for additional research. First, the framework focuses on the prioritization of the development of new automation tasks. Healthcare organizations would benefit from research regarding the maintenance of these technologies, including governing the tasks with respect to ever-changing government and insurance regulations.

Secondly, the theoretical framework developed in this research study was not tested or validated. We believe, but have not empirically validated, that this framework will help healthcare executives in their decision-making process with regards to AI/RPA automation. Thus, future research or case studies should be done to validate the framework for its effectiveness and efficiency.

Recommendations

AI/RPA technologies are at the forefront of disruptive technologies and have tremendous potential to transform the healthcare revenue cycle. However, there is much to be explored about the implications of this emerging technology on the healthcare revenue cycle before it can be fully implemented. Additional testing of RPA and actual implementation on sections of the revenue cycle is necessary to obtain a better understanding of its benefits and challenges. This study focused on developing a theoretical framework to assist healthcare executives in determining if AI/RPA implementations aligned with their organizational needs.

In the meantime, it seems that AI/RPA can be used to automate segments of the RCM process. However, caution and due diligence are needed in its development, implementation, and monitoring due to the unknowns with the payor and federal regulatory issues. The higher level of monitoring may cancel out the organizational benefits until more knowledge is gained around the risks of these technologies.

Although initial assessments of the value-add of AI/RPA indicate that it can lead to improved patient satisfaction and better financial and organizational benefits, it would be interesting to measure its usefulness in real-time with a large RCM department. However, this type of implementation may not be easy to do until prototypes are ready for deployment. As more about the cost and benefits of AI/RPA is revealed over time, it will be necessary for healthcare executives to become familiar with its potential application in their organization.

This study recommends that future studies continue examining other factors that may influence the cost/benefit analysis of AI/RPA implementations. For example, this study suggests adding other risk constructs to the model, such as new government regulations. These areas are changing so fast that these items would be required to be built into the model. Additionally, utilizing major payor rules and regulations is highly recommended to examine other factors that influence the expected outcomes of AI/RPA within the healthcare RCM processes.

Summary

The problem addressed by this study is a lack of understanding regarding the specific risks and benefits associated with AI implementation in healthcare settings. Many administrative tasks are currently completed manually in healthcare, which takes high labor costs and increases human computation error potential. However, it is unknown to what extent AI may improve these administrative tasks and address challenges (CAQH, 2018).

There is a lack of understanding regarding the risks and benefits associated with AI/RPA implementations in healthcare revenue cycle settings. Healthcare companies are confronted with stricter regulations and billing requirements, underpayments, and more significant delays in receiving payments. Despite the continued interest of practitioners, revenue cycle management has not received much attention in research.

In order to expand the knowledge of the use of AI/RPA in the healthcare revenue cycle, the researcher conducted a thorough analysis of the existing literature and combined that with conducting interviews of key individuals. Using this data, the researcher conducted a triangulation of the responses and current literature to help develop a theoretical framework that may be applied to a healthcare organization in an effort to migrate from their current revenue management technique to one that includes the use of AI/ML/RPA as a means of future cost control and revenue boost.

The goals of this research study were:

1. To expand on the current literature surrounding the use of AI in the health care revenue cycle and provide a framework to allow health care executives to quickly visualize the benefits or drawbacks of such a technology in their specific healthcare revenue cycle departments.
2. To create a framework that may be applied to a healthcare organization in an effort to migrate from their current revenue management technique to one that includes the use of AI/ML/RPA as a means of future cost control and revenue boost.

To achieve the stated goals of the research, the main research questions were:

R1. What prospective benefits can be generated by using AI revenue cycle applications for healthcare organizations?

R2. What are the risk factors associated with AI implementation in healthcare?

R3. What outcomes are derived by using a Lean Six Sigma (LSS) designed framework for healthcare executives deciding to implement AI/RPA in the healthcare revenue cycle?

In order to answer these research questions, a qualitative semi-structured interview was conducted with ten key stakeholders responsible for managing or developing revenue cycles, including healthcare administrators, accounting/financial management officers, and information technology (IT) staff members.

The semi-structured interview consisted of 12 questions in three thematic areas:

1. How AI-based technologies will benefit the healthcare revenue cycle management processes
2. How to address risk factors that negatively impact the healthcare revenue cycle management processes
3. Inviting the participants to discuss risk management and problem-solving strategies that guide decision-making processes in the organizational context

Finally, the interview responses underwent a triangulation process against multiple existing studies to determine the validity of responses aligned with the extant literature. Following Creswell and Creswell (2018), the triangulation process ensured that the outcomes of the research participant's responses were aligned with those in previous studies done in the areas of AI/RPA studies. An audit trail was developed by transcribing the semi-structured interview responses that were recorded via a Microsoft Forms engine. These responses were stored without any personally identifiable information to ensure the confidentiality of the interview participants.

