2022

Assessing the Relationship Between Automated Technology Expenditure and Revenue Cycle Performance

Kelsey Macapagal
Walden University

Walden University

College of Health Professions

This is to certify that the doctoral study by

Kelsey Macapagal

has been found to be complete and satisfactory in all respects,
and that any and all revisions required by
the review committee have been made.

Review Committee
Dr. Sheryl Richard, Committee Chairperson, Health Sciences Faculty
Dr. Lee Bewley, Committee Member, Health Sciences Faculty
Dr. Heather Alonge, University Reviewer, Health Sciences Faculty

Chief Academic Officer and Provost
Sue Subocz, Ph.D.

Walden University
2022

Abstract

Assessing the Relationship Between Automated Technology Expenditure and Revenue Cycle Performance

by

Kelsey Macapagal

MPH, Boston University, 2016

BA, University of California, Irvine, 2012

Doctoral Study Submitted in Partial Fulfillment

of the Requirements for the Degree of

Doctor of Healthcare Administration

Walden University

May 2022

Abstract

Despite evidence that the automation of administrative processes may lead to both cost reductions and performance benefits, there was little to no empirical evidence that holistically examined the impact of technology within the healthcare revenue cycle. The purpose of the current quantitative study was to examine the relationship between automated technology expenditure and revenue cycle performance. Correlational analyses were used to determine the relationship between automated technology expenditure and labor, revenue, and denials, respectively, within the revenue cycle of a single, multi entity health system in California. Regression analysis was used to determine the relationship between variables over a 4-year timeframe. The results from correlational analyses revealed a weak, negative relationship between automated technology expenditure and labor that was not statistically significant; however, strong, positive, statistically significant relationships were found between automated technology expenditure and revenue as well as automated technology expenditure and denials. The impact of automation within healthcare administration should be addressed and subsequently adopted on a larger scale than what the nation has in place today. When new technology is introduced, employees tend to view the change with skepticism and have heightened anxiety around job security. As such, findings from the current study may support positive social change through informed decision making when investing in automated technology. Finally, results may aid support open dialogue around the impact of automated technology within the workforce and with respect to financial metrics, aid in the communication of shared goals at all levels, and subsequently support social change at the organizational level.

Assessing the Relationship Between Automated Technology Expenditure and Revenue Cycle Performance

by

Kelsey Macapagal

MPH, Boston University, 2016

BA, University of California, Irvine, 2012

Doctoral Study Submitted in Partial Fulfillment

of the Requirements for the Degree of

Doctor of Healthcare Administration

Walden University

May 2022

Dedication

For Sydney and Michael Toledo, who underpin everything I am; to say I would not be where I am today without you both by my side, in my heart, and without your guidance is a gross understatement. Thank you for always seeing the best in me, for believing in me when odds and opinions are against me, and for always catching me before I fall.

Acknowledgements

To Christee Thomas: Thank you - for everything. Your leadership, mentorship, and friendship has guided me into a new world of knowledge and opportunity beyond what I had ever thought was possible for myself. Thank you for showing me what a true support system is and for challenging me to be better every day. I am humbled and forever grateful to be your Padawan.

To my committee chairs, Dr. Sheryl Richard and Dr. Lee Bewley: Thank you both for your endless support, patience, and collaboration over the past few years.

Table of Contents

List of Tables

List of Figures

Section 1: Foundation of the Study and Literature Review

The financial infrastructure within the United States healthcare industry is inherently complex. The absence of a universal reimbursement model, coupled with distinct guidelines for payment that vary by insurance company, has placed significant administrative burden on health systems and provider organizations (Gottlieb et al., 2018). Research studies and economic reports have highlighted that the United States spends nearly twice as much on healthcare (as a share of the country's economy) compared to nations of similar wealth and demographics (Himmelstein et al., 2020; Tikkanen et al., 2020). Not only is the cost of healthcare-related goods and services much higher in the United States but also a greater portion of overall healthcare spending is attributed to administrative costs rather than clinical patient care, infrastructure, or other needed resources (Tseng et al., 2018).

Industries such as manufacturing, food services, and transportation have already adopted widespread automation in labor-intensive, administrative functions; however, the United States healthcare sector has not yet leveraged technology to the same extent (Chui et al., 2017). By some research accounts, greater automation within the administrative space may yield annual savings between $11 billion–$44 billion, depending on the type and level of automation in review (Cutler, 2018; Pollack, 2018). Additionally, 43% of financial and insurance-related tasks have the potential to move toward automated workflows, which may further reduce error-prone, manual workflows to optimize the back-end workflow (Carrus et al., 2020). Administrative activities associated with the timely and appropriate collection of payment for patient services rendered are collectively known as the revenue cycle and represent workflows with the greatest opportunity for automation. Revenue cycle functions, such as insurance authorization, billing, and insurance follow-up, may expand the use of automated technology, which will subsequently lower the overall cost of healthcare, reduce patient financial-related errors, and increase the speed in which an organization can collect revenue and maintain financial viability (Ayabakan et al., 2021; Carrus et al., 2020; Ratia et al., 2018; Singh et al., 2021). An annual report produced by the Council for Affordable Quality Healthcare (CAQH; 2019) identified that $40.6 billion was spent on eligibility and benefit verification, prior authorization, claim submission, attachments, coordination of benefits, claim status inquiry, claim payment, and remittance advice, and of that, 33% (or $13.3 billion) could be saved by transitioning from manual processing to an electronic workflow. A closer examination of automated technology within the revenue cycle is needed to understand the nation's hesitation to adopt such technology on a wider scale.

Problem Statement

Payment policies, such as the pay-for-performance structure introduced under the Affordable Care Act, have placed significant pressure on healthcare organizations to identify innovative ways to reduce costs and simultaneously increase the value of a patient's care experience (Cardon et al., 2018; Holloway et al., 2018). Nearly all industries have been, and will continue to be, impacted by the development of advanced technologies and automated workflows (Manyika et al., 2017). Within the healthcare industry, the automation of various administrative processes may reduce administrative costs, operational resource burden, and open new opportunities for innovation that simultaneously support a health system's financial well-being and advance capabilities within the revenue cycle (Muro et al., 2019; Zengul et al., 2018).

Though the high cost of administrative functions is a well-known problem within healthcare and despite evidence in other industries that automated technology relieves resource burden and reduces cost, there is little to no empirical evidence that holistically examines the impact of automated technology within the healthcare revenue cycle. Specifically, existing literature has focused on the relationship between automated technology and the healthcare revenue cycle but does not examine staff variables and the operational costs of implementation. The problem is that healthcare administrators do not know how spending on automated technology impacts labor and revenue. Many leaders have been hesitant to choose the purchase new, automated technology over resource allocation in other areas (Carrus et al., 2020). I found no extant studies that explored the initial cost of investment, the interplay between internal and external labor after automated technology has been adopted, timelines for benefit realization, or the level of investment in automated technology needed to realize greater revenue cycle efficiency. However, for healthcare organizations to reduce operational cost, improve performance, increase patient satisfaction, and remain competitive, the opportunity to leverage automation within the back-end revenue cycle must be addressed.

Purpose of the Study

The purpose of this quantitative study was to examine the relationship between automated technology expenditure made within the revenue cycle, associated labor hours, revenue, and denials. I assessed performance in terms of monthly revenue between fiscal year (FY) 2018–FY 2021. The timeframe selected followed the initial purchase of specific automated technologies and allowed multiple years of postimplementation data collection. When examining the impact of technology on firm performance, research on only 1 year of data has been thought to be misleading due to the time lag between automated technology expenditure and actual performance or economic returns (Bharadwaj, 2000). Thus, within the current study, I selected a 4-year timeframe to compare the correlation between variables at multiple stages related automated technology expenditure. As a result, conclusions from the current study may provide insight into the automated technology expenditure relative to financial and performance returns within the revenue cycle.

Research Questions and Hypotheses

The following research questions and hypotheses guided this study:

RQ1: What is the relationship between organizational expenditures on automated technology and labor hours within the revenue cycle?

$H_0$1: There is no statistically significant association between automated technology expenditure and revenue cycle labor hours.

$H_1$1: There is a statistically significant relationship between automated technology expenditure and revenue cycle labor hours.

RQ2: What is the relationship between organizational expenditures on automated technology and revenue?

$H_0$2: There is no statistically significant relationship between automated technology expenditure and revenue.

$H_1 2$: There is a statistically significant relationship between automated technology expenditure and revenue.

RQ3: What is the relationship between organizational expenditures on automated technology and denials?

$H_0 3$: There is no statistically significant relationship between automated technology expenditure and denials.

$H_1 3$: There is a statistically significant relationship between automated technology expenditure and denials.

Furthermore, the research encompassed a multiyear timeframe, whereby I examined the dependent variables prior to initial expenditure on automated technology and after automated technology was implemented. As such, the following research question and corresponding hypotheses were examined and trended over time:

RQ4: How does automated technology expenditure impact revenue cycle labor hours, revenue, and denials over time?

$H_0 4_1$: There is no significant trend in automated technology expenditure and revenue cycle labor hours over time.

$H_1 4_1$: There is a statistically significant trend in automated technology expenditure and revenue cycle labor hours over time.

$H_0 4_2$: There is no statistically significant trend in automated technology expenditure and revenue over time.

$H_1 4_2$: There is a statistically significant trend in automated technology expenditure and revenue over time.

H_04_3: There is no statistically significant trend in automated technology expenditure and denials over time.

H_14_3: There is a statistically significant trend in automated technology expenditure and denials over time.

Theoretical Foundation for the Study

In the current study, I examined automated technology expenditure against two distinct, but related, operational and performance metrics: labor and performance. As such, it was necessary to examine multiple theories that assess the impact of technology on labor and financial indicators of performance.

Information Technology Investment and Real Option Theory

Performance outcomes that result from investment in information technology (IT) vary across organizations due to organization-specific factors, capabilities, and strategic decisions (Aral & Weill, 2007). Aral and Weill (2007) categorized a firm's IT investment into four distinct types based on the strategic purpose of investment: IT infrastructure, transactional investments, informational investments, and strategic investments. In the current study, transactional investments were the primary investment of focus, as defined by an organization's investment in technology, which is targeted to automate specific processes, cut costs, or to increase the business volume of output per unit cost (see Aral & Weill, 2007).

IT investment is expected to increase the effectiveness and efficiency of an organization by enhancing performance factors and the value of activities (Kim & Sanders, 2002). Prior to investment in IT, Kim and Sanders (2002) described the *real* *option valuation* within the decision-making process, whereby leaders examine the potential investment in IT and the perceived impacts of the investment. The value of an IT investment is broken into two categories: economic value and real option value. The economic value of an investment directly relates to the reduction in costs achieved as a result of IT investment. The real option value of investment estimates the long-term value of IT investment achieved from a strong strategic fit between the investment and internal and external factors (Kim & Sanders, 2002).

Furthermore, Kim and Sanders (2002) expanded on the real option value by emphasizing the *path dependency* of IT investment. In essence, the ability to invest in and successfully implement IT is largely based on an organization's prior investments and the technological capabilities already in place. Future technological ability is thus dependent on what an organization has executed in the past and is influenced by five factors: prior experience, network externalities, economies of scale, technological interrelatedness, and increasing returns of information (Kim & Sanders, 2002).

IT investment has also been linked to profitability (Mithas et al., 2012). Under a resource-based view, Mithas et al. (2012) associated IT investment with revenue growth and cost reduction. IT investments may facilitate greater revenue through new value propositions and improved management of the customer life cycle (Mithas et al., 2012). Additionally, IT investment is associated with cost reduction through improved operational efficiency and the promotion of lean transformation efforts (Mithas et al., 2012).

Automated Technology and Labor

Across industries, the growth of technology is often followed by changes within the workforce (Muro et al., 2019). Acemoglu and Restrepo (2018) proposed a task-based framework that explores how automation, artificial intelligence, and robots impact labor, productivity, and various global marketplaces. The authors acknowledged the existence of a displacement effect in which labor, wages, and employment declined after the implementation of automation: however, the displacement effect may be negated if three counterbalances are sufficiently met:

1. Productivity effect: As automation increases and the cost of conducting automated activities declines, the demand for labor will increase in other areas that are not impacted by automation.
2. Capital accumulation: As the productivity effect increases, both the demand for automation in capital and the demand for labor will increase in parallel.
3. The deepening of automation: As productivity increases in areas already covered by automation, the productivity effect will increase without the consequence of displacement.

The framework's original intent was to compare the impact of automation on workers across various countries and to understand the wider consequences on the labor markets, economies, and cultures (Acemoglu & Restrepo, 2018). Though the framework is not directly related to automation in the healthcare sector, the overarching purpose is in direct alignment with that of the current study: to examine the post automation effects technology on the workforce and demand.

In the framework, Acemoglu and Restrepo (2018) also posited a production function to assess the impact of automation on labor. The production function is as follows:

production function = $F($AL, BK)

Whereby L represents labor and K represents capital investment in automated technology. The production function shows how changes (or in this case, increases) to automated technology correspond to an increase in A and supports the displacement effect if the elasticity of substitution between capital and labor is relatively small (Acemoglu & Restrepo, 2018). This function is supported in research conducted by the CAQH (2019), in which the adoption of electronic eligibility and benefit verification decreased the average transaction time from 23 minutes per transaction to roughly 10 minutes per transaction. However, I found no extant studies in which the implementation of automation led to a positive or negative impact on displacement.

Nature of the Study

In the current quantitative study, I used a bivariate correlational analysis to examine the relationship between automated technology expenditure and revenue cycle performance. Pearsons's correlation coefficients were calculated for each month between FY 2018–FY 2021. This study approach was determined to be most appropriate due to the nature of the continuous variables selected and the overall objective to determine the existence of a relationship between variables.

The independent variable of interest was the monetary expense on automated technology. I reviewed expenses related to a specified technology through monthly cost reports and related data from FY 2018–FY 2021. The dependent variables were labor hours, denials, and revenue. The relationship between automated technology expenditure and these dependent variables were examined for each month within the timeframe identified. Additional consideration was input to account for the time-lag between expenses made toward automated technology and outcomes of collection (i.e., denial versus revenue received).

I extracted the secondary data from a multi entity health system in California. Specifically, reports from the FY 2018, FY 2019, FY 2020, and FY 2021 were used to examine financial and operational performance metrics. Datapoints selected from the reports included labor hours – expressed as full-time equivalents (FTEs) – denials, and revenue. Data for the dependent variables were collected from the Revenue Cycle departments that purchased automated technology over the course of the 4 years noted above. Notably, I quantified the relationship between automated technology, labor, and revenue using financial cost reports across each month between FY 2018– FY 2021. This approach was in contrast to the approaches taken in previous studies, such as Alsharief et al. (2018), Polykarpou et al. (2018), Ratia et al. (2018), and Piercy and Gist-Mackey (2021), who often used qualitative surveys and interview responses from healthcare end-users to make conclusions related to technology and performance.

