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Between 2008 and 2018, US hospitals invested over $35B on Health Information Technology (HIT) in an effort to improve safety, satisfaction, and health outcomes of the patients while simultaneously reducing costs of care. Information Systems (IS) researchers have studied the impact of individual HIT systems on the cost and quality of care and found mixed results across dimensions of health outcomes, patient satisfaction and the cost of care. The healthcare literature shows that patient complexity, arising from patients' multiple comorbidities as well as from social and economic factors, has a significant impact on patients' health outcomes as well as on hospital financial outcomes. Yet, most HIT research does not directly consider the impact of patient complexity on patients' health outcomes or on the cost of care. This research only controls for clinical complexity as measured by case mix index. We use the theoretical lens of organizational information processing and econometric analysis techniques to investigate whether *routinized HIT interventions are effective in mitigating the impact of multidimensional patient complexity on cost and quality of care outcomes*. Routinized HIT refers to the inextricably interwoven patterns of clinical work and HIT embodied in routines employed by hospitals. Using 4 years of panel data for 5,101 US hospitals. We obtained mixed results when measuring the effect of routinized HIT on cost of care. We found the multidimensional operationalization of patient complexity to be useful for identifying areas of concern and found the moderating effect of use of routinized HIT in hospitals to be most effective for extreme cases of clinical, and social complexity.

EXAMINING THE EFFECT OF HEALTH INFORMATION TECHNOLOGY ON HOSPITAL EFFECTIVENESS AND QUALITY OF CARE

by

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Approved by

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Dr. Rahul Singh
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DEDICATION

There were a lot of people involved in the process of completing my PhD journey. I am thankful to each and every one of them. Whether I understood your input or advice at the time it was given or not, I appreciate your willingness to help me. There are several people that I wish to thank individually. First, I'd like to thank my parents, without their support and encouragement, I would not have even begun this journey, much less had the audacity to attempt such a drastic change of course at this stage of my life. I cannot express how grateful I am to be your son. Thank you. For my wife and children, I appreciate how many sacrifices that you have made over the past four years. You have indulged my need to prioritize school tasks. I know the past four years have not been easy for you. Thank you for enabling me to complete this journey. I offer my sincere thanks and gratitude to my committee chair, Dr. Rahul Singh. I appreciate all the hard work that you have performed on my behalf to guide and sometimes push me to this point. Without the support and encouragement of each of the members of my dissertation committee, this work would not be possible. I appreciate all the time spent reviewing my work and guiding its improvement. Thank you. I offer a special thank you to my dear friends Steve and Lynne MacDowall. The encouragement, food, and fun helped me retain my sense of humor and a positive outlook throughout the PhD journey; maybe I could have done it without you, but it would have been miserable. Also, I offer a big thank you to all the PhD students that walked along side me at any part of this journey. I enjoyed learning from each of you. Thank you.