The research findings suggest that AI/RPA implementations can improve the healthcare revenue cycle's effectiveness and efficiency. Healthcare organizations should be cautious about which workflows that they implement AI/RPA into due to governmental regulations and payor complexities. These findings are consistent with recent literature and the interview data collected, which suggests that some tasks do not benefit from risk payoff.

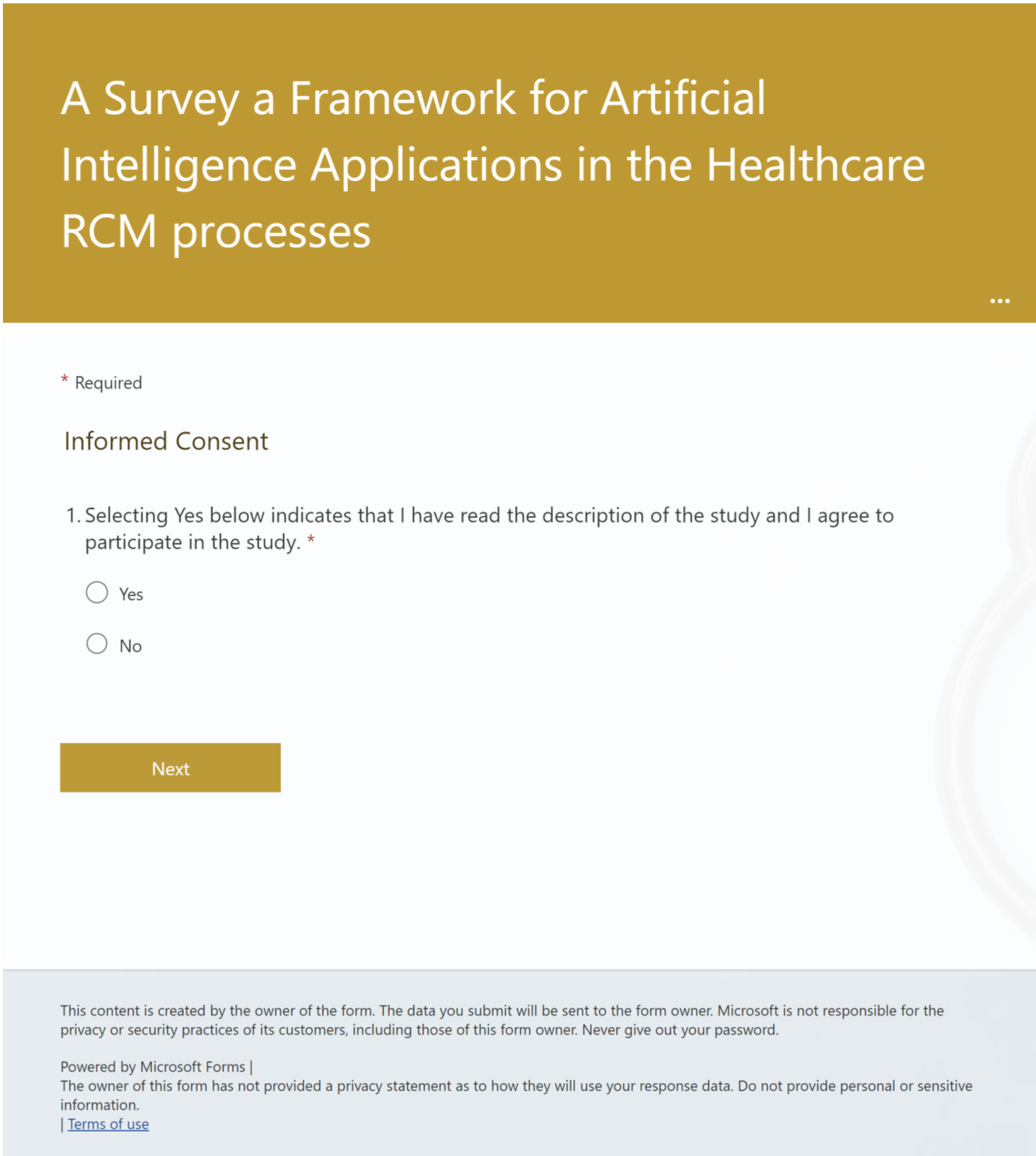
The limitations of this research study included factors, such as sample size and sample technique. The sample size was small, which affected the accuracy of the results, and the sampling technique was convenient, which is not generalizable. Additionally, this study collected information about AI/RPA thoughts from key individuals. This research was based on semi-structured interviews, which could affect participants' truth in answering the questions and, consequently, the study results' accuracy.