In this study, I primarily focused on three departments within the organization's Revenue Cycle: Patient Access, Coding, and Health Information Management (HIM). At the start of FY 2018, these three departments represented the areas with the highest labor footprints and the lowest amount of automation intertwined within workflows, relative to all other revenue cycle departments. In effort to reduce costs and improve performance, the departments received capital funding to purchase and implement automated technology in FY 2019; all of which had been designed to improve revenue collections. As a result, the Patient Access, Coding, and HIM departments showed the largest areas of opportunity in relation to the current study and were thus selected for further examination.

Literature Search Strategy

Library databases and search engines used to locate literature for the current study included the Walden University Library, JSTOR, Google Scholar, EBSCO, and PubMed. I used the following keyword search terms and phrases: *revenue cycle management, revenue cycle automation, automation in healthcare, investment in automation technology, administrative burden in healthcare, cost of healthcare administration, revenue cycle and artificial intelligence, healthcare denials, and healthcare administrative labor*.

My initial search for literature and peer-reviewed studies did not include a date range for publication. The intent was to include seminal articles around the healthcare revenue cycle, administrative costs in the United States healthcare industry, and understand automated technology in healthcare and other industries. After sufficient background knowledge had been gained around the high cost of healthcare and the consequences of administrative inefficiency in the United States, I then narrowed the search date range of literature publication to 2016–2021 to understand the current state of the healthcare revenue cycle and industry automation.

The healthcare revenue cycle has not been widely discussed or examined within peer-reviewed studies and extant research. The gap in peer-reviewed studies highlights an asymmetry of information within the industry; organizations may be hesitant to publicize the history, detail, and success around the automated technology and automation implemented in order to remain competitive (Mindel & Mathiassen, 2015). Consequentially, health systems must decide to innovate and invest at their own risk with potentially minimal prior knowledge on what other organizations have found effective or useful (Mindel & Mathiassen, 2015). The lack of data and empirical studies around revenue cycle automation may subsequently lend to a general reluctance to invest in greater administrative automation and may help explain the lower level of automation within healthcare as compared with other industries. However, because the medical industry, in general, frequently publishes research findings related to clinical care, the same case should be argued for greater research around back-end, operational efficiencies.

Despite the dearth of empirical studies on revenue cycle automation, I identified a sizeable amount of opinion articles, white papers, and periodicals that discussed the potential for greater revenue cycle management (RCM) and tools for efficiency. Organizations, such as the Healthcare Financial Management Association (HFMA) and *Healthcare Financial Times*, provide the largest avenues for peer discussion and published most of the aforementioned articles. As such, I thoroughly examined the discussion papers to identify reference literature for the current study.

Literature Review Related to Key Variables and/or Concepts

I conducted a literature review to understand the administrative costs of healthcare in the United States and areas of opportunity for technology and automation within the administrative workflow. As mentioned previously, empirical and peer-reviewed studies on automation within the healthcare revenue cycle have been limited. Opinion articles around automation and new technology were frequently found but seldom quantified the investment or benefits achieved as a result and rarely provided data behind each opinion or success story.

Administrative Cost of Healthcare in the United States

The United States consistently spends more on healthcare than any other country (Papanicolas et al., 2018). The interplay between third-party payers, federal regulation, and various payment structures has created administrative complexity and subsequently increased the overall cost of healthcare (Himmelstein et al., 2020; Wyatt-Elkins, 2020). According to the Centers for Medicare and Medicaid Studies (2020), the United States' healthcare expenditure reached $3.8 trillion in 2019, which translated to 17.7% of the nation's gross domestic product.

A true figure of administrative spending remains up for debate. Between 2018-2021, a variety of research studies estimated administrative spending to be anywhere between 7%–31% of total healthcare spending, or between $266 billion–$1.2 trillion, respectively (CAQH, 2020; Carrus et al., 2020; Gottlieb et al., 2018; Himmelstein et al., 2020; Kim et al., 2018; Singh et al., 2021; Tseng et al., 2018). The complex payment and reimbursement system between healthcare providers, third party insurance payers, and patients had resulted in a high volume of administrative work (Himmelstein et al., 2020). A continuous loop of communication, documentation, and related correspondence among numerous parties has consequently led to significant administrative costs and highlighted the need for effective RCM (Mindel & Mathiassen, 2015). In this literature review, I focus primarily on administrative work on the backend of healthcare, specifically billing and insurance-related (BIR) activities that are estimated to collectively account for 62% of administrative costs (see Tseng et al., 2018).

The revenue cycle is comprised of various activities to ensure appropriate payment is received for patient services rendered. These activities include appointment scheduling, registration, charge entry, coding, billing, claims processing, insurance follow-up, and payment processing (Tseng et al., 2018). To better understand the full breadth of billing investments from the physician perspective, Tseng et al. (2018) created a model to estimate the cost of billing for primary care visits, emergency visits, ambulatory surgical procedures, and inpatient surgical procedures at a large academic health center. All billing activities within the revenue cycle were identified, then measured using a time-drive, activity-based costing method to associate each activity with a dollar figure cost per encounter. Across the four visit types, the authors identified discrepancies in billing costs and percentage of total revenue due to the number and complexity of procedures involved in the coding process for each identified specialty. For example, primary care visits had the lowest billing cost per encounter of $20.49, the billing costs were 14.5% of the revenue received as a result of each encounter. On the other hand, inpatient surgery had the highest billing cost per patient encounter ($141.54), but the associated billing costs were only 3.1% of the revenue received as a result of each encounter. Though primary care visits were not necessarily more complex than surgical procedures, the billing and procedure codes associated with primary care visits necessitated more time and resources to code. However, across all specialties, billing costs were most associated with the labor needed to conduct billing activities and included direct, supervisory, support, and overhead labor costs (Tseng et al., 2018). Furthermore, Tseng et al. concluded that high billing costs were a consequence of divergent coding and billing requirements set forth by multiple third-party payers and health plans.

The financial impact and complexity that results from payer-specific billing requirements was similarly highlighted by Gottlieb et al. (2018) who examined the differences in claims resolution and payment outcomes between public and private insurers in terms of time to payment, number of interactions between the insurer and physician, claim denial, and nonpayment. They found the highest level of billing complexity among Medicaid claims that had the highest number of challenged claims, denial rate, and the most days to payment compared to Medicare and commercial payers. Because insurance coverage through Medicaid is targeted toward underserved populations, a call for reimbursement reform was raised to prevent further challenges in patient access to care (Gottlieb et al., 2018).

The payer-specific billing requirements described above highlight the broader issue of the United States' reimbursement system for healthcare. Third-party insurance payers exercise leverage over healthcare providers through the provision of specified claims, billing, and documentation requirements for payment (Tseng et al., 2018). Contracts and terms for payment between insurance payers and healthcare providers are negotiated privately and differ at the organizational level (Cooper et al., 2018; Craig et al., 2018). Payer-specific billing requirements prevent full standardization across the billing process. Failure to comply with the exact claim details and documentation requirements will place the patient encounter at risk for denied payment (Kovach & Borikar, 2018). By Ayabakan et al.'s (2021) account, roughly 80% of medical bills contain errors, in part due to erroneous rules set forth by different insurance payers.

Denied payment on claims sent to insurance payers is frequently used as a key performance indicator (KPI) and as a measure of success within RCM. As such, a range of research studies by Kim et al. (2020), Kovach and Borikar (2018), Ayabakan et al. (2021), and Gottlieb et al. (2018) examined the process of claim denials and the subsequent impact on healthcare organizations. The researchers measured denials at different times within the billing and insurance follow-up process, which resulted in inconsistent estimates of insurance denials across the studies.

Insurance payers often attribute incorrect procedural coding or misaligned billing codes as primary reasons for denied payment (Ayabakan et al., 2021). Ayabakan et al. (2021) and Gottlieb et al. (2018) noted that contract language around actual reimbursement and in-depth claims processes differ due to individual negotiations between insurance companies and healthcare organizations or providers. Because of stringent payer policies and general billing errors by staff, denials may be anticipated on a subset of claims upon first submission. Kim et al. (2020) estimated that 5%–11% of all hospital claims are initially denied, which then averaged to $5 million in payments at risk per year.

After a claim is initially denied, providers may send an appeal with supporting documentation back to the insurance carrier as a second request for payment (Gottlieb et al., 2018). Because the process and number of attempts for appeal differ based on payer-provider contracts, a claim may be denied and appealed multiple times before a resolution is achieved. As a result, Gottlieb et al. (2018) surmised that multiple attempts to recuperate payment on denied claims result in $11 billion–$54 billion of annual challenged revenue between physician offices and insurance payers.

The appeals process on denials is often labor intensive, time consuming, and represents rework within the billing process that ultimately delays revenue collection (Kovach & Borkiar, 2018). Kim et al. (2020) indicated that 63% of denied claims may be recovered through the appeals process; however, the administrative resources needed for appeals translated to an additional labor expense of $120 per claim.

Not all denial appeal efforts result in successful payment. Kovach and Borikar (2018) estimated annual net revenue lost from insurance denials between 3%–5% per health system. As such, physician offices have been faced with the decision to hire additional billing staff to follow up with insurance payers on outstanding payments or to invest in upgraded billing technology to help secure incoming cash flow (Gottlieb et al., 2018).

Revenue Cycle Process Improvement

The options to increase labor or purchase technology, as posed by Gottlieb et al. (2018), often require substantial investment of time, resources, and funding. A common alternative to hiring additional staff within a department is business process outsourcing (BPO). In a BPO relationship, a parent organization, such as a health system or hospital, will contract with an external vendor to hand off responsibility of specified functional activities, such as medical coding or billing (Sunder & Kunnath, 2019). BPO and consulting services are expected to continue to grow in popularity and at a rapid pace, in part due to the overall growth of healthcare services and emergence of novel technological developments (Reddy et al., 2018; Sunder & Kunnath, 2019). The United States healthcare industry is estimated to generate roughly $12.9 billion in annual revenue toward the global payer outsourcing market (Sunder & Kunnath, 2019).

Parent organizations maintain accountability for outcomes and results when the strategic decision is made to engage with a BPO, despite the transfer of operational ownership of defined functions (Sunder & Kunnath, 2019). When the quality of work outsourced is not sufficiently monitored, Sunder and Kunnath (2019) found a 20% increase in operational expense to resolve errors and to rework accounts appropriately. In their case study of an outsourced BPO in relation to claims management, the authors identified half a million dollars in lost revenue due to incorrect payments from BPO processes. Among the popular BPO activities, claims management should be highlighted as it represents 58% of the value chain in healthcare BPO (Sunder & Kunnath, 2019).

When financial resources are not immediately available to expend on additional labor or technology, revenue cycle leaders often turn to process improvement strategies that leverage existing resources to improve performance and reduce costs. Said strategies, such as lean and six sigma, follow process improvement frameworks that focus on increasing the efficiency and accuracy of work at the staff level (Kovach & Borikar, 2018). For example, six sigma methodology was used to improve revenue cycle processes at Texas Children's Hospital where a pilot test was conducted to reduce registration-related denials through enhanced collection of patient insurance information at the time of the encounter (Kovach & Borikar, 2018). Through investigation of current state processes and collaboration with frontline staff, the improvement team successfully identified root causes for registration denials and was subsequently able to create very specific mitigation strategies to minimize registration denials.

Identification of process gaps and improvement opportunities may not always be apparent. Effective leadership, management, and strategic planning may require simple skill development (Wyatt-Elkins, 2020). Employee training and development resources were recommended for healthcare managers to identify issues and better facilitate solutions, with the ultimate goal of reducing administrative costs (Wyatt-Elkins, 2020).

Revenue Cycle Technology

Within the healthcare administrative space, the shift toward increased use of technology came as a result of federal incentives and the availability of big data. In 2009, introduction of the HITECH Act reserved $29 billion over 10 years for healthcare organizations to implement electronic health record (EHR) systems in a meaningful way

(Lee & Choi, 2016). As clinical and administrative data began to grow through use of EHRs, Alsharief et al. (2018), Ratia et al. (2018), and Reddy et al. (2018) reported the challenge posed by data processing and analytics, which have required additional resources to use the data effectively, in a timely manner, and for process improvement.

Expenses related to healthcare services technology and automation has increased significantly over the past decade. Reddy et al. (2018) estimated that venture capitalists and private equity owners invested a whopping $60 billion in healthcare services between 2012–2017. Furthermore, interest in and demand for automated software, technology, and related platforms is expected to increase (Reddy et al., 2018).

Within the revenue cycle, opportunity exists to automate specified functions. Research conclusions from Muro et al. (2019) and Ratia et al. (2018) agreed that administrative functions may be greatly optimized by automation and support from technology when the process in question is routine, repetitive, and requires a high level of labor support to complete. Repetitive tasks should specifically be targeted as overly monotonous workflows often have high risk for errors as staff become fatigued or disengaged (Ratia et al., 2018). Through automation of specified functions, not only does output increase and frequency of errors decrease, but also staff can then be redeployed to other areas that need support and cannot be automated, thus increasing the value of work output produced (Muro et al., 2019).

Research conducted by Reddy et al. (2018) concluded that low productivity and waste cost the healthcare industry half a trillion dollars annually. Investment in automated technology has thus increased in appeal as organizations seek to cut costs while simultaneously increasing volume and quality of output (Muro et al., 2019). In contrast to human workers, machines can continue tasks throughout the night, do not need breaks or time off, and are less expensive on a per unit basis (Muro et al., 2019; Piercy & Gist-Mackey, 2021).

With ongoing pressure to reduce administrative costs in favor of more efficient and value-based processes, the CAQH has published an annual report which reviews the cost, labor hours, and level of automation associated with six distinct transactions processes which largely contribute to administrative burden: eligibility and benefit verification, prior authorization, claim submission, coordination of benefits/crossover claim, claim status inquiry, claim payment, and remittance advice (CAQH, 2020). Potential industry savings opportunity increased from $12.4 billion to $13.3 billion as total industry transaction volume rose by 15% (CAQH, 2020). The variables most relevant to the current study are those within the back end of the revenue cycle: claim status inquiry, claim payment, and remittance advice.

The CAQH noted that all functional areas in review had moved toward greater automation – and thus greater cost and time savings – from 2017 to 2018, with the exception of remittance advice. The remittance advice process reconciles and confirms reimbursement between the provider and the insurance company (CAQH, 2019). Significant opportunity exists within the back-end administrative arena to shift from paper-based correspondence and payment toward an electronic and automated workflow. If healthcare organizations were to eliminate the paper-based payment process, the CAQH estimates an annual savings of $2.4 billion, with the additional benefit of the payment process time cut in half (CAQH, 2019). However, use of manual methods for the remittance advice process increased by 9% from 2017 to 2018, which highlights the need for further investigation and a potential area of opportunity for savings and optimization.

The results from the CAQH annual report support the need for greater automation within the healthcare revenue cycle and provide a standardized methodology to calculate transactional costs, potential savings, and identifies specific functional areas to target for automation – all of which have been proven feasible with effective results. However, one limitation to the report was the nature of data collection. Participation in the study and the provision of data was purely voluntary among healthcare providers and insurance companies. As a result, the data may show more or less actual automation and transactional costs, dependent on participants motivation to participate or not.