TFID

APPROVAL PAGE

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CHAPTER I: INTRODUCTION

1.0 Background

In 2009, the Obama Administration added provisions to the American Recovery and Reinvestment Act (ARRA) included provisions that would allocate over $25 billion in funding for the acquisition and installation of Hospital Information Technology. The section of ARRA that includes these funds, which is referred to as the Health Information Technology for Economic and Clinical Health (HITECH) Act. The HITECH Act also included guidelines on minimum functionalities that the implemented systems should contain to provide value to the overall US Healthcare system, or requirements for "meaningful use". The Meaningful Use requirements were intended to ensure that the EHRs would improve care coordination, reduce healthcare cost, and improve healthcare quality (HITECH Act, 2009) through the availability and use of health information technology (HIT). This investment in HIT greatly accelerated the adoption of HIT in hospitals. The adoption rate went from 3.2% in 2008 to 14.2% in 2015. By 2017, 86% of office-based physicians had adopted an EHR and 96% of non-federal acute care hospitals has implemented certified health IT (Office of the National Coordinator, 2018). This has also increased the research that academics have made in the area of HIT. Many studies have investigated the effects of the investment in HIT. In 2006, Chaudhry et al. (2006) identified 257 studies investigating the impact of HIT on organizational and health outcomes published between 1995 and 2005. They found mixed evidence in the literature as to the improvements in organizational outcomes attributable to HIT use, but that the positive reports of improvements in quality of care attributed to HIT use were gained through better adherence to guidelines, enhanced disease surveillance, and reductions in medication errors. At the time of their review, the effect of HIT on efficiency was seen to be mixed. The literature regarding the presence of HIT's impact on cost was also inconclusive. Shortly thereafter, Goldzweig et al. (2009) described an additional 182 published studies from 2005 to June 2007. They reported many of the same observations from the literature. They state that although there is great promise for the use of HIT much of the positive research comes from a handful of systems that were custom developed by internal IT staff at large organizations. Nearly 20 percent of all HIT studies published in this time period were written about the custom, in-house developed HIT employed by six organizations. The issues of facilitating implementations and barriers to adoption became more prevalent in the research during this period. Goldzweig and her colleagues (2009) explicitly call out the need for additional cost-benefit research. These literature reviews were performed from the perspective of health care providers and depict the perspective on the state of research through 2007. The remainder of this literature review we will look at the HIT literature from the IS perspective starting at the turn of the 21st century. Even with all this research, the results remain inconclusive as to the value of HIT The enhanced communication and interactions across units facilitated through the use of HIT have been found to help mitigate medical errors, improve patient safety, and reduce costs associated with extended waiting periods and unnecessary medical treatments (Orszag & Emanuel, 2010). These improvements have not consistently been observed in prior research. The presence of HIT has been observed to increase the occurrence of missed nursing care (Piscotty et al., 2015), positive effects when supporting Clinical activities, negative effects when supporting Administrative activities, and no significant effect on Strategic activities (Bhattacherjee et al., 2007), improve adherence to medication schedules, and increase the observed mortality rate for children who were transported for specialized care (Han et al., 2005).With nearly two decades of use, the literature is still unclear about the value of HIT and how it affects business outcomes for hospitals and health outcomes for patients mixed results seen in prior research that investigated the effects of HIT in hospitals (DesRoches et al., 2010; Devaraj & Kohli, 2000; Jha et al., 2009; Tsai & Jha, 2014). The results of some studies supported the claim that HIT improved readmission rates (Muchiri et al., 2022; Yuan et al., 2019), have no impact on mortality rates (Yuan et al., 2019) and increase the observed mortality rate for children who were transported for specialized care (Han et al., 2005). The motivation for the research for this dissertation was to investigate the value of HIT now that it has been in use for over two decades in US hospitals.

2.0 Complexity

Hospitals are complex. The scope of their operations is necessarily broad. There are more than 14,000 different diagnoses in the current coding scheme, International Statistical Classification of Diseases and Related Health Problems (ICD-10). More than 6,000 prescription drugs (designated RxNORM in the National Library of medicine), more than 4,000 medical and surgical procedures, and more than 3,000 standard observations from hospital laboratory tests in the Logical Observation Identifiers Names and Codes (LOINC). With the trend in US healthcare for specialization of caregivers and single disease management programs, treating patients often involves care givers from multiple hospital units.

The patients that the hospitals treat are also complex. It has been established that more clinically complex patients generally have higher costs to treat and worse perceptions of the care they receive (Krieger, 2001; Lynch & Smith, 2005). The more complex the patient the more it costs to treat them and the higher the risk is for a poor health outcome for the patient (Lipsitz, 2012). As a result, complex patients contribute a disproportionately high share of the nation's health care costs, with 5% of the patient population accounts for 50% of the country's annual healthcare spending costs (Blumenthal, Bruce, Fulmer, John, & Jeffrey, 2016; Blumenthal & Abrams, 2016). The extant IS and HIT research considers the question of describing patient complexity as being completely answered by the hospital's case mix index (CMI). The CMI represents the relative effort and resources required to treat a patient (Carling et al., 2003). In this literature, CMI is often used as a control variable, but there is little literature that considers the effect of complexity on hospital and patient outcomes. However, the healthcare literature has established that there are other considerations beyond a patients clinical condition that influence how complicated it is to provide care for the patient (Elixhauser et al., 1998; Safford et al., 2007). Patient characteristics such as socioeconomic and prior health conditions have a great effect on the cost to treat a patient (Barnett et al., 2015).