This research study contributed to prior healthcare literature in three main ways. First, it expanded on the current literature surrounding the use of AI in the health care revenue cycle. Second, the research quantified the past research and was able to draw similarities and likeness by interviewing prominent information technology professionals as well as healthcare executives. Finally, this research was able to construct a theoretical framework, thereby allowing health care executives to quickly visualize the benefits or drawbacks of such a technology in their specific healthcare revenue cycle departments.

This study recommended opportunities for future research to examine other AI/RPA implementations in different organizations while modifying the developed theoretical model to fit the organization's terminology. Future research is needed to test the theoretical model to ensure that it has the intended outcomes and displays the benefits as expected. Moreover, major payor and government regulations could be added to the theoretical model for further investigation. Another recommendation is to recruit a large and diverse sample using experimental research design to ensure the generalizability of results.

Appendices

Appendix A: Interview Questions



A Survey a Framework for Artificial Intelligence Applications in the Healthcare RCM processes

...

* Required

Informed Consent

1. Selecting Yes below indicates that I have read the description of the study and I agree to participate in the study. *

Yes

No

Next

This content is created by the owner of the form. The data you submit will be sent to the form owner. Microsoft is not responsible for the privacy or security practices of its customers, including those of this form owner. Never give out your password.

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A Survey a Framework for Artificial Intelligence Applications in the Healthcare RCM processes

* Required

Risk Factors with AI in Healthcare

The next three interview questions will involve asking the participants to address risk factors that negatively impact the healthcare revenue cycle management processes.

Please enter N/A if you do not have a response

6. Which risks specific to your organization left the most significant impacts on decision-making after integrating AI-based or other types of technologies into healthcare revenue cycle management? *

Enter your answer

7. How have these risks driven past performance and shaped decision-making? Which risks still demand critical attention in the present? *

Enter your answer

8. What do you believe will mitigate future risks when some issues impacting healthcare revenue cycle management remain? *

Enter your answer

Back

Next

A Survey a Framework for Artificial Intelligence Applications in the Healthcare RCM processes

* Required

Risk Management and Problem-solving Strategies

The next five interview questions will invite you to discuss risk management and problem-solving strategies that guide decision-making processes in the organizational context.

Please enter N/A if you do not have a response

9. Which risk management strategies, if any, did you apply in the past to ensure that your organization could integrate AI-based technologies effectively? *

Enter your answer

10. How did you apply these strategies to mitigate current and future risks? *

Enter your answer

11. Which strategies do you believe are still effective and why? *

Enter your answer

12. Which strategies do you wish the organization would eliminate? What examples can you provide to support any changes in administrative or other types of decision-making in the organizational environment? *

Enter your answer

13. How have the past and current strategies impacted your ability to develop yourself professionally while gaining knowledge of how revenue cycle management functions? *

Enter your answer

Back

Submit

A Survey a Framework for Artificial Intelligence Applications in the Healthcare RCM processes ...

* Required

Themes related to how AI-based technologies

The first four interview questions will address themes related to how AI-based technologies will benefit the healthcare revenue cycle management processes.

Please enter N/A if you do not have a response

2. What types of patterns or processes have you seen as a healthcare administrator, accounting/financial management officer, or information technology (IT) staff member that have influenced your healthcare revenue cycle management perceptions? *

   Enter your answer

3. Which of these patterns or processes has the most significant impact on organizational performance? Why do you believe these patterns or processes play such an essential role? *

   Enter your answer

4. How do you believe that AI-based technologies can inform the triple aim of healthcare when financial and related schemes appear challenging to manage?

   The Triple Aim's three areas of focus are:

   1. Improving patient experience
   2. Reducing the per capita costs of health care
   3. Improving the health of populations overall

   *

   Enter your answer

5. How do you believe AI-based technologies may contribute to improvements in administrative, financial, or other forms of professional decision-making? *

   Enter your answer

Back   Next

Appendix B**:** IRB Exempt Initial Approval Memo

NOVA SOUTHEASTERN UNIVERSITY
Institutional Review Board

MEMORANDUM

To: Leonard Pounds
College of Engineering and Computing

From: Ling Wang, Ph.D.
College Representative, College of Engineering and Computing

Date: July 7, 2021

Subject: IRB Exempt Initial Approval Memo

TITLE: A Framework for Artificial Intelligence Applications in the Healthcare Revenue Cycle Management– NSU IRB Protocol Number 2021-301

Dear Principal Investigator,

Your submission has been reviewed and Exempted by your IRB College Representative or their Alternate on **July 7, 2021**. You may proceed with your study.

Please Note: Exempt studies do not require approval stamped documents. If your study site requires stamped copies of consent forms, recruiting materials, etc., contact the IRB Office.

Level of Review: Exempt

Type of Approval: Initial Approval

Exempt Review Category: Exempt 2: Interviews, surveys, focus groups, observations of public behavior, and other similar methodologies

Post-Approval Monitoring: The IRB Office conducts post-approval review and monitoring of all studies involving human participants under the purview of the NSU IRB. The Post-Approval Monitor may randomly select any active study for a Not-for-Cause Evaluation.