Research on the relationship between health IT expenses and hospital revenue had been conducted by Lee and Choi (2016) across a large sample of hospitals in Texas. Results found that hospitals with higher health IT expenses also had higher total revenue. Specifically, when health IT expenses increased by 100%, hospitals saw an 8% increase in total revenue (Lee & Choi, 2016). Additionally, through the study’s longitudinal research design, the authors found that investment in automated technology for financial, administrative, and clinical areas resulted in lower hospital costs roughly 3-5 years after the technology’s implementation (Lee & Choi, 2016). Overall, the presence of and investment in health IT improved revenue by eliminating inefficiency, increasing the processing speed of claims and reimbursement, and by allowing the capture of previously lost revenue through data analysis and coordination (Lee & Choi, 2016).

In response to payer variation, Kim et al. (2020) proposed a deep claim learning framework to predict claim response by third-party payer. Raw claims data was analyzed to predict a given claim's probability for denial, probabilities for specific denial reasons, payer response timeframe, and to flag items within the claim that may be questioned for payment (Kim et al., 2020). Pilot results from two large health systems found that the deep claim learning framework predicted 22.1% more denials compared to baseline. Implications for practice of this deep claim learning system will support resource allocation to other critical areas if follow-up on claims denial outweighs the expected returns (Kim et al., 2020).

Issues With Technology

The risks and challenges associated with the implementation of new technology must not be overlooked. The quantifiable benefits of IT investment have long been in debate, as not all organizations experience the same level of success. The concept – described as the IT paradox by Khallaf et al. (2017) – highlights the disparate results between investment in technology and organizational performance among research studies. Notably, the authors discuss four main reasons why results and IT payoff differ throughout the literature: the mismanagement of IT assets, variations in measurements of success between studies, time lags between IT investments and subsequent impact on performance measurements, and the redistribution of assets within an industry (Khallaf et al., 2017). Likewise, research by Muro et al. (2019) identified similar reasons why IT success may fall short, including: technological feasibility, challenges with implementation and deployment, and institutional or external regulatory factors.

Conclusions made by Mugdh and Padilla (2012), Kovach and Borikar (2018), and the CAQH (2019) agreed that the implementation of automated technology to replace specified manual processes may lead to both cost reductions and performance benefits if approached in collaboration with stakeholders and in a clear, defined manner. Despite the general consensus, Khallaf et al. (2017) made a claim that empirical evidence around the improvement in performance due to technological investment has not been conclusive. Variance in reported returns on investment had largely been the result of differences in approach and calculations method used by each research team. However, variation in success had also been from challenges in the initial decision-making process. For example, Mindel and Mathiassen (2015) identified a level of difficulty faced by many hospital leaders to identify and select technology that could best support their unique circumstance. Challenges among leaders to obtain sophisticated data, metrics, and analytics related to their organization's performance, coupled with and a lack of comprehensive understanding of theory and evidence to support technological decision making had subsequently contributed to variation in IT performance (Mindel & Matthiassen, 2015; Morse, 2019).

Multiple studies highlight the issue of human error within technology – most notably at the point of implementation. Technologies such as EHRs and robotic process automation (RPA) are built and designed based on an organization's workflow to ensure the technology is customized to meet the consumer's need. However, it is not uncommon for improper practices to be built into the technology's workflow as described by Ayabakan et al. (2021) and Ratia et al. (2018). Specific to implementation of EHRs, erroneous rules and workflows that are inconsistent with best practice may be built into the enterprise EHR and cause issues and business disruption down the road (Ayabakan et al., 2021). Likewise, errors in process will not be fixed with RPA unless resolved prior to implementation. Absent any needed corrections to workflow, RPA and process errors will both continue to scale if not fixed appropriately (Ratia et al., 2018).

Implementation of technology was not meant to overcome challenges with reimbursement in the healthcare industry (Singh et al.,2021). Third-party payer requirements for billing may still require specialized coding and billing staff (Tseng et al., 2018). In some cases, EHRs have been found to increase claims rejections and denials as the system becomes more sensitive to billing rules and exceptions (Ayabakan et al., 2021).

Additionally, once billing workflows have been optimized and streamlines, the presence of an EHR alone may not be sufficient to show positive financial gains or cost savings. When examining billing costs at a large academic system with a certified EHR system, Tseng et al. (2018) found that high administrative costs remained, even in the absence of performance issues or inefficient billing processes. High administrative costs persisted because physicians were still required to manually document patient encounter details and conduct administrative tasks for appropriate coding, which ultimately took time away from actual patient care and clinical services. The authors subsequently concluded that despite significant investment in health information technology, the

United States healthcare industry has not seen a correlated decline in overall billing costs (Tseng et al., 2018).

Future State of Technology

The shift toward greater use of automated technology is expected to continue. However, integration of these systems is needed as the healthcare industry currently lacks integrated platforms that allow systems to interact at a wide scale. A holistic view of industry and system processes is needed to allow greater interaction between stakeholders and may solicit input from other industries (Reddy et al., 2018). For administrative technology to reach its full potential in terms of workflow optimization and cost savings, system flexibility is needed to adapt to ever-changing payer requirements and must ensure that patient information remains private and protected (Ayabakan et al., 2021; Reddy et al., 2018).

The potential for technology and automation to improve financial performance and lead to industry-wide cost savings has been well documented in literature. Findings by Ayabakan et al. (2021) suggested that EHRs may reduce uncompensated care through enhanced accuracy in the collection and processing of patient billing information. Likewise, when examining the billing and reimbursement process, Carrus et al. (2020) estimated that 43% of workflows related to claims administration, data collection, and member enrollment have potential for technical automation and thus necessitate greater investigation and focus.

Automated technology does not serve as a full substitution for human labor. In fact, Muro et al. (2019) argued that not only does automation complement labor, but in some instances may lead to job creation and increase demand for labor. The authors suggest that machines were meant to substitute specific tasks, rather than entire jobs. With workers focused on high value work – rather than repetitive activities – innovation may ensue and allow workers to upgrade their skills or shift into new roles (Muro et al., 2019).

Alignment between technology and labor is critical for success. Furthermore, alignment is needed beyond solely administrative staff and must extend across all stakeholders. Carrus et al. (2020) noted that successful automation in healthcare depends on an organization's ability to coordinate technology and automated activities across the enterprise, achieve buy-in from various stakeholder groups, and to orchestrate a scalable deployment model that includes innovative ways to reskill and deploy employees to other critical areas. In line with these findings, Singh et al. (2021) identified four competing logistics that decision makers must balance in order to ensure financial stability without sacrificing patient care:

1. Logic of Care: Focused on the delivery of patient care and treatment
2. Logic of Business: Focused on receipt of payment for patient care services rendered
3. Logic of Management: Focused on day-to-day operations within the organization
4. Logic of Technology: Focused on allocating appropriate technological and IT support to clinical and nonclinical areas

The exact interplay between all four competing logics is not always clear to leadership and will require a customized approach to ensure all four areas have appropriate attention and resources.

The optimization and automation of revenue cycle processes require the consistent alignment of goals, priorities, and communication between an organization's revenue cycle operations and IT department. Administrative inefficiency has often originated from disconnect between the two aforementioned teams (Alsharief et al., 2018). Thus, when a hospital looked to implement new technology at the front-end, both Alsharief et al. (2018) and Kokina and Blanchette (2019) cited the need for a collaborative governance structure which represented both departments and whose purpose was to make decisions and set strategic priorities. The manner and extent of IT involvement in all stages of technology was found to hold a strong influence on related KPIs and the subsequent capability of revenue cycle staff to achieve improvements (Alsharif et al., 2018). Additionally, Alsharief et al. (2018) offered four recommendations to ensure strategic alignment between operational and IT teams: consistent organizational communication, enhanced governance, specified scope and technology architecture, and development of organizational and human skills (Alsharief et al., 2018). In the absence of such partnership and without alignment of interests, any potential or expected improvements or efficiencies had not materialized (Mindel & Matthiassen, 2015).

Consistent engagement between departments was necessary to ensure all stakeholders and interests were aligned and represented. While the needs, capacity, and selection process had differed for each health system, Mugdh and Pilla (2012) and

Kokina and Blanchette (2019) offered two frameworks to guide the decision-making process. Mugdh and Pilla (2012) examined concurrent efforts to optimize the revenue cycle and to improve financial performance through the people, process, technology framework. Through a literature review of numerous hospital performance improvement initiatives, the authors concluded that organizations should select and implement technology through a "clean sheet approach" which focused on organizational-based criteria of need, supported streamlined processes, reduced potential for human error, and avoided delays in processes (Mugdh & Padilla, 2012). Though the authors provided a comprehensive literature review with various case studies aimed at change management and performance improvement, no metric-based data or KPIs were provided; it may thus be difficult to determine the actual extent of change or improvement discussed within the studies.

In comparison to the people, process, technology framework, Kokina and Blanchette (2019) examined the implementation of new technology from a more targeted lens and utilized the task-technology-fit (TTF) model to study themes of robotic process implementation within the accounting and finance industry. Successful results and performance outcomes were found in the automation of repetitive, rules-based, and structured tasks with digital input. Identified benefits of RPA included cost savings, improved reporting, lower error rates, and greater measurement of process improvement (Kokina & Blanchette, 2019). Though Kokina and Blanchette's (2019) research had focused solely on the Accounting and Finance industry, it may be argued that the revenue cycle – as the main focus in the current research study – represents a branch of finance.

With the mutual goal to ensure the stability and improvement of an organization's financial health, all three areas must also practice accurate documentation and closely monitor and improve revenue and costs within the enterprise.

The research and conclusions made by Alsharief et al. (2018), Mindel and Matthiassen (2015), and Mugdh and Padilla (2012) agreed that the fluidity of external factors – such as federal regulations and third-party payor guidelines – ultimately drove change within a hospital's internal operations. The relationship between external and internal factors has created a complex network in which a hospital's revenue cycle must constantly adapt to in order to ensure the financial health and viability of the organization. Though only one study specifically examined the healthcare revenue cycle, all authors had relevant components or applications to revenue cycle automation. The limitation of generalizability was expected, as all health systems experience a unique mix of internal and external factors – such as need, resources, and environment, among others – which subsequently necessitate a customized solution.

Definitions

Administrative labor: Person(s) directly involved in the provider billing process and includes supervisory and support staff (Tseng et al., 2018).

Automated technology: Software created to replace the manual work activities conducted by human labor, with the aim of reducing unit cost and errors, while increasing output productivity (Muro et al. 2019).

Appeals: The process to dispute denials for payment sent by insurance companies. If an organization received a denial on a claim determined to be properly coded and submitted, the healthcare organization will begin a process of appeal with the insurance company by providing additional documentation related to the patient service that defends the bill submit (Kovach & Borikar, 2018).

BIR activities: Requirements for payment imposed by third-party insurance companies prior to payment of claims. BIR activities include, but are not limited to: preauthorization of services, verification of patient insurance eligibility, documentation of services provided, procedure coding, and follow-up on previously submitted bills (Cutler, 2018 & Tseng et al., 2018).

External labor: Human labor provided by a third-party company that is contracted with a parent organization to support a specified part of the internal business workflow (Sunder & Kunnath, 2019).

RCM: The effective management of all activities related to the delivery of healthcare services and obtaining appropriate reimbursement for services rendered (Singh et al. 2021). Revenue cycle activities include appointment scheduling, registration, charge entry, coding, billing, claims processing, insurance follow-up, and payment processing (Tseng et al., 2018).

Assumptions

In the study, I assumed that financial and labor-related data reported from the healthcare organization accurately reflects the metrics reported each month. At the end of each month, preliminary financial reports were distributed from managers and directors for further review. In the second week of the new month, senior and executive leadership within the Finance, Accounting, Operations, and revenue cycle departments met to review the preliminary reports, approved adjustments as needed, and obtained final approval on all financial reports and the general ledger. As such, the current assumption was that that the reports received reflect finalized and approved financials, with no additional adjustments made after distribution.

Scope and Delimitations

Numerous research studies highlight the administrative burden within the healthcare industry and the financial consequences associated with admirative errors made within the billing and payment process (CAQH, 2020; Gottlieb et al., 2018; Kim et al., 2020; Tseng et al., 2018; & Wyatt-Elkins, 2020; &). Additionally, previous research has indicated that the automation of administrative functions may reduce operational costs and that the healthcare industry has not adopted the same levels of automation as other industries (Ayabakan et al., 2021; Carrus et al., 2020; Chiu et al., 2017; Ratia et al., 2018; & Singh et al. 2021). As such, the current study assessed the relationship between automated technology expenditure and revenue cycle performance.

The population derived from a multi entity healthcare system in California. Technology expenses and labor-related data were only examined from revenue cycle departments that had purchased automated technology within the 4-year timeframe defined. Due to the nature of secondary data collection and the defined population above from only one health system in California, the study was be limited in generalizability to the broader healthcare industry.

Limitations

The current study only examined automated technology expense and revenue cycle performance data produced between FY 2018-FY 2021. If the benefits of automated technology were not realized until after the 4-year timeframe and span 5-10 years to fully realize, then the timeframe proposed may serve as a limitation to the overall study results.

A second limitation was the presence of externalities – such as contract negotiations – which may affect financial performance toward favorable outcomes that were not influenced by the independent variable. For example, a health system may have seen higher revenue after favorable contract negotiations with third party insurance providers and the subsequent reimbursement increase should not subsequently be associated with higher revenue cycle performance. To account for this cofounding variable, third party insurance contract reimbursement increases were examined over the FY 2018 – FY 2021 timeframe and were adjusted appropriately to remove any misleading improvements to revenue indicators. Third party reimbursement rates from FY 2018 were be used as a baseline. If a contract reimbursement increase occurred between FY 2019- FY 2021, the payer reimbursement amount was adjusted to reflect FY 2018 contract rates.

Significance, Summary, and Conclusions

Revenue cycle automation has not been widely studied from an empirical research perspective (Mindel & Matthiassen, 2015). Though the topic has become more common among periodicals – such as the Healthcare Financial Management Association – peer-reviewed studies and quantified performance metrics and impact have seldom been identified.

However, a variety of research studies exist related to automation in non-healthcare industries. In the literature review presented above, automation and technology in numerous industries were examined and multiple commonalities were identified (Mindel & Matthiassen, 2015). The idea of new technology and automation, in general, has often been followed by fear among employees related to job security (Ordonez de Pablos et al., 2018; Ramaswamy, 2017 et al). However, theories such as those posed by Acemoglu and Restrepo (2018), argued the opposite: automation was not a precursor to job loss; rather, certain counterbalances may have increased demand for labor after automation. The benefits to automated technology had been widely discussed and included: a reduction in errors, an improvement in productivity, and an increase in quality of work (Bughin et al, 2017; Kokina & Blanchette, 2019). Furthermore, staff development had often been cited as a critical factor in the successful transition to new technology. Alsharief et al. (2018), Mugdh and Padilla (2012), and Mindel and Matthiassen (2015) all highlighted the importance of investment in training and skill development for staff, especially during times of change and strategic transformation.