3.0 Design of Research

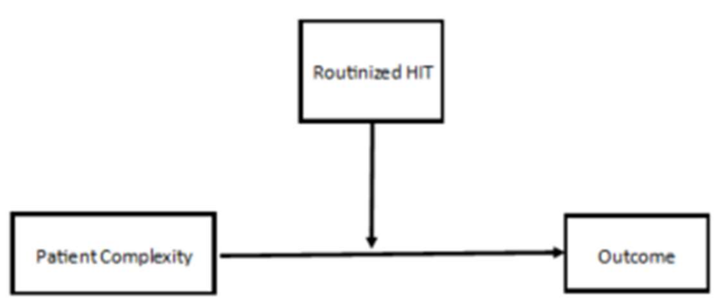
This research was focused on determining if a broader conceptualization of patient complexity could add some additional insights into the technology-performance between HIT and the outcomes of the hospital and the patients. In the healthcare literature, Safford and colleagues (2007) put forward a vector model of patient complexity. They argue that the "determinants of health include biology/genetics, socioeconomics, culture, environment/ ecology, behavior, and the medical system". In their vector model of patient complexity, they describe each of these determinants of health to be additive and variable from patient to patient. The Vector model of Complexity proposed by Safford and her colleagues is the only model that we found that provides insight into how the dimensions of complexity might interact and be combined. We adopted the Vector Model of Patient Complexity as our model for patient complexity.

In reviewing the HIT literature, we found that there was a variety of outcomes that were studied in attempts to establish a technology to performance relationship. Menon et al. (2000) treated 18 years of longitudinal data from 55 hospitals in Washington State and found that HIT investment was related to increased hospital revenue. However, with the high standard deviation reported with the mean marginal revenue contribution estimator, this result is not convincing. Devaraj and Kohli (2000) also saw that the presence of HIT lead to higher revenues, but they observe that the improvements from HIT investments are seen after a lag period. For the deployment of Decision Support Systems, they found that a three-month lag existed between deployment and measurable benefits in cost and quality of care. In their 2003 treatment of the same 36 month data set that covered the operations from 8 hospitals, Devaraj and Kohli (2003) observed that system usage is a better predictor of organizational performance improvements than investment or presence of particular HIT. They observed that HIT use was related to lower mortality rates, but the primary source of the improvements came through business process reengineering, not from the presence of the HIT. Kohli and Kettinger (2004) found that the care coordination afforded by HIT could improve cost of care. One study did see an unexpected increase in mortality rate at a children's hospital immediately after HIT was implemented (Han et al., 2005). DesRoches and colleagues (2010) found similar results to those of Devaraj and Kohli's research from seven years earlier, that HIT adoption was not sufficient to see improvements in organizational outcomes. However, in their study they only consider two types of HIT applications – Computerized Physician Order Entry and Electronic Health Records. There are HIT systems in other areas of the hospital such as the laboratory and radiology that help inform clinicians in their decisions on care that are not included in the DesRoches study. Much of this early research was focused on results from a few large custom developed HIT systems (Chaudhry, 2006). However, the ONC specified that HIT incentives would only be available for “certified systems”, therefore the expectation is that the majority of HIT adoption since the enactment of the HITECH Act would have come through the purchase and implementation of commercial off-the-shelf (COTS) systems (Agarwal et al., 2010). As COTS systems are not custom built or maintained, their value to a company could be significantly different as the cost for