Annual Status of Research Update: You are required to notify the IRB Office annually if your

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(954) 262-5369 • 866-499-0790 • Fax: (954) 262-3977 • Email: *irb@nova.edu* • Web site: *www.nova.edu/irb*

research study is still ongoing via the *Exempt Research Status Update xForm*.

Final Report: You are required to notify the IRB Office within 30 days of the conclusion of the research that the study has ended using the *Exempt Research Status Update xForm*.

Translated Documents: No

Please retain this document in your IRB correspondence file.

CC: Ling Wang, Ph.D.

Greg Simco

Appendix C: Email Invitation

Dear (Participant),

I am conducting interviews as part of a research study at Nova Southeastern University. This study is in fulfillment of my dissertation requirements. The study aims to increase the understanding of the specific risks and benefits associated with Artificial Intelligence and/or Robotic Process Automation (AI/RPA) implementations in healthcare revenue cycle settings.

As an experienced healthcare administrator, accounting/financial management officer, and/or information technology (IT) staff member, you are in an ideal position to give us valuable first-hand information from your perspective.

The interview takes around 30 minutes and is very informal. We are simply trying to capture your thoughts and perspectives on the use of AI/RPA within the revenue cycle. Your responses to the questions will be kept confidential. Each interview will be assigned a number code to help ensure that personal identifiers are not revealed during the analysis and write-up of findings.

There is no compensation for participating in this study. However, your participation will be a valuable addition to my research, and findings could lead to a greater understanding of the use of AI/RPA in the healthcare setting.

If you are willing to participate, please suggest a day and time that suits you, and I will do my best to be available. If you have any questions, please do not hesitate to ask.

Thank you for your time and consideration.

Leonard Pounds

lpounds@mynsu.nova.edu

954-661-2794

Appendix D: Informed Consent Form

INSTITUTIONAL REVIEW BOARD
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Fort Lauderdale, Florida 33314-7796
PHONE: (954) 262-5369

General Informed Consent Form
NSU Consent to be in a Research Study Entitled
A Framework for Artificial Intelligence Applications in the Healthcare Revenue Cycle Management

Who is doing this research study?

College: College of Computing and Engineering

Principal Investigator: Leonard Pounds, M.S.

Faculty Advisor/Dissertation Chair: Dr. Greg Simco, PhD

Co-Investigator(s): N/A

Site Information: Various/Online

Funding: Unfunded

What is this study about?

This is a research study, designed to test and create new ideas that other people can use.

The purpose of this study is to:

1) To expand on the current literature surrounding the use of AI in the health care revenue cycle and provide a framework to allow health care executives to quickly visualize the benefits or drawbacks of such a technology in their specific healthcare revenue cycle departments.

2) To create a framework that may be applied to a healthcare organization in an effort to migrate from their current revenue management technique to one that includes the use of AI/ML/RPA as a means of future cost control and revenue boost.

Why are you asking me to be in this research study?

You are being asked to take part in this research study because you are a either a healthcare administrator, accounting/financial management officer, or a information technology (IT) staff member

This study will include about 10 people.

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What will I be doing if I agree to be in this research study?

While you are taking part in this research study, you will be required to answer 12 interview style questions via an online form. This process should take no longer than 15-20 minutes.

Are there possible risks and discomforts to me?

This research study involves minimal risk to you. To the best of our knowledge, the things you will be doing have no more risk of harm than you would have in everyday life.

What happens if I do not want to be in this research study?
You have the right to leave this research study at any time, or not be in it. If you do decide to leave or you decide not to be in the study anymore, you will not get any penalty or lose any services you have a right to get. If you choose to stop being in the study, any information collected about you **before** the date you leave the study will be kept in the research records for 36 months from the end of the study but you may request that it not be used.

What if there is new information learned during the study that may affect my decision to remain in the study?
If significant new information relating to the study becomes available, which may relate to whether you want to remain in this study, this information will be given to you by the investigators. You may be asked to sign a new Informed Consent Form, if the information is given to you after you have joined the study.

Are there any benefits for taking part in this research study?

There are no direct benefits from being in this research study. We hope the information learned from this study will expand the knowledge on the specific risks and benefits associated with AI/RPA implementations in healthcare revenue cycle settings.

Will I be paid or be given compensation for being in the study?

You will not be given any payments or compensation for being in this research study.

Will it cost me anything?

There are no costs to you for being in this research study.

Ask the researchers if you have any questions about what it will cost you to take part in this research study (for example bills, fees, or other costs related to the research).

How will you keep my information private?