Research on revenue cycle optimization through automation and the true impact of said relationship – in terms of dollars expensed on automated technology and returns on performance and net revenue – has been limited (Mindel & Matthiassen, 2015). Anecdotal support for automation has been published across professional organizations within the niche financial subset of the healthcare industry, such as the HFMA. However, these case studies seldom disclosed any actual data to justify statements and the methodology to support datapoints or improvement realized from automation are rarely discussed, if at all. As such, the current study utilized a single case study and leveraged a longitudinal, bivariate correlational research design to examine and quantify the impact of technology on revenue cycle labor and financial performance.

Section 2: Research Design and Data Collection

The purpose of this quantitative study was to explore the relationship between automated technology expenditure and revenue cycle performance. Specifically, I examined the expenses related to the purchase of automated technology within the revenue cycle's Patient Access, Coding, and HIM departments regarding the effect on labor hours, denials, and revenue. In this section, I detail the research design, methodology, and sampling procedures used in the study. Additionally, the instrumentation and operationalization of constructs are identified alongside an in-depth review of the data analysis plan.

Research Design and Rationale

Variables of Interest

The independent and dependent variable of interest focused on financial and operational metrics within the revenue cycle. I collected the data for all variables for each month between FY 2018–FY 2021.

Independent Variables

The independent variable of interest was the financial expense related to automated technology. Specifically, I examined the purchase of automated technology within the three designated revenue cycle departments: Patient Access, Coding, and HIM. Within the Patient Access department, expenses were made toward automated technology that identified additional insurance coverage information on patients that were otherwise uninsured. The intent of the technology was to lower self-pay liability for patients, especially those with low-income who are often unaware that they have insurance and claim to be uninsured. Within the Coding department, expenses were made in automated technology that automatically coded a defined set of procedure codes and removed manual coder intervention and review. Lastly, within the HIM department, expenses were made toward automated technology that scanned patient documentation, handwritten exam notes, and other health-related papers then subsequently indexed each piece of documentation into the appropriate section of a patient's medical record.

Dependent Variables

The dependent variables of interest were labor hours, revenue, and denials. Internal labor hours were recorded through revenue cycle financial statements and produced on a monthly basis. External labor hours were recorded through vendor service invoices and subsequently uploaded into the organization's cost reporting system. Monthly reports were produced, by department, which allowed for the capture of productive hours, overtime, expense, and other labor metrics for both internal staff and external vendor support staff.

Lastly, revenue data was collected for FY 2018-FY 2021. Only revenue related to patient services was examined, while non-patient revenue, such as revenue from the cafeteria, parking, and gift shops, for example, was excluded from the current study.

Mediating Variables

Potential mediating variables included contracted rate increases from third party insurance payers as a result of renewed contract negotiations. Contract rate increases would have reflected an increase in revenue and should not have influenced the relationship between automated technology and revenue. To remove any revenue improvement that directly resulted from contract rate increases, I examined third party insurance rates between FY 2018–FY 2021 to determine if any changes to payor pricing models occurred. If a contract rate increase was identified, a revenue baseline would be determined in terms of FY 2018 contract rates and revenue reflected in FY 2019–FY 2021 would be adjusted accordingly.

Research Design

I used a longitudinal, bivariate, correlational research design to examine the relationship between the independent and dependent variables. Pearson's correlation was calculated to identify the direction of the correlation between the independent and dependent variables. Pearson's correlation was determined to be the most appropriate calculation for the current study because it measures the strength of association between interval and ratio variables with a normal distribution (see Lewis-Beck et al., 2011). Previous research studies that explored the effect of automated technology within the healthcare industry used similar longitudinal and correlational research designs (Lee & Choi, 2019; Thouin et al., 2008). Additionally, the relationships between the independent variable and dependent variables were examined over the 4-year timeframe through a multi regression trend analysis to investigate these relationships over time. identified in the current study.

Time and Resource Constraints

Because the study utilized secondary data collected from initiatives that were since completed, I assumed the time or resource constraints that affected the retrospective review and analysis to be minimal.

Design Choice

Use of a correlational research design was determined to be the most appropriate choice because the aim of this study was to examine the relationship between an organization’s expenditure on automated technology and revenue cycle performance utilizing secondary data. Other research designs, such as experimental research, were not appropriate for the current study because the data cannot be manipulated and the impact from the independent variable on the dependent variables was sought.

Methodology

Population

In the current study, the population of interest was revenue cycle departments within a healthcare organization that had purchased automated technology. The full population size was not currently known because healthcare organizations do not publicly report automated technology-related expenses and not all healthcare organizations have a defined revenue cycle department.

Sampling and Sampling Procedures

Healthcare organizations are not mandated to publish data on automated technology expenditure. In general, public visibility into an organization’s automated technology measures is rare and difficult to obtain. As such, I selected a single healthcare system in California as the sample frame due to the approved access and subsequent availability to the organization’s automated technology data. Furthermore, within the healthcare system study site, the revenue cycle is broken down into multiple departments, including Coding, HIM, Customer Service, and Accounts Receivables Management.

Because I was interested in how automated technology expenditure relates to performance measurements, any revenue cycle department that did not purchase automated technology was excluded from the sample. Thus, nonprobability convenience sampling was used as the primary sampling technique to isolate only revenue cycle departments that purchased automated technology between FY 2018–FY 2021. The selected method of sampling had been used in previous research studies when participant selection was based on availability of either participants or data (Frey, 2018).

I selected three departments within the health system's revenue cycle for participation in the study: Patient Access, Coding, and HIM. The departments selected represented functional areas with the highest labor footprints and the lowest amount of automation intertwined within workflows, relative to all other revenue cycle departments, at the start of the study timeframe in FY 2018. In an effort to reduce costs and improve performance, all three departments received capital funding to purchase and implement automated technology in 2019; all of which had been designed to improve revenue collections. As a result, the Patient Access, Coding, and HIM departments showed the largest areas of opportunity in relation to the current study and were thus selected for further examination in this study.

The Patient Access department was considered the "front-end" of the revenue cycle and was responsible for preregistration, registration, insurance verification, and financial counseling. The Coding department represented a large portion of the "middle" revenue cycle and translated patient information and documentation from a single encounter into procedural and diagnostic codes for billing and reimbursement (LaPointe, 2018). Lastly, the HIM branch of the revenue cycle was responsible for the scanning and indexing of medical records and supporting medical record chart completion.

Participants in the study were revenue cycle staff within the Patient Access, Coding, and HIM departments at the study site healthcare system. I gained access to financial and revenue cycle performance data through approval from the health system's corporate vice president of revenue cycle. Additionally, access to the department-specific labor and expense data was gained through approval of the department's senior directors. I presented the details of the study, including the problem statement, hypotheses, and methods, to each leader for approval.

I collected data for each independent and dependent variable on a monthly basis across 4 years: FY 2018, FY 2019, FY 2020, and FY 2021. The 4 years selected served as comparison time periods for each datapoint because different levels of automated technology use were present among all 4 years. For example, FY 2018 was the period prior to the implementation of automated technology and served as a baseline. On the other hand, in FY 2020, the automation of both technologies of interest had been fully implemented.

I used a correlation sample size calculator developed by the University of California, San Francisco Clinical & Translational Science Institute (n.d.) to identify the appropriate sample size. A significance level of 0.05 was selected, in accordance with the industry standard level of acceptability (see Frankfort-Nachmias & Leon-Guerrero, 2018). The power level was set at 80%, which is a common level selected when beginning research (see Brydges, 2019). Lastly, because I expected a strong, positive correlation between the variables, the expected correlation coefficient was estimated at *r* = 0.80. Using the sample size calculator, the following calculations were determined:

$\alpha = Z\alpha = 1.9600$

$\beta = Z\beta = 0.8416$

$C = 0.5 * \ln[(1+r)/(1-r)] = 1.0986$

Total sample size = $N = [(Z\alpha+Z\beta)/C]2 + 3 = 10$

From these calculations, I identified a correlation sample size of 10.

Data Collection

The variables selected for the study represented service and expenses associated with automated technology, labor hours, and associated revenue. Methods of data collection for each variable differed and will be discussed in the following section. I discussed all requests for reports and data points with the organization's revenue cycle corporate vice president as well as the specified department's senior director. Approval to use reports was received for each metric discussed below and was subsequently blinded for publishing.

Automated Technology Expense Data

I collected data on expenses toward automated technology through monthly invoices paid toward the external product's company. Historical data for each month-end financial expense report were collected between October 2017–September 2021 and represented the organization's FY periods of 2018, 2019, 2020, and 2021. The study site organization studied defined a FY as October – September of the following year. For example, FY 2018 was defined as October 2017–September 2018. I further isolated the financial data to assess only the Patient Access, Coding, and HIM departments within the revenue cycle branch of the organization. Expenses for automated technology across the three departments was subsequently consolidated into a single value.

Due to the resources required and potential return on investment, automated technology projects were subject to a “capital review” in which the proposal, budget, and all allocated resources were first approved by the hospital’s Board of Directors. Monthly updates for both projects were documented, reported, and maintained in a specified capital workbook archive from the implementation to stabilization phase. These data were used for analysis in the current study.

Labor Data

The staff population of interest included only those within the Patient Access, Coding, and HIM departments between FY 2018-FY 2021. Furthermore, I only collected labor hours for staff involved in processes related to the automated technology initiatives and departments selected. No demographic groups were excluded from the staff population studied.

I collected data on internal labor hours through year-end financial reports, which were created for each revenue cycle department. Labor hours were examined on a month-by-month basis to determine if department labor changed postimplementation of automated technology.

External labor hours were recorded through vendor service invoices and were uploaded into the organization’s cost reporting system. Monthly reports were produced, by department, that captured productive hours, overtime, expense, and other labor metrics for both internal staff and external vendor support staff.

Revenue Data

I collected data on revenue between FY 2018–FY 2021. Only revenue related to patient services was examined; non-patient revenue, such as revenue from the cafeteria, parking, and gift shops, for example, was excluded from the current study.

Instrumentation and Operationalization of Constructs

I collected all data from previously run reports that were generated by a revenue cycle analyst throughout the project's implementation and stabilization phases and have since been archived into the organization's online database.

I obtained financial data and capital workbooks through an "enterprise performance management tool" that archived all historical financial data, by department, at the end of every month. Data points extracted from the database included department labor and full-time equivalents, labor hours by month, labor cost by month, and expense reporting by month.

I obtained operational and performance metrics, including automated technology implementation timelines and automation reports associated with both technologies, from senior leadership as archived in each respective department's shared folder on the organization's internal network database.

Table 1 displays the operationalization process for each variable.

Table 1

Operational Definitions of Variables

Variable	Definition	Measurement	Calculation	Variable Type
Automated technology expenditure	Dollars expensed on the specified automated technology of interest.	Dollars	Sum of expenses attributed to the specified automated technology per month.	Continuous
Internal labor hours	Number of labor hours accrued for staff employed by the health system at the end of each month, among the department of interest.	Hours	Sum of all internal labor hours accrued for the specified department at the end of each month expressed as full-time equivalents. One full-time equivalent is equal to 40 labor hours worked in a 5-day work week.	Continuous
External labor hours	Number of labor hours expensed to an external vendor company for support services related to the department of interest.	Hours	Sum of all external labor hours accrued for the specified department at the end of each month expressed as full-time equivalents. One full-time equivalent is equal to 40 labor hours worked in a 5-day work week.	Continuous
Denials	Denials for payment received from insurance companies related to patient service claims.	Percentage	Amount of denials received in month ($) divided by the amount of bills submit three months prior.	Ratio
Revenue	Patient service revenue collected for services rendered.	Dollars	Net patient service revenue collected at the end of each month.	Continuous

Data Analysis Plan

All data sets were reviewed in Excel and subsequently uploaded to Statistical Packaging for the Social Sciences (SPSS) software for data analysis. A bivariate correlational analysis was conducted with Pearson's correlation coefficient to determine if a relationship existed between the independent and dependent variables. A trend analysis with multiple regression was then conducted to examine the relationship between variables over a multiyear timeframe. Statistical significance was reported at the

0.05 level, in accordance with the industry standard level of acceptability (Frankfort-Nachmias & Leon-Guerrero, 2018).

Research Questions

As previously noted, the following research questions were examined:

RQ1: What is the relationship between organizational expenditures on automated technology and labor hours within the revenue cycle?

$H_0$1: There is no statistically significant association between automated technology expenditure and revenue cycle labor hours.

$H_1$1: There is a statistically significant relationship between automated technology expenditure and revenue cycle labor hours.

RQ2: What is the relationship between organizational expenditures on automated technology and revenue?

$H_0$2: There is no statistically significant relationship between automated technology expenditure and revenue.

$H_1$2: There is a statistically significant relationship between automated technology expenditure and revenue.

RQ3: What is the relationship between organizational expenditures on automated technology and denials?

$H_0$3: There is no statistically significant relationship between automated technology expenditure and denials.

$H_1$3: There is a statistically significant relationship between automated technology expenditure and denials.

RQ4: How does automated technology expenditure impact revenue cycle labor hours, revenue, and denials over time?

H_04_1: There is no significant trend in automated technology expenditure and revenue cycle labor hours over time.

H_14_1: There is a statistically significant trend in automated technology expenditure and revenue cycle labor hours over time.

H_04_2: There is no statistically significant trend in automated technology expenditure and revenue over time.

H_14_2: There is a statistically significant trend in automated technology expenditure and revenue over time.

H_04_3: There is no statistically significant trend in automated technology expenditure and denials over time.

H_14_3: There is a statistically significant trend in automated technology expenditure and denials over time.

Threats to Validity

The study design used non-probability sampling and examined staff, performance, automated technology expenditure, and outcomes from a healthcare system in California. Due to the singular source of data used for research, the threat to external validity must be noted; results from the study do not suggest that automated technology expenditure will always yield the same results across all healthcare systems. Rather, results from the study support the continued discussion and engagement around automated technology within the revenue cycle; data and findings may provide quantified benefits – if any – and examine the implementation of automated technology and subsequent benefits in an empirical manner.

A historical threat to internal validity may be present, specifically related to the automation within Patient Access and the identification of insurance to support payment of a patient's hospital visit. The Patient Access initiative was assessed across the FY of 2018, 2019, 2020, and 2021. As a note, the organization underwent a phased implementation of a new EHR system between FY 2016-FY 2018. The transition from the legacy system to the new EHR system occurred one hospital at a time. Due to the full migration of patient data to a new system, along with gap periods in which one hospital had already rolled out the new system while other locations had not, determination and quantification of lost patient data would pose a challenge. Thus, some insurance information recorded in the Legacy system may have been lost during the EHR conversion – which may increase patient financial liability and reduce collectible revenue from insurance companies – only to later be rediscovered by the automated technology and miscredited as an operational performance improvement.

Ethical Procedures

The current study examined employee-specific data within the revenue cycle of a single organization. To ensure the security and privacy of all related data, any employee identifiers – including the information of the organization's leadership – was blinded and remained confidential. In addition, approval was obtained by the organization's executive leadership and accountable department senior leaders to use archived data and historic financial reports. Prior to the receipt of any employee-specific data, the department's senior leadership removed all employee names from reports and replaced each with generic title patterns, such as “employee #1” and “employee #2.”.

Data was transmitted from the organization through a secure portal and was not publicized as a full data s et all reports used within the study were securely stored with password protections to open each file. The transmission of the data was also tracked by the organization, with safeguards installed to identify any user who attempted to use the secure portal, per the organization’s security and policy guidelines.