acquisition and maintenance of the systems should be less, however the features and functionality of the system may not be completely tailored to the needs of the hospital, thereby weakening the benefits when compared to custom built HIT. Improved quality of care in diabetes treatment was seen in hospitals that with the use of EMR systems (Cebul et al., 2011), however, the same improvement in quality of care was not seen in ambulatory care (Linder et al., 2007). Researchers did find evidence of a positive relationship between extent of HIT use and patient satisfaction, with non-academic hospitals seeing a larger benefit (Queenan et al., 2011). The influence of HIT on the market value of non-publicly traded hospitals was studied by Kohli, Devaraj, and Ow (2012) they found support for their assertions that HIT would enhance the market value of these non-publicly traded hospitals. The ability of HIT to improve the quality of medication administration at medium-to-large acute care hospitals was studied by Appari et al. (2012). They found that the odds of adherence to quality of medication scores were appreciable higher for the hospitals that used HIT. Further, they found that the length of time that the HIT was in use was an important determinant of the magnitude of the improvement. HIT investments made to improve data safety and system resilience were found to be much more cost effective as proactive investments rather than in response to a data breach (Kwon & Johnson, 2014). Ayabakan and colleagues (2014) saw that HIT increased information sharing resulted in a reduction in duplicate testing and thereby operating costs across a healthcare system. IT capabilities as well as user capabilities are significant in realizing organizational performance improvements (Serrano & Karahanna, 2016). Ederhof and Ginsburg (2019) found that longer use of HIT was related to reductions in cost. HIT was shown to have the capacity for improving efficiency of tasks as well as allocation of resources (Devaraj et al., 2013; Thompson et al., 2020; Yeow & Goh, 2015). Menon and Kohli (Menon & Kohli, 2013) showed that HIT investment was related to improvements in quality of care and lower malpractice insurance premiums. Appari and Anderson (2013) saw that there were some improvements to quality that could be realized through HIT adoption, however, they observed quality of care decline when more advanced systems were implemented. Adler-Milstein and her colleagues (2015) studied the impact of HIT adoption on various measures of quality of care, finding that the effects of the HIT were positive and significant for process adherence patient satisfaction, further that these effects were more pronounced with longer use. Researchers found that the implementation of HIT specific to clinical work processes was related to improved quality of care, but not cost improvements (Sharma et al., 2016). HIT was shown to increase care coordination and thereby patient satisfaction (Romanow et al., 2018). However, there were studies that suggest that measures for HIT investment or for presence of HIT were not sufficient in explaining the connection between HIT technology and the outcomes it influences. Devaraj and Kohli (2000) put this question in the title of their study, "Performance impacts of information technology: Is actual usage the missing link?". The influence of HIT use rather than HIT investment was further confirmed by (Romanow et al., 2018). They found that value from HIT was realized when it was used in ways to support the structure of the clinical tasks.