Information we learn about you in this research study will be handled in a confidential manner, within the limits of the law and will be limited to people who have a need to review this information. All anonymous data will be stored on an encrypted drive with limited access with a

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random participant number. This data will be available to the researcher, the Institutional Review Board and other representatives of this institution, and any regulatory and granting agencies (if applicable). If we publish the results of the study in a scientific journal or book, we will not identify you. All confidential data will be kept securely and encrypted within the universities approved Microsoft OneDrive storage. All data will be kept for 36 months from the end of the study and destroyed after that time by being deleted and the drive scrubbed with an approved data destruction mechanism.

Whom can I contact if I have questions, concerns, comments, or complaints?

If you have questions now, feel free to ask us. If you have more questions about the research, your research rights, or have a research-related injury, please contact:

Primary contact:
Leonard Pounds, MS can be reached at (954) 661-2794

If primary is not available, contact:
Dr. Greg Simco, PhD can be reached at (954) 262-2017

Research Participants Rights
For questions/concerns regarding your research rights, please contact:

Institutional Review Board
Nova Southeastern University
(954) 262-5369 / Toll Free: 1-866-499-0790
IRB@nova.edu

You may also visit the NSU IRB website at www.nova.edu/irb/information-for-research-participants for further information regarding your rights as a research participant.

All space below was intentionally left blank.

NSU Florida
NOVA SOUTHEASTERN UNIVERSITY

INSTITUTIONAL REVIEW BOARD
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Fort Lauderdale, Florida 33314-7796
PHONE: (954) 262-5369

Research Consent & Authorization Signature Section

Voluntary Participation - You are not required to participate in this study. In the event you do participate, you may leave this research study at any time. If you leave this research study before it is completed, there will be no penalty to you, and you will not lose any benefits to which you are entitled.

If you agree to participate in this research study, sign this section. You will be given a signed copy of this form to keep. You do not waive any of your legal rights by signing this form.

SIGN THIS FORM ONLY IF THE STATEMENTS LISTED BELOW ARE TRUE:
- You have read the above information.
- Your questions have been answered to your satisfaction about the research

Adult Signature Section

I have voluntarily decided to take part in this research study.

Printed Name of Participant	Signature of Participant	Date
Printed Name of Person Obtaining Consent and Authorization	Signature of Person Obtaining Consent & Authorization	Date

Appendix E: NVIVIO Codes

Name of codes	**Description**
Benefits of AI in HRCMP	How AI-based technologies will benefit the healthcare revenue cycle management processes
Cost reduction and revenue growth	AI is a massive enabler in improving funds flow and reducing billing mistakes resulting in reduced capital cost.
Improved data quality	AI will eliminate numerous manual mistakes, timing issues with manual inputting of data by providers and front desk staff, and delays in submission of claims
Organizational benefits	
Decrease or reduce workforce	Decrease of the workforce means the quantity of work needed by staff become less and reduce means to bring down the size (less no of people are required to perform a task)
Enhances teamwork	A thorough examination of all systems and processes of AI-based projects has brought organizations together.
Make better quick decisions	Using AI technologies, data will be better and easily accessible, resulting in more time for analysis that leads to better quicker, better decisions.
Patients benefits	
Help in early diagnosis	The patient population's needs are anticipated by AI systems and by its early intervention, results in preventing more severe conditions AI systems can alert patience of visits, medication refills, and can also monitor the progress of improved health outcomes
Improved patients' experience	AI would be able to enhance the patient experience by streamlining their admission and care process and giving doctors and medical staff more time to focus on the patients and not the process.
Reduces patients’ denial rate	Claim denials are one of the most common barriers to effective revenue cycle management. Using AI systems can anticipate denials, edits can be put in place, and new claims will be paid on initial submissions.
The negative impact of risk factors on HRCMP	risk factors that negatively impact the healthcare revenue cycle management processes
Impact of the human component	The risks of human errors will still exist and can adversely affect even the most finely implemented software.
Increase in cost	The cost of implementing and maintaining the entire web of processes results in extra costs to healthcare
Need to retrain employees	The staff does not perform the processes manually soon. They will lose the knowledge which is vital for the system's upkeep and adjustment
Security and privacy concerns	Data integrity and security are significant concerns with implementing any new technology as data going out to a third party.