Due to the nature of the study and the use of secondary data, minimal risk was involved with respect to unethical research procedures (Walden University, 2021). Nonetheless, an ethics review was conducted by the university Institutional Review Board to ensure compliance with all ethical requirements as defined by Walden University (IRB approval number: 12-08-21-0994129).

Summary

Consistent with prior studies around automated technology in the healthcare industry, the current study utilized a bivariate correlational analysis to examine the relationship between automated technology expenditure and revenue cycle performance. Specifically, automated technology expenditure was examined with regard to its effect on labor hours, revenue, and denials, and revenue within Patient Access, Coding, and HIM. The independent and dependent variable of interest focused on financial and operational metrics within the revenue cycle, including labor expense, denials, and revenue data collected between FY 2018 – FY 2021. Lack of generalizability was noted as the most apparent threat to external validity because results from the current study may not apply to all organizations or all implementations of similar technology. However, the overarching intent of the current study was to provide an empirical review of automated technology within the revenue cycle, as such discussion has seldom been found in historic research. In the following section, results and findings will be discussed.

Section 3: Presentation of the Results and Findings

The purpose of this study was to examine the relationship between automated technology expenditure, labor hours, revenue, and denials within the revenue cycle. I developed four research questions to provide insights into automated technology expenditure relative to the financial and performance returns within the revenue cycle. The aim of the first three research questions was to determine if a relationship exists between organizational expenditures on automated technology and labor, revenue, and denials, respectively. In the null hypotheses, I posited that no statistically significant relationship exists between automated technology expenditure and the dependent variable of interest. Conversely, in the alternative hypotheses, I posited that a statistically significant relationship does exist between automated technology expenditure and the dependent variable of interest. The fourth research question addressed the relationship between the independent and dependent variables over time. I examined the dependent variables through separate sets of hypotheses, with the null hypotheses stating there is no significant trend in automated technology expenditure and the dependent variable over time and the alternative hypotheses stating that there is a statistically significant trend in automated technology expenditure and the dependent variable over time. The following section will discuss the data collection process and results of the study.

Data Collection of Secondary Data Set

I collected secondary data over the course of 1 month to ensure that the data retrieved were in line with the variable definitions defined in Section 2. The recruitment of individual participants was not applicable for the current study; instead, secondary data were collected through archived financial reports that were obtained in partnership with the revenue cycle and General Accounting departments at the partner organization. All requests for data points received responses from the appointed contacts and were reviewed and approved by the partner organization's Legal and Internal Audit and Compliance departments.

Discrepancies

The primary data discrepancy identified was in the delineation between internal and external labor hours. As described in Section 2, I expected collection of external labor hours through monthly vendor service invoices for additional labor supplied to a department. Upon closer examination of external labor within the Coding department, a variation among invoice methodology was identified wherein vendors were primarily paid on a per transaction basis rather than per additional employee supplied.

As a result of the vendor contracts variance, I used a holistic metric of full-time equivalents based on monthly financial summary reports produced by the General Accounting department. Full-time equivalents combined payrolls for internal employees and external labor invoiced for the month. From an internal labor perspective, a full-time equivalent records 40 hours of work per week. Two part-time employees who record 20 hours of work per week would subsequently equate to one full-time equivalent employee. Additionally, I added monthly expenses toward external labor to each department's total monthly labor expense report. Thus, each department's monthly labor expense represents both internal and external labor for a given month. To determine the number of full-time equivalents for a department, the number of internal employees, additional labor equivalents accumulated from overtime hours, and external labor invoices expensed were translated into a single metric.

The second data discrepancy was found in the analysis of data by month. The original methodology I proposed was to compare variables month-by-month; however, once the data were reviewed, I identified fluctuations in monthly automated technology expenses. The lack of consistency reported was due to the timing of invoices paid by the organization. Though the organization received invoices from automated technology vendors on a monthly basis, actual payment was sometimes delayed, with multiple months' worth of invoices paid in a single month. As such, I used a quarterly snapshot of automated technology expense to provide a more accurate and normalized view of expenses.

Because automated technology expenditure was analyzed by quarter, all independent variables were subsequently reviewed by quarter as well, for consistency. Table 2 shows the quarterly grouping for each year.

Table 2

Overview of Quarterly Timeframe by Year

Fiscal Year (FY)	Quarter 1 (Q1)	Quarter 2 (Q2)	Quarter 3 (Q3)	Quarter 4 (Q4)
FY 2018	October – December 2017	January– March 2018	April– June 2018	July– September 2018
FY 2019	October – December 2018	January– March 2019	April– June 2019	July– September 2019
FY 2020	October – December 2019	January– March 2020	April– June 2020	July– September 2020
FY 2021	October – December 2020	January– March 2021	April– June 2021	July– September 2021

I calculated quarterly metrics for automated technology expense, revenue, and denials as the sum of three months' worth of data. For example, monthly revenue in January, February, and March of 2020 were added together to calculate the FY 2020 Q2 revenue metric. However, when analyzing labor by full-time equivalents (FTEs), a monthly sum would not be appropriate and would triplicate the actual number of FTEs for any given quarter; if the sum of FTEs each month were taken for a quarter, the labor metric would increase threefold and assume that each month of labor is a net new add of FTEs to total labor. Because the labor variable would be 3 times the actual amount, the relationship between labor and the independent variable would be skewed. Therefore, the quarterly metric for labor was calculated as the average of 3 months' worth of data. For example, the average number of FTEs in April, May, and June of 2021 was calculated to determine the FY 2021 Q3 labor metric.

Baseline Characteristics

The sample population within the study was derived from a single health system in California. Within the health system's revenue cycle, I isolated only the departments that purchased automated technology between FY 2018–FY 2021 for further examination. However, within the departments selected for the study, no demographics were excluded and demographic information in general was not collected.

The number of participants within each department was recorded as FTEs. One individual staff member may have accounted for more or less than one FTE, depending on the number of hours the individual recorded within a month. As such, descriptive characteristics of the sample was limited to the volume of FTEs in each department between FY 2018–FY 2021. The average number of FTEs for each department are provided in Table 3.

Table 3

Average Full-Time Equivalents per Fiscal Year (FY)

Department	FY 2018	FY 2019	FY 2020	FY 2021	FY 2018–FY 2021
Patient Access	53.1	53.2	51.7	55.5	53.4
Coding	47.2	91.1	62.1	46.9	61.8
HIM	50.5	51.3	46.7	24.7	43.1
Total	150.4	195.6	160.4	127.0	157.4

External Validity

Public data sets related to the automation, technological expenditure, and/or denials of a revenue cycle within the healthcare industry are rare. Healthcare organizations may choose to maintain proprietary information confidential to avoid competitive threats in the market. Additionally, many leaders lack of comprehensive understanding of theory and evidence to support technological decision making had subsequently contributed to variation in IT performance (Mindel & Matthiassen, 2015; Morse, 2019). Regional, demographic, or other categorical comparisons would not have been feasible given the study variables identified and the limited availability of related data; therefore, I used nonprobability sampling within a single healthcare system in this study. With these factors in mind, the total population for the study remained difficult to determine; for context, as of May 2021, the California Health and Human Services Agency (2021) has recorded financial data on 439 hospitals within the state of California alone. As such, the results and related findings from this singular case study are limited in generalizability; this was a known and expected limitation of the study.

Results

Figure 1 summarizes the overall automated technology expenditure for the three departments between FY 2018–FY 2021. Automated technology expenditure increased year-over-year and showed the most presence in the Patient Access department. Automated technology expenditure increased by 74% from 2019 to 2020 and increased further by 59% from 2020 to 2021. The total sample size for each variable collected was 16.

Figure 1

Automated Technology Expenditure per Fiscal Year – 2018-2021

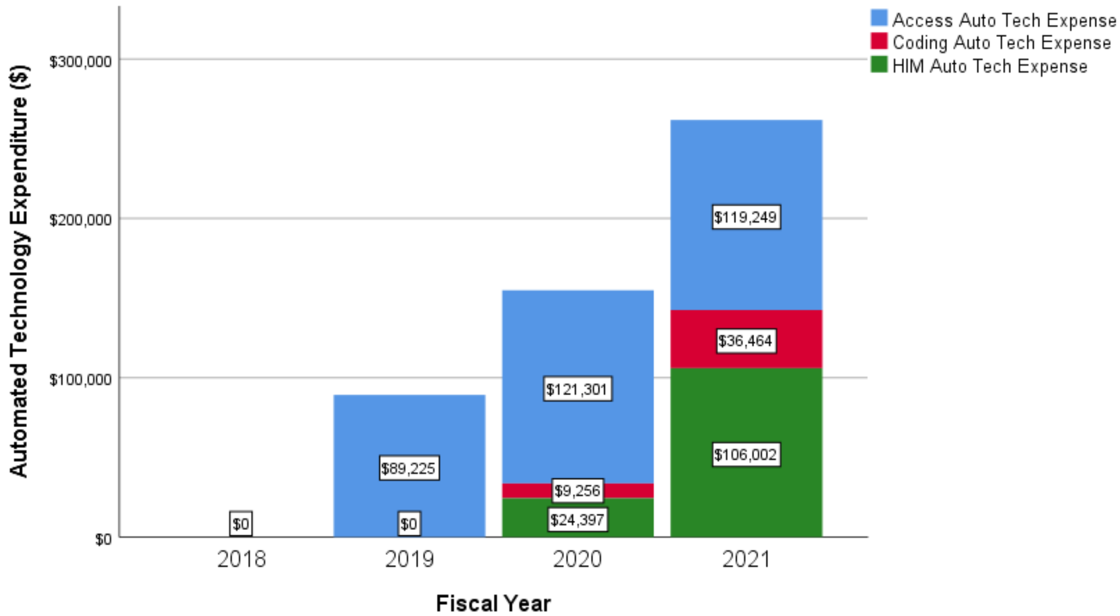


Figure 2 represents the patient revenue recognized by the hospital between FY 2018-FY 2021, shown in millions. Revenue increased year-over-year, with the largest increase seen between FY 2020 and FY 2021.

Figure 2

Revenue per Year – FY 2018-FY 2021

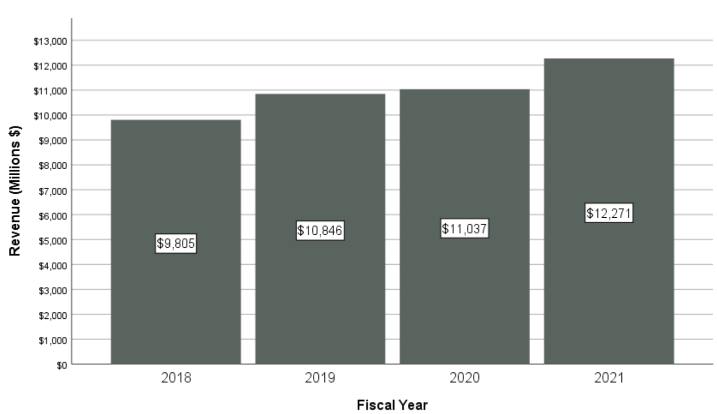


Table 4 displays descriptive statistics calculated for each variable.

Table 4

Descriptive Statistics

Variable	Minimum	Maximum	*M*	*SD*
Automated technology expense	$0	$1.2 M	$367.4 K	$350.5 K
Labor*	120.1 FTEs	197.1 FTEs	157.4 FTEs	31.0 FTEs
Denials	$17.0 M	$489.6 M	$296.0 M	$175.3 M
Revenue	$2.3 B	$2.7 B	$915.8 M	$2.7 B

Note. Labor is expressed in terms of full-time equivalents (FTEs).

Statistical Assumptions

To examine the relationship between variables, I calculated the correlation between variables, specifically with Pearson's coefficient. In the Pearson correlation, two statistical assumptions exist: data normality and linearity (Boston University School of Public Health, 2016). Data normality was examined by calculating the skew of each variable in SPSS. Guidelines for normal distribution of data target a skew result between +2 and -2 (Garson, 2012). I calculated skew for each dependent variable: labor = 0.146, denials = -0.515, and revenue = 0.639. Based on the guidelines noted above, all variables were normally distributed based on skew.

I assessed linearity through scatterplot graphs for each dependent variable in relation to the independent variable. Scatterplots are commonly used graphs to assess data linearity due its ability to provide visual context to the relationship between variables (Halford, 2020). Best fit lines were created for each graph and showed linearity for all three dependent variables as displayed in Figures 3, 4, and 5.