The Implementation of Information Systems has been conceptualized as a 6 stage process: initiation, adoption, adaption, acceptance, routinization, and infusion (Cooper & Zmud, 1990). As these HIT systems have been in use for some time now, in several cases more than 20 years, it is safe to conclude that a majority of the hospitals that use HIT are beyond the acceptance phase of their HIT implementations. Routinization occurs through the incremental accumulation of experience (Luo & Ling, 2013). Routinization was conceptualized as a stage that occurred after the acceptance and go-live of the Information System and was characterized as a special form of system exploitation that required little additional learning and one that promotes efficiency advantages in daily work (Cooper & Zmud, 1990; Luo & Ling, 2013). In literature that investigates the process of realizing value from IS, routinization is described as a state where the IS has become normalized into the work process. (Saga & Zmud, 1994) into *regular* and *repetitive* patterns (Feldman, 2000). In a healthcare context, routinization has been defined as "*the interplay between technology and patterns of clinical work embodied in routines*" ((J. M. Goh et al., 2011; K. T. Goh & Pentland, 2019). We will adopt this definition as our working definition of routinization.

To investigate the value that HIT can provide to hospitals we arrived at the following conceptual model.

Figure 1 - Conceptual Model.



In the first essay, we perform an extensive literature review. This literature review is focused on understanding the work that has been performed in understanding the value that HIT brings to the hospital. Particularly, it is focused on understanding the concepts, constructs, methods, and theories that have been used to connect the value generated by HIT to the efficiency of delivering care and quality of care. We identify specific gaps in the understanding of how HIT mediates the relationship between patient complexity and the cost to provide care and the quality of care that the hospital provides. In the second essay, we investigate how routinized HIT affects the relationships between the dimensions of a multidimensional conceptualization of patient complexity and cost of care. This essay attempts to perform empirical research providing evidence that describes the effect of routinization of HIT on the performance of the hospital which is lacking in the literature. The purpose of the essay is to investigate how routinized HIT impacts a hospital's cost performance when treating complex patients. In the third essay, we address the gap in the literature that exists as there is little research that investigates the effects of routinized use of HIT; specifically, research providing empirical evidence that describes the effect of routinization of HIT on the quality of care provided by hospitals. The purpose of this essay is to addresses this gap in the literature by investigating the impact of routinized use on hospital performance as measured by 30-day readmission rate, and 30-day mortality rate for select chronic (AMI, COPD, and heart failure) and non-chronic conditions (CABG, pneumonia, stroke).

4.0 Data

To complete these investigations, we have created what we believe is a novel panel data set comprised of HIT usage and system maturity information from the HIMMS database, hospital operating characteristic data published by the CMS, income data from the IRS, and population characteristics collected by the US Census Bureau to describe the effects. To our knowledge, this is the first data set that constructs patient characteristic data from the ZIP codes of the patients that are actually treated by the hospital rather than taking the catchment area of the hospital. The unit of analysis in this study is the U.S. acute care hospital. We collected secondary data from multiple sources for the four calendar years from 2014 to 2017 for 5,011 U.S. acute care hospitals included in the CMS database as of 2017 resulting in an unbalanced panel containing nearly 19,000 observations. The data is panel data as values for the same set of variables was collected annually, however it is unbalanced as not all hospitals had reported data in each of the reporting periods. In the cases of the data for the mortality rates and readmission rates for the conditions included in the Hospital Readmission Reduction Program (HRRP), which are acute myocardial infarction (AMI), coronary artery bypass graft (CABG), chronic obstructive pulmonary disease (COPD), heart failure (HF), pneumonia (PN), and stroke (STK). As per CMS guidelines, only measures that are based on a sample of at least 25 patients for a given condition are included in the study. Unbalanced panel data was used to maximize the observed variability in the data. We took data concerning HIT usage and hospital expenses from the Healthcare Information and Management Systems Society (HIMSS, previously the Dorenfest Institute for Health Information Technology Research) database. The HIMSS database is a nationally representative survey that includes meta data, IT usage metrics, and operational data from over 5000 hospitals. The readmission and mortality rate data were collected from the Hospital Quality Initiative (HQI) data set published by the CMS. The data set from the CMS did not include data that would allow us to study the effects of socio-economic complexity, so we had to find ways that would allow us to approximate the social and economic attributes of the patients that the hospital treated while maintaining the hospital as the unit of analysis. As our collected data is at the individual health care facility, we approximated the social, economic, and cultural composition of the patients by taking measures for these parameters from the populations that the health care facilities serve. We used weighted averages for these values based on the ZIP codes of the patients treated by the hospital for each of the four years considered in the study. The exact number of patients treated by ZIP Code is annually reported by the CMS.

5.0 Conclusion

The remainder of this dissertation is organized in the following manner. The next chapter will contain the literature review, chapter 3 will contain the essay that considers how cost of care is affected by the use of routinized HIT for complex patients. Chapter 4 contains the investigation that looks at how the use of routinized HIT affects the relationship between patient complexity and hospital mortality and readmission rates.

CHAPTER II: LITERATURE REVIEW

1.0 Introduction

At the turn of the 21st century, healthcare began to use information systems to increase awareness of costs and inconsistent outcomes (S. S. Feldman et al., 2018). The healthcare industry invested in IT and information systems relatively late when compared to other industries (Menon & Lee, 2000). Early adopters of Healthcare Information Technology (HIT) created custom systems to process information in the hospital, with commercial systems not being widely available until the early 2000's (Boyles, 2019). In the decade following the passage of the American Recovery and Reinvestment Act, HIT went from sparse usage to near ubiquitous presence with over 95% of hospitals adopting EHRs by 2014 (https://www.healthit.gov/data/quickstats/national-trends-hospital-and-physician-adoption-electronic-health-records).