Technological complexity	Understanding how new technologies work and how can they be practically implemented in cycle management is quite complex and is an ever-changing paradigm,
Risk management and problem-solving strategies	
Data security	Data security should be paramount. The evaluation must be carried out to keep the patient's data and the company's financial information safe.
Identification of risks	Any potential risk should be identified and monitored to minimize its impact
Implementing NLP	Implementing NLP (Natural language processing) to translate the clinical notes automatically
Properly trained staff	Training of the staff to use the AI processes
Review and audit of Processes	The data should be analyzed and assessed at regular intervals.
Transparency of processes	It means regular reports should be generated to identify issues in the system and the documentation of all the processes and workflow designs to understand easily

Appendix F: Triangulation of Data

Identified Themes from survey	Literature			
	How AI can transform hospital revenue cycle management (Scott Becker and Ayla Ellison - August 12th, 2019)	How Artificial Intelligence Is Optimizing Revenue Cycle Management (Jacqueline LaPointe April 10, 2020)	Pursuing innovation in the revenue cycle to transform operations (CHANGE Healthcare Dec 01, 2019)	The rise of artificial intelligence in healthcare applications (Adam Bohr and Kaveh Memarzadeh June 26, 2020)
Benefits of AI in HRCMP				
Cost reduction and revenue growth	One major area of opportunity in the revenue cycle for AI is in predicting denials. Constantly changing payer guidelines and human error are among the reasons hospitals and other provider organizations struggle with high claim denial rates. Reworking claims is costly, and every claim that is rejected or denied introduces the risk of a hospital not getting paid. It's estimated that hospitals lose more than $260 billion annually from insurance denials.	"We have seen some early successes with cash coming in a little more quickly, claims getting resolved more quickly. It's working" MidLantic Urology is leveraging AI through a financial clearance workflow automation solution that "provides visual cues to practice executives, so [they] know where each patient is in the financial clearance process, in real-time, and what needs to happen next." The solution has already helped the group improve gross revenue by 18 percent, a number Thompson expects to increase by 12 percentage points this year. The group is also working on 85 percent fewer claims at any given time, she reported.	Dan Malloy: I would say tighter margins is a primary factor. At Butler Health, we've experienced a decline in reimbursements from both government and commercial health plans, at least over the last five years. We are also seeing more competition in the market from other traditional providers as well as non-traditional sources like minute clinics and virtual care options. As a result, we are looking for ways to streamline operations and avoid revenue leakage. By associating physician data with facility data, particularly regarding denials, we also can be more proactive about preserving revenue integrity. if we're expecting a payer to pay within 38 days based on its historical performance, and we are approaching that timeframe and haven't received payment, our data analytics solution highlights the issue to trigger follow-up. We've also used analytics to examine bad debt accruals, anticipating the negative impacts of aging and prompting us to intervene.	the cost savings that AI can bring to the healthcare system is an important driver for implementation of AI applications. It is estimated that AI applications can cut annual US healthcare costs by USD 150 billion in 2026.
Organizational benefits				
Decrease or reduce workforce	AI and automation also present an opportunity for hospitals and health systems to cut costs by streamlining and optimizing manual processes. Based on the number of revenue cycle positions that could potentially be performed by AI and automation, Crowe predicts the cost to collect at healthcare organizations will decrease between 25 percent and 50 percent over the next five to 10 years.	Those interactions add up. Physicians and their staff spend almost two full business days each week completing prior authorizations, and more than one in three physicians has staff who work exclusively on the task, the AMA survey found. "Whether it's matching a patient with the right provider, estimating out-of-pocket costs, or coding the claim, those are things that have long lists of variables associated with them, and AI is pretty uniquely good at evaluating those variables and coming up with an ever-improving success rate of getting to the right outcome against any of those process steps," he said. "Those manual, redundant tasks that are taking place in patient access, coding, billing, collections, and denials, those tasks themselves that are performed by the revenue cycle departments can actually be automated using AI." MidLantic Urology realized a 50 percent reduction in anticipated staffing requirements for its newly centralized billing department. Yale New Haven Health also saw workforce optimization results by using AI to improve prior authorizations. "It has never been to eliminate positions. It's been more about refining processes and then moving further ahead," Seidman said. "Getting to more of those value-adding functions sooner so that we could focus on what's really important to us, which is our patient." A good place to start with AI investments is identifying use cases. Providers should be looking for opportunities to use automation to perform tasks that negatively impact net revenue. Then, they should assess staffing costs, Moore stated. He encouraged stakeholders to ask: How many people are performing a specific function? And where can automation free up capacity for more value-adding activities?	objective requires tools like RPA that reduce the amount of labor involved in collecting money. There are opportunities in the mid revenue cycle, health information management (HIM) and coding, which have highly repetitive tasks that are ideal for this type of automation.	Interpretation of data that appears in the form of either an image or a video can be a challenging task. Experts in the field have to train for many years to attain the ability to discern medical phenomena and on top of that have to actively learn new content as more research and information presents itself. However, the demand is ever increasing and there is a significant shortage There are numerous areas in healthcare where robots are being used to replace human workforce, augment human abilities, and assist human healthcare professionals. These include robots used for surgical procedures such as laparoscopic operations, robotic assistants for rehabilitation and patient assistance, robots that are integrated into implants and prosthetic, and robots used to assist physicians and other healthcare staff with their tasks. patients will be able to interact with the device in a remote manner and access their biometric data, all the while feeling that they are interacting with a caring and empathetic system that truly wants the best outcome for them. This setting can be applied both at home and in a hospital setting to relieve work pressure from healthcare workers and improve service.
Enhances teamwork				
Make better quick decisions		"When the technology is used inside of Epic, Cerner, or our standalone clinical intelligence products, it looks based on what it learns in the document, and then it renders the information to the appropriate party," stated Michael Clark, senior vice president and general manager for provider solutions within Nuance's healthcare division. "Providers need to know in real-time who is cleared to be treated financially and who is not to make the most informed decisions for the practice. Patients, too, need to know what they're responsible for paying so they can choose treatment options that are right for them," said MaryAnne Thompson, controller at MidLantic Urology LLC, a group of 70-plus physicians in Pennsylvania.	organizations are using AI to help prevent denials and underpayments, improve eligibility verification and enhance the financial clearance process.	NLP Facilitate decision-making for members of healthcare team upon need (for instance, predicting patient prognosis and outcomes).