Figure 3

Scatterplot: Automated Technology Expense and Labor

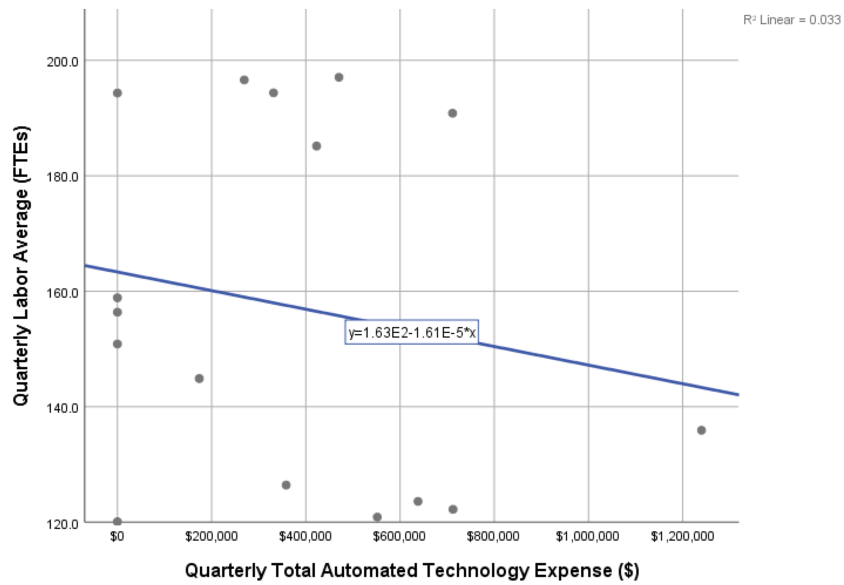


Figure 4

Scatterplot: Automated Technology Expense and Revenue

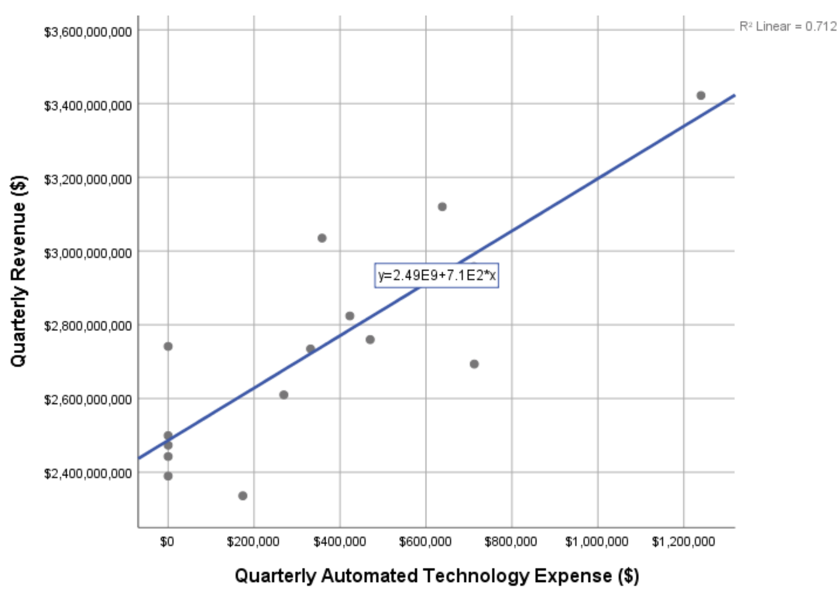
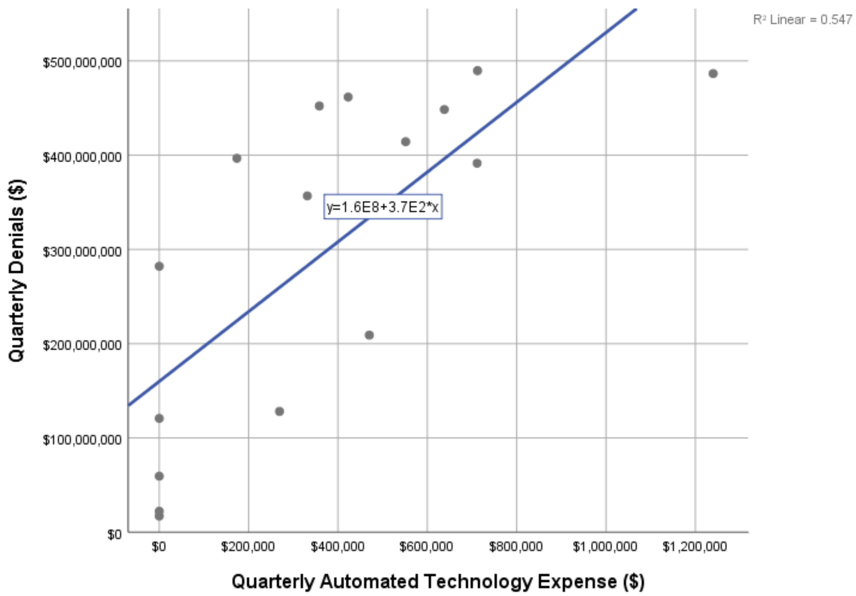


Figure 5

Scatterplot: Automated Technology Expense and Denials



Findings

I conducted bivariate correlational analyses for each dependent variable in relation to the independent variable to determine if a relationship exists. Pearson's correlation coefficient was then calculated for RQ1, RQ2, and RQ3. Because the alternative hypotheses suggested only that a relationship existed between the independent and dependent variable and did not specify the direction of the relationship, a 2-tailed test was used for each correlational analysis (see Teachout, 2018). To determine the strength of the relationship, I used the following ranges for *r*: strong (+0.7 to +0.9; -0.7 to -0.9), moderate (+0.4 to +0.6; -0.4 to -0.6), weak (+0.1 to +0.3; -0.1 to -0.3), and no relationship (0; see Akoglu, 2018).

Automated Technology Expenditure and Labor

In the first research question, the relationship between automated technology and labor was examined.

RQ1: What is the relationship between organizational expenditures on automated technology and labor hours within the revenue cycle?

$H_0 1$: There is no statistically significant association between automated technology expenditure and revenue cycle labor hours.

$H_1 1$: There is a statistically significant relationship between automated technology expenditure and revenue cycle labor hours.

Table 5 summarizes the correlational analysis output between automated technology expenditure and labor.

Table 5

Correlational Analysis: Automated Technology Expenditure and Labor

		Labor (FTEs) - Total	Automated Technology Expenditure - Total
Labor (FTEs) - Total	Pearson correlation	1	Labor (FTEs) - Total
	Sig. (2-tailed)		.500
	N	16	16
Automated technology expenditure - Total	Pearson correlation	-.182	Automated technology expenditure - Total
	Sig. (2-tailed)	.500	
	N	16	16

Note: Labor is expressed in terms of full-time equivalents (FTEs)

Automated technology expenditure and labor showed a correlation coefficient of $r = -.182$ and thus represented a weak, negative relationship. Significance was calculated at 0.500, which was well above the determined threshold of significance of $p < 0.05$. Thus, we fail to reject the null hypothesis that there is no statistically significant association between automated technology expenditure and revenue cycle labor hours.

Additionally, automated technology expenditure and labor for each department was analyzed to identify if a relationship existed between variables at the department level. The Patient Access department saw a weak, positive relationship with a correlation coefficient of $r = .338$, while the Coding department saw a weak, negative relationship with a correlation coefficient of $r = -.279$. However, within the HIM department, a correlation coefficient of -.639 was found alongside a test of significance at .008. Thus, automated technology expenditure and labor within the HIM department only showed a moderate, negative relationship and was statistically significant at the 0.01 level.

Table 6

Correlational Analysis: Automated Technology Expenditure and Labor – Patient Access

		Labor (FTEs) – Patient access	Automated technology expenditure – Patient access
Labor (FTEs) – Patient access	Pearson correlation	1	.338
	Sig. (2-tailed)		.200
	N	16	16
Automated technology expenditure – patient access	Pearson correlation	.338	1
	Sig. (2-tailed)	.200	
	N	16	16

Note: Labor is expressed in terms of full-time equivalents (FTEs)

Table 7

Correlational Analysis: Automated Technology Expenditure and Labor – Coding

		Labor (FTEs) – Coding	Automated technology expenditure – Coding
Labor (FTEs) – Coding	Pearson correlation	1	-.279
	Sig. (2-tailed)		.296
	N	16	16
Automated technology expenditure – Coding	Pearson correlation	-.279	1
	Sig. (2-tailed)	.296	
	N	16	16

Note: Labor is expressed in terms of full time equivalents (FTEs)

Table 8

Correlational Analysis: Automated Technology Expenditure and Labor – HIM

		Labor (FTEs) – HIM	Automated technology expenditure – HIM
Labor (FTEs) – HIM	Pearson correlation	1	-.639**
	Sig. (2-tailed)		.008
	N	16	16
Automated technology expenditure – HIM	Pearson correlation	-.639**	1
	Sig. (2-tailed)	.008	
	N	16	16

Note: Labor is expressed in terms of full-time equivalents (FTEs)
**. Correlation is significant at the 0.01 level (2-tailed).

Automated Technology Expenditure and Revenue

The second research question examined automated technology expenditure and revenue, as defined by the following research question and hypotheses:

RQ2: What is the relationship between organizational expenditures on automated technology and revenue?

*H*₀2: There is no statistically significant relationship between automated technology expenditure and revenue.

*H*₁2: There is a statistically significant relationship between automated technology expenditure and revenue.

Table 5 summarizes the correlational analysis output between automated technology expenditure and revenue.

Table 9

Correlational Analysis: Automated Technology Expenditure and Revenue

		Revenue – Total	Automated technology expenditure - Total
Revenue – Total	Pearson correlation	1	.844**
	Sig. (2-tailed)		.000
	N	16	16
Automated technology expenditure - Total	Pearson correlation	.844**	1
	Sig. (2-tailed)	.000	
	N	16	16

*. Correlation is significant at the 0.01 level (2-tailed).

Automated technology expenditure and revenue showed a correlation coefficient of r =.844 and thus represented a strong, positive relationship. The t test of significance was calculated at 0.000 and was determined to be significant at $p < 0.01$. Thus, we reject the null hypothesis that there is no statistically significant association between automated technology expenditure and revenue.

Automated Technology Expenditure and Denials

The third research question examined automated technology expenditure and denials, as defined by the following research question and hypotheses:

RQ3: What is the relationship between organizational expenditures on automated technology and denials?

$H_0$3: There is no statistically significant relationship between automated technology expenditure and denials.

$H_1$3: There is a statistically significant relationship between automated technology expenditure and denials.

Table 6 summarizes the correlational analysis output between automated technology expenditure and denials.

Table 10

Correlational Analysis: Automated Technology Expenditure and Denials

		Denials	Automated technology expenditure - Total
Denials	Pearson correlation	1	.740**
	Sig. (2-tailed)		.001
	N	16	16
Automated technology expenditure - Total	Pearson correlation	.740**	1
	Sig. (2-tailed)	.001	
	N	16	16

**. Correlation is significant at the 0.01 level (2-tailed).

Automated technology expenditure and denials showed a correlation coefficient of $r = .740$ and thus represented a strong, positive relationship. The test of significance was calculated at 0.001 and was determined to be significant at $p < 0.01$. Thus, we reject the null hypothesis that there is no statistically significant association between automated technology expenditure and denials.

Furthermore, the relationship between automated technology expenditure and denials was examined at the department level. There were no denial categories which fell under the HIM department's ownership; therefore, only Patient Access and Coding were analyzed.

Within the Patient Access department, automated technology expenditure and denials showed a correlation coefficient of $r = .639$ which was determined as a moderate, strong relationship. The test of significance was calculated at .008 and thus significant at $p < 0.01$.

Table 11

Correlational Analysis: Automated Technology Expenditure and Denials – Patient Access

		Denials – Patient access	Automated technology expenditure - Patient access
Denials – Patient access	Pearson correlation	1	.639**
	Sig. (2-tailed)		.008
	N	16	16
Automated technology expenditure – Patient access	Pearson correlation	.639**	1
	Sig. (2-tailed)	.008	
	N	16	16

**. Correlation is significant at the 0.01 level (2-tailed).

Within the Coding department, automated technology expenditure and denials showed a correlation coefficient of $r = .437$ and thus a moderate, positive relationship. The test of significance was calculated at 0.090, which was above the determined threshold of significance of $p < 0.05$. Thus, we fail to reject the null hypothesis that there is no statistically significant association between automated technology expenditure and coding-related denials.

Table 12

Correlational Analysis: Automated Technology Expenditure and Denials – Coding

		Denials – Coding	Automated technology expenditure - Coding
Denials – Coding	Pearson correlation	1	.437
	Sig. (2-tailed)		.090
	N	16	16
Automated technology expenditure – Coding	Pearson correlation	.437	1
	Sig. (2-tailed)	.090	
	N	16	16

Relationship of Variables Over Time

The fourth and final research question examined the impact of automated technology expenditure and labor, revenue, and denials over time, as defined by the following research question and hypotheses:

RQ4: How does automated technology expenditure impact revenue cycle labor hours, revenue, and denials over time?

$H_0 4_1$: There is no significant trend in automated technology expenditure and revenue cycle labor hours over time.

$H_1 4_1$: There is a statistically significant trend in automated technology expenditure and revenue cycle labor hours over time.

$H_0 4_2$: There is no statistically significant trend in automated technology expenditure and revenue over time.

$H_1 4_2$: There is a statistically significant trend in automated technology expenditure and revenue over time.

H_04_3: There is no statistically significant trend in automated technology expenditure and denials over time.

H_14_3: There is a statistically significant trend in automated technology expenditure and denials over time.

Tables 13-15 summarize the regression analysis output between automated technology expenditure, labor, revenue, and denials, respectively.

Table 13

Regression Analysis: Automated Technology Expenditure and Labor Over Time

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.182[a]	.033	-.036	31.6018

a. Predictors: (Constant), Automated Technology Expenditure

ANOVA[a]

Model		Sum of Squares	*df*	Mean Square	*F*	Sig.
1	Regression	479.519	1	479.519	.480	.500[b]
	Residual	13981.465	14	998.676		
	Total	14460.984	15			

a. Dependent Variable: Labor (FTEs)

b. Predictors: (Constant), Automated Technology Expenditure

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	*t*	Sig.
1	(Constant)	163.329	11.644		14.027	.000
	Automated Technology Expenditure	-1.613E-5	.000	-.182	-.693	.500

Coefficients[a]

Model		95.0% Confidence Interval for B Lower Bound	95.0% Confidence Interval for B Upper Bound
1	(Constant)	138.355	188.302
	Automated Technology Expenditure	.000	.000

a. Dependent Variable: Labor (FTEs)

The regression model above showed an R^2 result of .033 which suggests that automated technology expenditure does not explain the variation in labor over time. The ANOVA F ratio $F(46, 47) = .480$ and significance of 0.500 shows that automated technology expenditure did not add statistically significant to the prediction, with $p < 0.05$.

Table 14

Regression Analysis: Automated Technology Expenditure and Revenue Over Time

Model Summary

Model	*R*	*R* Square	Adjusted *R* Square	Std. Error of the Estimate
1	.844[a]	.712	.692	$163,821,408.342

a. Predictors: (Constant), Automated Technology Expenditure

ANOVA[a]

Model		Sum of Squares	*df*	Mean Square	*F*	Sig.
1	Regression	929367134092374780.000	1	929367134092374780.000	34.629	.000[b]
	Residual	375724353634654210.000	14	26837453831046728.000		
	Total	1305091487727028990.000	15			

a. Dependent Variable: Revenue

b. Predictors: (Constant), Automated Technology Expenditure

Coefficients[a]

Model		Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	*t*	Sig.
1	(Constant)	2486432825.879	60361118.191		41.193	.000
	Automated Technology Expenditure	710.193	120.685	.844	5.885	.000

Coefficients[a]

Model		95.0% Confidence Interval for B Lower Bound	Upper Bound
1	(Constant)	2356971103.116	2615894548.642
	Automated Technology Expenditure	451.350	969.037

a. Dependent Variable: Revenue

The regression model above showed an R^2 of .712, which suggests that automated technology expenditure explained 71.2% of the variation in revenue. The ANOVA F ratio $F(46, 47) = 34.629$ and significance of .000 indicates that automated technology expenditure added statistically significant to the prediction, with $p < 0.05$.

Table 15

Regression Analysis: Automated Technology Expenditure and Denials Over Time

Model Summary

Model	*R*	*R* Square	Adjusted *R* Square	Std. Error of the Estimate
1	.740[a]	.547	.515	$122,113,458.022

a. Predictors: (Constant), Automated Technology Expenditure

ANOVA[a]

Model		Sum of Squares	*df*	Mean Square	*F*	Sig.
1	Regression	252415806534726240.000	1	252415806534726240.000	16.927	.001[b]
	Residual	208763752822291936.000	14	14911696630163710.000		
	Total	461179559357018180.000	15			

a. Dependent Variable: Denials

b. Predictors: (Constant), Automated Technology Expenditure

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	*t*	Sig.
1	(Constant)	160041419.784	44993538.677		3.557	.003
	Automated Technology Expenditure	370.119	89.959	.740	4.114	.001

Coefficients[a]

Model		95.0% Confidence Interval for B Lower Bound	95.0% Confidence Interval for B Upper Bound
1	(Constant)	63539876.987	256542962.581
	Automated Technology Expenditure	177.175	563.063

a. Dependent Variable: Denials

The regression model above showed an R^2 result of .740 which suggests that automated technology expenditure explained 74.0% of the variation in denials. The ANOVA F ratio $F(46, 47) = 16.927$ and significance of .001 indicates that automated technology expenditure added statistically significant to the prediction, with $p < 0.05$.