The Institute of Medicine released two reports stating that between 44,000 and 98,000 American's were dying annually from preventable medical errors and recommended that Healthcare Information Technology (HIT) was an important tool in efforts to reduce that number (Kohn et al., 1999; Erickson et al., 2003). This gave the Obama Administration the political capital needed to propose a large investment in public health. They banked on the experiences with HIT at the Veteran's Administration to justify significant investment in the US HIT infrastructure (Oliver, 2007). Between 2008 and 2018, US hospitals invested over $35B on HIT, and this number continues to grow. These investments were espoused to realize improvements in the safety, satisfaction, and health outcomes for patients, while reducing cost of care for hospitals (HITECH Act, 2009). The US government has been encouraging healthcare providers to accelerate their conversion to electronic health records through their allocation of over twenty-seven billion dollars in incentive payments included in the Health Information Technology and Clinical Health (HITECH) Act that was enacted as part of the 2009 American Recovery and Reinvestment Act (ARRA). These investments saw the adoption rate for comprehensive HIT systems increase from 3.2% in 2008 to 14.2% in 2015. By 2017, 86% of office-based physician practices, and 96% of non-federal acute care hospitals had implemented HIT (Office of the National Coordinator, 2018). The HITECH Act also included guidelines on minimum functionalities that the implemented systems should contain to provide value to the overall US Healthcare system, or requirements for "meaningful use". The Meaningful Use requirements were intended to ensure that the EHRs would improve care coordination, reduce healthcare cost, and improve healthcare quality (HITECH Act, 2009) through the availability and use of HIT.

Many studies have investigated the effects of the investment in HIT. Chaudhry et al. (2006) identified 257 studies investigating the impact of HIT on organizational and health outcomes published between 1995 and 2005. They found mixed evidence in the literature as to the improvements in organizational outcomes attributable to HIT use, but that the positive reports of improvements in quality of care attributed to HIT use were gained through better adherence to guidelines, enhanced disease surveillance, and reductions in medication errors. At the time of their review, the effect of HIT on efficiency was seen to be mixed. The literature regarding the presence of HIT's impact on cost was also inconclusive. Shortly thereafter, Goldzweig et al. (2009) described an additional 182 published studies from 2005 to June 2007. They reported many of the same observations from the literature. They state that although there is great promise for the use of HIT much of the positive research comes from a handful of systems that were custom developed by internal IT staff at large organizations. Nearly 20 percent of all HIT studies published in this time period were written about the custom, in-house developed HIT employed by six organizations. The issues of facilitating implementations and barriers to adoption became more prevalent in the research during this period. Goldzweig and colleagues (2009) explicitly call out the need for additional cost-benefit research. These literature reviews were performed from the perspective of health care providers and depict the perspective on the state of research through 2007. The remainder of this literature review we will look at the HIT literature from the Information Systems (IS) perspective starting at the turn of the 21st century.

While relatively fewer in number, complex patients incur high costs to a health system and are at high risk for poor health outcomes (Lipsitz, 2012). As a result, complex patients contribute a disproportionately high share of the nation's health care costs, with a frequently cited statistic that 5% of the patients account for more than 50% of the total cost of health care in the US (Blumenthal, Bruce, Fulmer, John, & Jeffrey, 2016; Blumenthal & Abrams, 2016). Literature recognizes that complex patients need coordinated care from the multiple specialties and care services within the health system (Albert et al., 2015; Bodenheimer, 2008). Different units in the health system must interact with each other to perform the diverse range of operations required of the complex care management efforts needed to care for complex patients (Kannampallil et al., 2011; Tan et al., 2005). These activities are managed across the health system and rely on efficient information sharing for seamless delivery of effective care (Albert et al., 2015; Iezzoni et al., 2016). Further, these complex patients are more likely to have poorer health outcomes as they are more likely to be older and have functional limitations such as impaired mobility or vision loss that impairs their ability to care for themselves (Hayes, et al., 2016)