Identified Themes from survey	Literature: How AI can transform hospital revenue cycle management (Scott Becker and Ayla Ellison - August 12th, 2019)	How Artificial Intelligence Is Optimizing Revenue Cycle Management (Jacqueline LaPointe April 10, 2020)	Pursuing innovation in the revenue cycle to transform operations (CHANGE Healthcare Dec 01, 2019)	The rise of artificial intelligence in healthcare applications (Adam Bohr and Kaveh Memarzadeh June 26, 2020)
Benefits of AI in HRCMP				
Patients benefits				
Help in early diagnosis		For years, innovative providers have been leveraging the technology to deliver better care for patients with everything from sleep disorders, eye disease, cancer, and even COVID-19. The technology has created hype for clinical care, promising to catch diseases faster, expand access to care in underserved or developing regions, reduce the burden of EHR use, and more.		A large part of these cost reductions stem from changing the healthcare model from a reactive to a proactive approach, focusing on health management rather than disease treatment. This is expected to result in fewer hospitalizations, less doctor visits, and less treatments. AI-based technology will have an important role in helping people stay healthy via continuous monitoring and coaching and will ensure earlier diagnosis, tailored treatments, and more efficient follow-ups. Many inherited diseases result in symptoms without a specific diagnosis and while interpreting whole genome data is still challenging due to the many genetic profiles. Precision medicine can allow methods to improve identification of genetic mutations based on full genome sequencing and the use of AI. Remote monitoring and picking up on early signs of disease could be immensely beneficial for those who suffer from chronic conditions and the elderly. Here, by wearing a smart device or manual data entry for a prolonged period, individuals will be able to communicate to their healthcare workers without the need of disrupting their daily lives [35]. This is a great example of algorithms collaborating with healthcare professionals to produce an outcome that is beneficial for patients. Remote monitoring and picking up on early signs of disease could be immensely beneficial for those who suffer from chronic conditions and the elderly. Here, by wearing a smart device or manual data entry for a prolonged period, individuals will be able to communicate to their healthcare workers without the need of disrupting their daily lives
Improved patients' experience		Yale New Haven Health's goal was to put the patient in the center of everything being done, so the health system went with a vendor whose mission was not to replace staff with AI, but redirect staff to doing more patient-centric activities, like talking about insurance benefits or setting expectations for patient financial responsibility.	At Sharp Healthcare, we're trying to accelerate information delivery to our patients and families and enhance the customer experience. We want to be the system of choice for a consumer and that requires creating and consistently providing high-touch, convenient interactions. we are actively implementing methods, such as mobile solutions, that can attract and retain customers and fully meet their expectations. the care and financial experiences will be more mobile. We're building a new hospital, and I recently had a discussion with the people in charge of the project asking if they geofenced the lobby, so that when patients walk in and have their phones, we can acknowledge that they are here and we're expecting them. By clicking a button on their phones, they can be guided to the correct floor and their admission paperwork can be ready for their signature. Other industries are doing this now. It's time for healthcare to catch up.	Telehealth technology is also relevant in developing countries where the healthcare system is expanding and where healthcare infrastructure can be designed to meet the current needs IBM Watson is being used to investigate for diabetes management, advanced cancer care and modeling, and drug discovery, but has yet to show clinical value to the patients. Deep Mind is also being looked at for applications including mobile medical assistant, diagnostics based on medical imaging, and prediction of patient deterioration If each patient is treated as an independent system, then based on the variety of designated data available, a bespoke approach can be implemented. This is of utmost importance for the elderly and the vulnerable in our societies. An example of this could be that of virtual health assistants that remind individuals to take their required medications at a certain time or recommend various exercise habits for an optimal outcome they allow remote video conversations between the patient and the physician. Normally, the patient books an appointment for a specific time, often during the same day. This provides them with ample time to provide as much information as possible for the physician responsible to review and carefully analyze the evidence before talking to the patient. The information can be in the form of images, text, video, and audio. This is extremely encouraging and creative as many people around the world lack the time and resources to visit a physician and allows remote work for the physician.
Reduces patients denial rate	Using AI, hospitals and health systems can pinpoint the reasons payers denied claims in the past and uncover denial trends. This enables healthcare organization to predict denials and resolve problems before claims are submitted, leading to lower denial rates and higher revenue.			
Improved data quality		The revenue cycle contains an abundance of tagged data, which means values are codified to data points to indicate certain events, like why a claim was denied or attributes of a patient's diagnosis, Polaris explained.		