Summary

Automated technology expenditure and labor revealed a weak, negative relationship that was not statistically significant. However, when analyzed at the department-level, automated technology expenditure and labor within the HIM department showed a moderate, negative relationship that was statistically significant. The relationship between automated technology expenditure and revenue was found to be moderate, positive, and statistically significant. Lastly, automated technology expenditure and denials showed a strong, positive relationship that was statistically significant. When analyzed at the department level, automated technology and denials within Patient Access showed a moderate, positive relationship that was statistically significant.

The results for each independent-dependent relationship remained consistent over time. Across the four-year time frame of the data, automated technology expenditure did not explain variations in labor. However, automated technology expenditure was found to have a statistically significant impact on revenue and denials, which subsequently explained 71.2% and 54.74% of the variation in each dependent variable, respectively.

Automated technology expenditure had a different relationship with each dependent variable. Though revenue and denials were both found to have a strong, positive, and statistically significant relationship with automated technology expenditure, the implication of these findings differ and will be detailed in the next section. Additionally, the correlations identified were not always consistent once examined at the department level. The varied impact of automated technology expenditure and implications for the revenue cycle will be discussed further in Section 4.

Section 4: Application to Professional Practice and Implications for Social Change

The purpose of this study was to examine the relationship between automated technology expenditure, labor, revenue, and denials within the healthcare revenue cycle. I accessed all variables from data collected on a quarterly basis between FY 2018–FY 2021. The data were analyzed through a bivariate correlational analysis to compare the relationships between variables at various stages related to automated technology expenditure. Conclusions from the current study will provide insight into the automated technology expenditure relative to financial and performance returns within the revenue cycle.

The results from correlational analyses revealed a weak, negative relationship between automated technology expenditure and labor that was not statistically significant; however, I found strong, positive, statistically significant relationships between automated technology expenditure and revenue as well as automated technology expenditure and denials. Comparable results were identified in regression analyses that examined the relationships between variables over time. Automated technology expenditure did not explain the variation in labor over time; however, automated technology expenditure did account for 71.2% and 54.7% of the variation in revenue and denials, respectively. Similar to the results identified in the correlational analyses, the relationships between automated technology expenditure and both revenue and denials showed statistical significance.

Interpretation of the Findings

Previous literature that examined the impact of automated technology within the healthcare revenue cycle had been limited and largely anecdotal. Therefore, the current study contributed quantified data and real results that may further the discussion on automated technology expenditure and revenue cycle performance among other organizations or empirical studies.

Automated Technology Expenditure

Reddy et al. (2018) indicated that expenses related to healthcare service technology would increase in the coming years. In line with this prediction, the results of the current study revealed an increase in year-over-year expenses related to automated technology. From FY 2019 to FY 2021, automated technology expenditure increased by 64%, supporting Reddy et al.'s prediction that technological expenses would increase over the years. From FY 2019 to FY 2021, automated technology expenditure increased 175% from $1.1 million to $2.9 million, respectively.

Automated Technology Expenditure and Labor

As automated technology replaces manual work conducted by humans, Acemoglu and Restrepo (2018) posited that a *displacement effect* will occur and the demand for labor will subsequently decline. However, Muro et al. (2019) argued the opposite and as automated technology increases, staff will have greater capacity to conduct other tasks and the demand for labor may increase as a result. In the current study, I conducted a correlational analysis and found that an increase in automated technology expenditure corresponded with a slight decrease in labor. However, the relationship was weak and, therefore, was not statistically significant.

Within the patient access department, labor increased as automated technology expenditure within the department decreased. Though the relationship was not found to be statistically significant, the positive relationship should be taken under advisement. If the demand for labor increased due to manual rework needed to fix mistakes made by the automated technology, then the expense toward automated technology would be an inhibitor to performance. However, if the demand for labor increased in areas unrelated to the work conducted by the automated technology, then the expense would be beneficial.

Automated Technology Expenditure and Revenue

Lee and Choi (2016) found that hospitals with higher IT expenses also achieved higher revenue. The current study had similar results, with automated technology expenditure and revenue being found to have a strong, positive relationship that was statistically significant. Additionally, in the regression analysis, 71.2% of the variation in revenue between FY 2019–FY 2021 was attributed to automated technology expenditure.

The positive relationship between automated technology expenditure and revenue is particularly relevant for revenue cycle leadership, especially those who are considering investing in automated technology. The positive relationship identified is favorable because it may indicate that the investment and expenditure on automated technology shows favorable results.

Automated Technology Expenditure and Denials

Payment denials on patient care services remain a challenge throughout the healthcare industry (Ayabakan et al., 2021; Kovach & Borikar, 2018). Kim et al. (2020), Kovach and Borikar (2018), Ayabakan et al. (2021), and Gottlieb et al. (2018) agreed that denials add substantial administrative burden, financial delays, and labor to the revenue cycle workflow. As such, many healthcare organizations monitor denials as a KPI and may decide to upgrade existing billing technology or hire additional billing staff to ensure financial health (Gottlieb et al., 2018).

Ayabakan et al. (2021) noted that a frequent root cause of denials is related to incorrect coding on payor-specific billing rules. Furthermore, denials may increase as electronic systems maintain sensitive billing rules that are not always flexible to payor-specific requirements (Ayabakan et al., 2021). Data from the current study confirm the issue of coding-related denials. In FY 2018, prior to automated technology expenditure, average coding denials were $20 million per quarter; however, in FY 2019, during initial implementation of coding-related automated technology and expenditure, coding denials increased to $108.1 million per quarter. After implementation and in the continued use and expense of automated coding technology, coding denials increased to $228.1 million per quarter in FY 2020 and to $292.4 million per quarter in FY 2021.

Real Option Valuation Framework

As discussed in Section 1, the real option valuation of technology has been utilized as a framework within the decision-making process where leaders examine the potential investment and perceived impacts of technological investment (see Kim &

Sanders, 2002). Moreover, the value of an IT investment is bifurcated into two categories: economic value and real option value.

Within the economic value of investment category, an organization should expect a reduction in costs as a result of an investment in technology (Carrus et al., 2020). Based on the findings related to automated technology expenditure and labor in the current study, an increase in automated technology expenditure actually increased cost due to the increase in labor hours. Though the relationship was not found to be statistically significant, it remains an important finding to understand the full impact of investment in automated technology.

Furthermore, in their annual report, the CAQH (2019) highlighted automated eligibility verification as a workflow that has increasingly moved to an electronic process. Transactional benefits of automated eligibility verification included lower processing time per transaction and additional monetary savings per transaction (CAQH, 2019). Despite the benefits reported by the CAQH, the current study showed unfavorable results related to automated technology that targeted insurance eligibility verification. Within this space, as expense toward automated technology increased, both the number of staff within the department and denials related to authorization and registration increased in a corresponding manner.

The long-term value of IT investment is examined in the real-option value of investment. In the current study, the relationship between automated technology and revenue showed a strong, positive correlation over time and, thus, supported the real-option value of investment. From FY 2018 to FY 2021, annual revenue increased by

25%, from $9.8 million in FY 2018 to $12.3 million in FY 2021. Despite this complementary evidence, the presence of the IT paradox must be addressed. Khallaf et al. (2017) viewed the IT paradox as the difference in performance results achieved by organizations that invested in similar technology.

Limitations of the Study

The first limitation of the study pertained to the limited external validity. Because I collected secondary data from a single hospital in California, the results may not be generalized to other hospitals in different regions.

Second, the timeframe of the data spanned between FY 2018–FY 2021. As such, the data were impacted by the COVID-19 pandemic, which had significant consequences to health systems around the world and drastically impacting the volume of patients seen in a hospital and restricting the types of services that could be performed in 2020 (Kaye et al. 2020). Additionally, government-sponsored programs, such as the Coronavirus Aid, Relief, and Economic Security Act, offered financial relief to qualifying hospitals and health systems, which subsequently impacted the revenue organizations realized in 2020 (Department of Health and Human Services, 2020). Furthermore, the COVID-19 pandemic specifically impacted the revenue cycle in terms of billing and coding rules, changes and exemptions related to patient financial responsibility, and the transition of staff to remote work and telecommuting in order to prevent the virus spread in the workplace (LaPointe, 2020). Thus, all variables examined in the current study may have presented different results if collected in a different timeframe.

Recommendations

The insights gained from the current study may offer opportunities for further research. First, as denoted in Section 1, empirical studies and public data around revenue cycle automation are sparse. While acknowledging the restrictions on available data, the need to conduct case studies (much like the current study) becomes apparent. Additional research is needed in different regional areas with health systems that are willing to participate and lend longitudinal data.

Second, the data examined in the present study ranged between FY 2018–FY 2021. The 4-year timeframe allowed for a baseline and multiyear insight into automated technology expenditure and revenue cycle metrics. Khallaf et al. (2017) identified an IT paradox wherein the lag time between initial technological investment and the impact on performance differed across the literature and led to mixed results. As such, additional observations and conclusions may be made with longitudinal data that spans over a wider time period. Furthermore, because the data within the present study were impacted by the COVID-19 pandemic, examining automated technology expenditure, utilization, and the revenue cycle in a post pandemic environment may be merited.

Lastly, I identified a strong, positive relationship between automated technology expenditure and denials in this study. The measurement of denials as a KPI is an important indicator of revenue cycle effectiveness (Kovach & Borikar, 2018). When an organization’s denial rate is high, it is important to identify the root cause of denials in order to address needed changes in workflow. In the current study, the positive relationship between automated technology expenditure and denials indicates that a change in workflow has led to an increase in denials. Therefore, additional research is needed to see if a similar trend is repeatedly observed. The translation of higher dollars expended on automated technology into greater revenue decrement should be addressed as it lends to an unfavorable return on investment.

Implications for Professional Practice and Social Change

Healthcare systems should consider the expansion of automated technology within the revenue cycle. The opportunity to increase administrative efficiency, reduce manual work, and improve net revenue were identified in the shift toward automated technology among a variety of previous research studies (Ayabakan et al., 2021; Carrus et al., 2020; Ratia et al., 2018; Singh et al., 2021). Once the decision to invest in automated technology is made, a methodical approach is needed to determine which specific functional areas and workflows within the revenue cycle should be automated (Muro et al., 2019). Possessing knowledge of the relationships identified in this study may support informed decision making in other organizations that look to invest in automated technology.

In the current study, I identified a strong, positive correlation between automated technology expenditure and revenue. Because both variables increased in a complementary manner, other organizations should consider the impact that automated technology may have on revenue. A price point should be determined in which an organization would expect defined financial returns. To do so, a comparison of vendor companies that offer comparable services is needed. Though the current study did not involve such an analysis, the opportunity may exist to purchase the same automated technology at a lower price point, without lowering expectations on the automated technology's financial return.

The positive relationship between automated technology expenditure and labor should also be taken under advisement. Based on research from Acemoglu and Restrepo (2018), the displacement effect in which labor declines after the integration of automated technology may be dismantled if the appropriate counterbalances are met. As such, if other organizations experience greater demand for labor after investment in automated technology (much like the results identified in the current study), then further examination may be required to understand the root cause of the additional labor demand. If the demand for labor increased due to the manual rework needed to fix mistakes made by technology, then the expense made toward automated technology would be an inhibitor to revenue cycle performance. On the other hand, if the demand for labor increased in areas unrelated to the work conducted by the automated technology, then the expense made on the automated technology would be beneficial. Furthermore, the increased demand for labor in other areas should target high-value work that cannot be automated. Examples include nonrepetitive work that would require decision making based on a user's historic experience or knowledge.

The current study offers the potential to impact positive social change, specifically at the organizational level. The introduction of automated technology has, historically, been met with skepticism and fear among employees regarding job security (Muro et al., 2019; Piercy & Gist-Mackey, 2021). Consistent communication is needed at all levels to ensure expenditure is made in the best interest of the organization's mission, toward the benefit of the patient population in which it serves, and to increase the value of the work conducted by employees. As a culture of change is promoted through leadership at all levels, employee engagement may increase with the confidence that front-line revenue cycle work impacts, not only the financial well-being of the organization, but also allows patient care resources to remain steady (Healthcare Financial Management Association, 2014).

Conclusion

The results of the current study highlight a well-known, yet understudied, area of optimization within the healthcare system. Despite the sizeable integration of automated technology in other industries, the healthcare sector has been relatively slow to adopt the same level of integration (Chui et al., 2017). The workflow within the revenue cycle has been placed at an optimal position to leverage automated technology within its administrative workflows, but to do so requires a significant level of coordination with other departments, deep understanding of the technology's impact to other revenue cycle departments, and a defined decision-making process to identify a sustainable and successful level of automation.

References

Acemoglu, D., & Restrepo, P. (2018). *Artifical intelligence, automation, and work* (Working Paper No. 24196). National Bureaus of Economic Research. https://www.nber.org/system/files/working_papers/w24196/w24196.pdf

Albright, S. C., & Winston, W. L. (2017). *Business analytics: Data analysis and decision making* (Vol. 6). Cengage Learning.

Alsharif, S., Benslimane, N., Khalifa, M., & Price, C. (2018). Healthcare IT strategic alignment: Challenges and recommendations. *Data Informatics and Technology: An Inspiration for Improved Healthcare*, 207-211. https://doi.org/10.3233/978-1-61499-880-8-207

Anderson, G. F., Reinhardt, U. E., Hussey, P. S., & Petrosyan, V. (2003). It's the prices, stupid: Why the United States is so different from other countries. *Health Affairs*, *22*(3), 89-103. https://doi.org/10.1377/hlthaff.22.3.89

Aral, S., & Weill, P. (2007). IT assets, organizational capabilities,and firm performance: How resource allocations and organizational differences explain performance variation. *Organization Science, 18*(5), 763-780. https://doi.org/10.1287/orsc.1070.0306

Ayabakan, S., Atasoy, H., & Pang, M. (2021). Where is my money? The interplay between healthcare information technologies and denied claims. *Information Systems & eBusiness Negative Results eJournal*. *https://doi.org/10.2139/ssrn.3810378*

Bayley, M., Calkins, S., Levine, E., & Machado-Pereira, M. (2013). *Hospital revenue cycle operations: Opportunities created by the ACA.* McKinsey & Company.

Boston University School of Public Health. (2016, January 6). *Correlation.* https://sphweb.bumc.bu.edu/otlt/MPH-Modules/BS/R/R5_Correlation-Regression/R5_Correlation-Regression3.html

Brydges, C. R. (2019). Effect size guidelines, sample size calculations, and statistical power in gerontology. *Innovating in Aging, 3*(4). https://doi.org/10.1093/geroni/igz036

Bughin, J., Manyika, J., Woetzel, J., Chui, M., Miremadi, M., George, K., Willmott, P., & Dewhurst, M. (2017). *A future that works: Automation, employment, and productivity.* McKinsey Global Instutite. https://www.mckinsey.com/~/media/mckinsey/featured%20insights/Digital%20Disruption/Harnessing%20automation%20for%20a%20future%20that%20works/MGI-A-future-that-works-Executive-summary.ashx

Burkholder, G. J., Cox, K. A., & Crawford, L. M. (2016). *The scholar-practitioner's guide to research design.* Laureate Publishing.