IS researchers have found that the enhanced communication and interactions across units are facilitated by the use of routinized HIT which helps to mitigate medical errors, improve patient safety, and reduce costs associated with extended waiting periods and unnecessary medical treatments (Orszag and Emanuel, 2010). The enhanced communication and interactions across units facilitated by the routinized use of HIT have been found to help mitigate medical errors, improve patient safety, and reduce costs associated with extended waiting periods and unnecessary medical treatments (Orszag and Emanuel, 2010). These improvements have not consistently been observed in prior research. The presence of HIT has been observed to increase the occurrence of missed nursing care (Piscotty et al., 2015), have positive effects when supporting clinical activities, negative effects when supporting administrative activities, and no significant effect on strategic activities (Bhattacherjee et al., 2007), improve adherence to medication schedules, and increase the observed mortality rate for children who were transported for specialized care (Han et al., 2005).With nearly two decades of use, the literature is still unclear about the value of HIT and how it affects operational outcomes for hospitals and health outcomes for patients (DesRoches et al., 2010; Devaraj & Kohli, 2000; Jha et al., 2009; Tsai & Jha, 2014).

2.0 How HIT has been Measured

Much of the literature concerning HIT has been focused on developing an elusive technology to performance linkage. The beginning of the search for this link started by investigating the idea that the presence of HIT or prior investment in HIT would lead to improvements in organizational outcomes like expense per bed, or revenue, and patient care outcomes like quality of care, and patient safety. There was resistance in the hospitals moving from the incumbent paper records to electronic records, so researchers looked to understand how that resistance formed (Lapointe & Rivard, 2005) and how to alleviate the resistance to HIT and better still prevent the resistance from forming (Kohli & Kettinger, 2004). Xue et al. (2008) investigated the process of how decisions to make HIT investments are reached and found that the nature of governance of the resultant HIT implementation projects influenced their ultimate ability to succeed.

As the research stream matured, researchers began looking at the impact of specific types of HIT and recognized that the presence of HIT was not sufficient, but that the effective use of HIT was also required to realize improvements in organizational and patient outcomes (DesRoches et al., 2010; Devaraj & Kohli, 2003). With the influence from the conditions set forth in the HITECH Act, research began to consider how the requirements for meaningful use of HIT influenced organizational and health outcomes (Appari et al., 2013). In the study by Appari and colleagues (2013), they found that hospitals that just met the Meaningful Use requirements of 2011 from the Centers for Medicare and Medicare Services (CMS) saw improvements in their organizational outcomes and quality of care measures, however they found that hospitals that had implemented HIT beyond these requirements saw decreases in these outcomes and measures. In this study, they did not consider the amount of time that the system has been in use, nor did they consider the degree to which this "extra" functionality has been deployed or how extensively it was used in the hospital. Research suggests that the length of time of HIT use (Devaraj & Kohli, 2003) and manner in which the HIT is used in the hospital (Romanow et al., 2018) are likely related to the hospital's ability to receive value from the HIT.

As the technology to performance link has not been convincing at the macro-level, researchers have also looked at individual units of the hospital to evaluate the effects of HIT use. Han et al. (2005) found an increase in childhood mortality at a hospital immediately after the implementation of a commercially developed HIT. Han and colleagues attributed this increase to the broader issues of systems integration and design of the human-machine interface, however, they could have also considered that the user capabilities (Serrano & Karahanna, 2016) of the clinicians had not been adequately developed prior to switching over to the new HIT. Miller and Tucker (2015) looked at HIT's ability to improve clinical efficiencies that improve diagnostics and patient monitoring to reduce infant mortality. Dobrzykowski and Tarafdar (2015) investigated the ways in which HIT can improve communicative relationships within the care team to improve care provider-patient communications.

There are many components to finding the technology to performance link, but to date there has not been a study that considers the completeness of the HIT deployed within the hospital and the length of time that it has been in use. By doing so, a researcher would combine the findings from Romanow (2018) concerning type of use, Serrano and Karahanna (2019) concerning the necessity for technical and user capabilities, and the need for ubiquitous use of the HIT (Devaraj and Kohli, 2000; Desroches et al., 2010).