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Negative impact of risk factors on HRCMP				
Increase in cost		Healthcare organizations that have yet to see the need for such technology or do not have the capital or infrastructure to support the investment may have to wait a little to unlock the benefits of AI-powered revenue cycle management.		
Impact of human component				
Need to retrain employees				
Security and privacy concerns				
Technological complexity		"AI-as-a-service is focusing on offering that maintenance aspect, as well as using machine learning capabilities and learning that's taking place across a neural network to enhance that bot."	revenue cycle management as we know it is getting increasingly more complex to execute. Pressured reimbursement models, provider consolidation, diverse technology platforms and constant regulatory changes are all making the process more difficult.	
Risk manangement and problem solving strategies				
Transparency of processes		"We had little to no reporting mechanisms in place and we weren't automated, so we couldn't identify the problem areas, where they stemmed from, who made them, or how to resolve them," Thompson stated. "These challenges were holding back the organization's overall success, so we started looking at cloud-based applications that could provide us with visibility into financial clearance as well as insights, metrics, and KPIs that would allow us to effect a positive change in our A/R."	There's an emphasis on engaging patients and helping them manage their financial liability, creating transparency around what's owed and why. To increase transparency, we've implemented mobile solutions that allow consumers to easily view statements, get estimates, make payments and view signed documents. Soon our customers will be able to set up their own payment plans as One of our goals is to improve transparency across the organization by getting everyone on the same electronic health record (EHR). Not only will this help us deliver better patient care, but it will allow us to provide clearer billing statements for the family.	The EMR databases contain the history of hospital encounters, records of diagnoses and interventions, lab test, medical images, and clinical narratives. All these datasets can be used to build predictive models that can help clinicians with diagnostics and various treatment decision support. As AI tools mature it will be possible to extract all kinds of information such as related disease effects and correlations between historical and future medical events
Data Security				
Identification of risks			Baxter: It's critical to spend time getting to know your organization's pain points before reaching out to vendors to find out what's possible. You want to be sure you	
Implementing NLP	Another aspect of AI in healthcare that shows promise for transforming the revenue cycle is natural language processing. NLP enables computer programs to process and analyze unstructured data, such as free-text physician notes written in an EHR. Within the revenue cycle, application of NLP can improve coding and clinical documentation.			NLP is crucial for many applications of big data analysis within healthcare, particularly for EMRs and translation of narratives provided by clinicians. It is typically used in operations such as extraction of information, conversion of unstructured data into structured data, and categorization of data and documents. There are many areas in healthcare in which NLP can provide sub- stantial benefits. Some of the more immediate applications include 1. Efficient billing: extracting information from physician notes and assigning medical codes for the billing process. 2. Authorization approval: Using information from physician notes to prevent delays and administrative errors. 3. Clinical decision support: Facilitate decision-making for members of healthcare team upon need (for instance, predicting patient prognosis and outcomes). 4. Medical policy assessment: compiling clinical guidance and formulation appropriate guidelines for care.
Lack of Properly trained staff		Providers should also bring in the employees who do the work to evaluate the solution, she recommended. "They can share the process that they're following in reality versus what we believed what was happening."	One area relates to denials that require clinical expertise to resolve. We don't have sufficient internal resources to effectively handle these denials, and the required skill set can be difficult to hire, so engaging in an outsourcing relationship is beneficial. We've also started working with an outside vendor to assist with pre-collect self-pay payments. We find the most success when the vendor is attuned to our goals and mission and provides ongoing training and support. Upgrades should be easy, and the vendor should periodically check in to make sure we're fully utilizing the tool.	
Review and audit of processes		"We had to take a much closer look at our processes because we didn't want to automate a bad process or an already efficient process. We did some pre-work to process map what we were doing," Seidman explained.	Geisinger uses data analytics to identify and solve problems across the organization. We have found it best to start with a high view of data and seek the capabilities to drill down as we become more aware of what the data is trying to tell us. When you start with loads of raw data, it can become overwhelming, but if you start by answering high-level questions and then follow the data level-by-level to your answer, you can address significant challenges.	

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