California Health & Human Services. (2021). *2019-2020 FY hospital annual selected file (May 2021 extract).* California Health & Human Services Agency. https://data.chhs.ca.gov/dataset/hospital-annual-financial-data-selected-data-pivot-tables/resource/f1aaf6ec-f9f0-4c24-bacf-83882c29728a

Council for Affordable Quality Healthcare. (2019). *2018 CAQH index: A report of healthcare industry adoption of electronic business transactions and cost savings.*

https://www.caqh.org/sites/default/files/explorations/index/report/2018-index-report.pdf

Cardon, M., & Robinette, T. (2018). *Innovative revenue cycle management is the sharpest blade for cutting costs.* MedData.

Carrus, B., Chowdhary, S., & Whiteman, R. (2020, Sept 16). *Making healthcare more affordable through scalable automation.* McKinsey & Company. https://www.mckinsey.com/business-functions/operations/our-insights/making-healthcare-more-affordable-through-scalable-automation

Chui, M., George, K., Manyika, J., & Miremadi, M. (2017, September 7). *Human + machine: A new era of automation in manufacturing*. McKinsey & Company. https://www.mckinsey.com/business-functions/operations/our-insights/human-plus-machine-a-new-era-of-automation-in-manufacturing#

Centers for Medicare & Medicaid Services. (2020, December 16). *National health expenditure accounts*.

Cobb, C. W., & Douglas, P. H. (1928). A theory of production. *American Eonomic Review*, 139-165. http://www.jstor.org/stable/40326423

Colpas, P. (2013, June). How automation helps steer the revenue cycle process. *Health Management Technology*.

Cooper, Z., Craig, S. V., Gaynor, M., & Van Reenen, J. (2019). The price ain't right? Hospital prices and spending on the privately insured. *The Quarterly Journal of Economics*, *2019*, 51-107. https://doi.org/10.1093/qje/qjy020

Craig, S. V., Ericson, K. M., & Starc, A. (2018, October). *How important is price variation between health insurers.* National Bureau of Economic Research. https://www.nber.org/system/files/working_papers/w25190/w25190.pdf

Creswell, J. W., & Cresswell, J. D. (2018). *Research design: Qualitative, quantitative, and mixed methods* (Vol. 5). Sage.

Cutler, D. M. (2018, July 31). *Reducing health care costs: Decreasing administrative spending.* Testimony for Senate Committee on Health, Education, Labor and Pensions. https://www.help.senate.gov/imo/media/doc/Cutler.pdf

Department of Health and Human Services. (2020, September 17). *CMS manual system: Pub 100-20 one-time notification.* https://www.cms.gov/files/document/r10361otn.pdf

Finn, P., Pellathy, T., & Singhal, S. (2009). *US healthcare payments: Remedies for an ailing system.* McKinsey.

Frankfort-Nachmias, C., & Leon-Guerrero, A. (2018). *Social statistics for a diverse society.* SAGE Publications, Inc.

Frey, B. B. (2018). Convenience sampling. *The SAGE Encyclopedia of Educational Research, Measurement, and Evaluation*. https://doi.org/10.4135/9781506326139.n155

Garson, G. D. (2012). *Testing statistical assumptions.* Statistical Associates Publishing. http://www.statisticalassociates.com/assumptions.pdf

Gee, E., & Spiro, T. (2019, April 8). *Excessive administrative costs burden the U.S. health care system.* Center for American Progress.

https://cdn.americanprogress.org/content/uploads/2019/04/03105330/Admin-Costs-brief.pdf

Gerr, R., Guambana, A., Navarro, L., Paul, A., Lin, C., Fontana, E., & Kerns, C. (2015). *Benchmarking revenue cycle performance: Results from the 2015 Revenue Cycle Benchmarking Survey*. The Advisory Board Company. https://www.ma-ri-hfma.org/wp-content/uploads/Advisory-Board-Rev-Cycle-Benchmarking-Study-2015-1.pdf

Goodhue, D. L., & Thompson, R. L. (1995). Task-technology fit and individual performance. *MIS Quarterly, 19*(2), 213-231.

Gottlieb, J., Shapiro, A., & Dunn, A. (2018). The complexity of billing and paying for physician care. *Health Affairs, 37*(4), 619-626. https://doi.org/10.1377/hlthaff.2017.1325

Halford, E. A. (2020, November 23). *Evaluating linear relationships*. Toward Data Science. https://towardsdatascience.com/evaluating-linear-relationships-1d239f51297b

Healthcare Financial Management Association. (2014, March). Achieving an integrated revenue cycle.

Hillman, D. (2020, February). The role of intelligent automation in reducing waste and improving efficiency in the revenue cycle. *HFM Magazine*, 36-39.

Himmelstein, D. U., Campbell, T., & Woodlander, S. (2020). Healthcare administartive costs in the United States and Canada, 2017. *Annals of Internal Medicine, 173*(5). https://doi.org/10.7326/L20-0983.

Hoagland, C., Zar, N., & Nelson, H. (2007, February). Leveraging technology to drive revenue cycle results. *Healthcare Financial Management Association*, 70-76.

Holloway, S. C., Peterson, M., MacDonald, A., & Pollak, B. S. (2018). *From revenue cycle management to revenue excellence.* McKinsey & Company.

Kaye, A. D., Okeagu, C. N., Pham, A. D., Silva, R. A., Hurley, J. J., Arron, B. L., Sarfraz, N., Lee, H.N., Ghali, G.E., Gamble, J.W., Liu, H., Urman, R.D., & Cornett, E. M. (2020). Economic impact of COVID-19 pandemic on healthcare facilities and systems: International perspectives. *Best Practice and Research: Clinical Anaesthesiology, 35*(3), 293-306. https://doi.org/10.1016/j.bpa.2020.11/009

Khallaf, A., Omran, M., & Zakaria, T. (2017). Explaining the inconsistent results of the impact of information technology investments on firm performance: A longitudinal analysis. *Journal of Accounting & Organizational Change*, *13*(3), 359-380. https://doi.org/10.1108/JAOC-11-2015-0086

Kilmon, C. A., Fagan, M. H., Pandey, V., & Belt, T. (2008). Using the task technology fit model as a diagnostic tool for electronic medical records system evaluation. *Issue in Information Systems, 9*(2), 196-203.

Kim, B.H., Sridharan, S., & Ganapathi, V. (2020). Deep claim: payer response prediction from claims data with deep learning. *ArXiv*. https://arxiv.org/pdf/2007.06229.pdf

Kim, Y. J., & Sanders, G. L. (2002). Strategic actions in information technology and investment based on real option theory. *Decision Support Systems, 33*, 1-11.

Kokina, J., & Blanchette, S. (2019). Early evidence of digitial labor in accounting: innovation with robotic process automation. *International Journal of Accounting Information Systems, 35*. https://doi.org/10.1016/j.accinf.2019.100431

Kovach, J. V., & Borikar, S. (2018). Enhancing financial performance: An application of lean six sigma to reduce inusrance claim denials. *Quality Management and Policy, 27*(3), 165-171. https://doi.org/10.1097/QMH.0000000000000175

LaPointe, J. (2017, July 27). *Breaking down the top 5 healthcare revenue cycle KPIs.* Rev Cycle Intelligence. https://revcycleintelligence.com/news/breaking-down-the-top-5-healthcare-revenue-cycle-kpis

LaPointe, J. (2018, June 15). *Exploring the fundamentals of medical billing and coding.* Rev Cycle Intelligence. https://revcycleintelligence.com/features/exploring-the-fundamentals-of-medical-billing-and-coding

LaPointe, J. (2020, March 10). *How COVID-19 is impacting the healthcare revenue cycle.* RevCycle Intelligence. https://revcycleintelligence.com/news/how-covid-19-is-impacting-the-healthcare-revenue-cycle

Lee, J., & Choi, J. Y. (2016). *Texas hospitals with higher health information technology expenditures have higher revenue: A longitudinal data analysis using a generalized estimating equation model.* BMC Health Services Research, *16* (117). https://doi.org/10.1186/s12913-016-1367-9

Lewis-Beck, M. S., Bryman, A., & Liao, T. F. (2011). Pearson's correlation coefficient. *The SAGE Encyclopedia of Social Science Research Methods*, 808-810. Sage Publications, Inc.

Manyika, J., Chui, M., Miremadi, M., Bughin, J., George, K., Willmott, P., & Dewhurts, M. (2017). *A future that works: automation, employment, and productivity*. McKinsey Global Institute.

Mindel, V., & Matthiassen, L. (2015). Contextualist inquirty into IT-enabled hospital revenue cycle management: Bridging research and practice. *Journal of the Association for Information Systems, 16*(12), 1016-1057.

Mithas, S., Tafti, A., Bardhan, I., & Goh, J. M. (2012). Information technology and firm profitability: Mechanisms and empircal evidence. *MIS Quarterly, 36*(1), 205-224.

Morse, S. (2019, April 1). *Hospital revenue cycle: Ready for change but facing challenges.* Healthcare Finance News. https://www.healthcarefinancenews.com/news/hospital-revenue-cycle-ripe-modernization-facing-big-challenges

Mugdh, M., & Pilla, S. (2012). Revenue cycle optimization in healthcare institutions: A conceptual framework for change automation. *The Healthcare Manager, 31*(1), 75-80.

Muro, M., Maxim, R., & Whiton, J. (2019, January 24). *Automation and artificial intelligence: How machines are affecting people and places.* Brookings. https://www.brookings.edu/research/automation-and-artificial-intelligence-how-machines-affect-people-and-places/

Nieman, J. M. (2010, September). Measuring the true return of your hospital's revenue cycle. *Healthcare Financial Management*.

Ordonez de Pablos, P., & Gayo, J. E. (2018). Rethinking key issues for understanding the new challenges of distruption and digital transformatino in companies and economies. *Behaviour & Information Technology, 38*(9), 873-875. https://doi.org/10.1080/0144929X.2019.1641663

Papanicolas, I., Woskie, L. R., & Jha, A. K. (2018). Healthcare spending in the United States and other high-income countries. *Journal of the American Medical Association, 319*(10), 1024-1039. https//doi.org/10.1001/jama.2018.1150

Piercy, C. W., & Gist-Mackey, A. N. (2021). Automation anxieties: perceptions about technological automation and the future of pharmacy work. *Human-Machine Communication, 2*. https://doi.org/10.30658/hmc.2.10

Polykarpou, S., Barrett, M., Oborn, E., & Salge, T. O. (2018). Justifying health IT investments: a process model of framing practices and reputational value. *Information and Organization*, *28*, 153-169. https://doi.org/10.1015/j.infoandorg.2018.10.003

Ramaswamy, K. (2018). Technological change, automation, and employment: A short review of theory and evidence. *Indira Ghandi Institute of Development Research*.

Ratia, M., Myllärniemi, J., & Helander, N. (n.d.). Robotic process automation - creating value by digitalizing work in the private healthcare? *Proceedings of the 22nd International Academic Mindtrek Conference.* https://doi.org/10.1145/3275116.3275129

Rauscher, S., & Wheeler, J. R. (2008). Effective Hospital Revenue Cycle Management: Is There a Tradeoff Between the Amount of Patient Revenue and the Speed of Revenue Collection? *Journal of Healthcare Management, 53*(6).

Reddy, P., Onitskansky, E., Singhal, S., & Velamoor, S. (2018, May 3). *Why the evolving healthcare services and technology market matters.* McKinsey & Company: https://healthcare.mckinsey.com/wp-content/uploads/2020/02/Why-the-evolving-healthcare-services-and-technology-market-matters.pdf

Richmond, C. (2011, September). Focused training boosts revenue cycle skills, accountability. *Healthcare FInancial Management*, pp. 110-116.

Salkind, N. (2010). Causal-comparative design. *Encyclopedia of Research Design, 1-10*.

Singh, R., Durcikova, A., & Matthiassen, L. (2021). Revenue cycle management in the wake of EHR implementation: a competing logics perspective. *Proceedings of the 54th Hawaii International Conference on System Sciences* (pp. 3664-3673). HICSS. https://doi.org/10.24251/HICSS.2021.444

Staples, D. S., & Seddon, P. (2004). Testing the technology-to-performance chain model. *Journal of Organizational and End User Computing, 16*(4).

Sunder, V., & Kunnath, N. R. (2019). Six sigma to reduce claims processign errors in a healthcare payer firm. *Production Planning & Control: The Management of Operations*. https://doi.org/10.1080/09537287.2019.1652857

Teachout, M. (2018). Quantitative Relationships: The Correlation Test. In M. Teachout, *Introduction to Statistics for Community College Students.* Santa Clarita, California: College of the Canyon.

http://teachoutcoc.org/files/section4H_intro_to_stats_for_community_college_students.pdf#:~:text=Two-Tailed%20Correlation%20Test%3A%20For%20determining%20if%20variables%20are,quantitative%20variables%20in%20the%20population%20are%20not%20related.%29

The Council of Economic Advisers. (2004). In N. G. Mankiw, K. J. Forbes, & H. S. Rosen, *Economic Report of the President* (pp. 190-192). Washington, D.C.: United States Government Printing Office. https://www.presidency.ucsb.edu/sites/default/files/books/presidential-documents-archive-guidebook/the-economic-report-of-the-president-truman-1947-obama-2017/2004.pdf

Thouin, M. F., Hoffman, J. J., & Ford, E. W. (2008). The effect of information technology investment on firm-level performance in the healthcare industry. *Healthcare Management Review, 33*(1), 60-68.

Tikkanen, R., & Abrams, M. K. (2020, January 30). *U.S. healthcare from a global perspective, 2019: Higher spending, worse outcomes?* The Commonwealth Fund. https://www.commonwealthfund.org/publications/issue-briefs/2020/jan/us-health-care-global-perspective-2019

Tseng, P., Kaplan, R. S., Richman, B. D., Shah, M. A., & Schulman, K. A. (2018). Administrative costs associated with physician billing and insurance-related activities at an academic health center. *Journal of the American Medical Association, 319*(7), 691-697. https://doi.org/10.1001/jama.2017.19148

University of Caliornia San Francisco Clinical & Translational Science Institute. (n.d.). *Correlation Sample Size*. Sample Size Calculators for Designing Clinical Research: https://sample-size.net/correlation-sample-size/

Weill, P., & Sinan, A. (2007). IT Assets, Organizational Capabilities, and Firm Performance: How Resource Allocations and Organizational Differences Explain Performance Variation. *Organizational Science, 18*, 763-780. https://doi.org/10.1287/orsc.1070.0306.

Woolhandler, S., Campbell, T., & Himmelstein, D. U. (2003). Costs of Healthcare Administration in the United States and Canada. *New England Journal of Medicine, 349*, 768-775. https://doi.org/10.1056/NEJMsa022033

Wyatt-Elkins, P. (2020). *Using human capital development to reduce healthcare administrative costs.* Walden Dissertations and Doctoral Studies.

Zengul, F. D., Weech-Maldonado, R., Ozaydin, B., Patrician, P. A., & O'Connor, S. J. (2018). Longitudinal analysis of high-technology medical services and hospital financial performance. *Healthcare Management Review, 43*(1), 2-11. https://doi.org/10.1097/HMR.0000000000000124