3.0 Unit of Analysis

The predominate unit of analysis in HIT research is the hospital, which is reasonable particularly for full-featured systems that span the operations of the hospital, as the HIT affects the operations and outcomes for the hospital in its entirety. There are some notable exceptions to using hospital as the level of analysis. Lapointe and Rivard (2005) studied HIT three implementations to derive their multi-level model of resistance to adoption. Xue, et al. (2008) studied HIT decision process governance by investigating 57 hospital IT projects. For their study on the effect of HIT on quality of care for diabetes patients, Cebul et al. (2011) reviewed data from over 27,000 adult diabetes patients. Serrano and Karahanna (2016) observed clinicians to investigate organizational performance. Ayabakan et al. (2014) used data from patient visits to find that HIT use decreases repeated testing within a healthcare system. Sergeeva and colleagues (2017) ethnographic observations in 16 operating rooms over a one year period investigating how the perceptions of onlookers influence the adoption of new HIT in the operating room. Pinsonneault et al.'s (2017) natural experiment included over 31,000 patients in a matched cohort study that looked at HIT's ability to affect continuity of care and quality of care. Thompson et al. (2020) studied HIT's capability to enact temporal displacement of care using 45,000 patient visit observations.

These studies have shown that there is a growing emphasis on patient-level analytics as researchers and clinicians have come to recognize that the ultimate impact of HIT should consider patient-level outcomes, and therefore, there have been calls for greater attention using patient-level data to generate useful and actionable insights (Angst et al. 2010, Gao et al. 2010), however we expect that researchers will continue in their efforts to establish a technology-performance link using hospital data.

4.0 Focus of Study

In the HIT literature there have been several themes that have served as the predominate foci of study, HIT Investment, Adoption and Diffusion, and Use of HIT.

4.1 HIT Investment

HIT investment was the first theme to be formed with much of the early research performed by Devaraj, and Menon (Devaraj et al., 2013; Devaraj & Kohli, 2000; Menon & Lee, 2000), however, the thematic has also been a more recent focus (Ederhof & Ginsburg, 2019; Hydari et al., 2019). Kohli et al.'s (2003) paper, cast doubt on the validity of HIT Investment or presence as a viable focus of study by pointing out that the prior research showed mixed results and by finding support for their assertion that measures of HIT use were needed to predict HIT's effect on organizational performance.

4.2 Adoption and Diffusion

Early studies of HIT were concerned with the clinicians' resistance to changing from paper records to HIT systems. Research concerning resistance to HIT use found that the culture of the hospital (Rivard et al., 2011), the perceived legitimacy of the message and the messenger (Kohli & Kettinger, 2004), and the initial impressions of the clinicians (Lapointe & Rivard, 2005) all impact the way in which new HIT is received and how enthusiastically it is used. Zheng et al. (2005) found a spectrum of users with different adoption patterns and opinions of the implemented HIT. Davidson and Chismar (2007) investigated the ways social structures changed as a result of the technical and institutionally triggered changes in work patterns and procedures following the adoption of HIT. They found that it was necessary to treat the HIT as an integral component in the change process rather than as a static, external change trigger. They found that as usage increased and interdependency between clinicians of HIT use was established that there was increased standardization in clinical decision making and multi-disciplinary cooperation. The process they describe is similar to the routinization stage of IT implementation as described by Cooper and Zmud (1990). At the hospital level, adoption and diffusion has also been studied. Angst et al. (2010) found that network effects were important in the successful adoption of HIT implementations. Goh, Gao, and Agarwal (J. M. Goh et al., 2011) found that one of the keys to successful implementations of HIT was to manage the co-evolution process between the process of working with HIT and changes to routines for care. This observation is further refined by Romanow et al. (2018) who observed a similar interplay between HIT usage and adaptation of work processes

This stream may be revisited in the future with HIT that is augmented with Artificial Intelligence (e.g. Zhou, et al., 2020).

4.3 HIT Use

Two studies that provide evidence that the presence of HIT is not sufficient to realize its expected benefits. Devaraj and Kohli (2003) found evidence that the more HIT is used by the clinicians, the more it affects organizational performance. In their study, there was no heterogeneity among the HIT considered. All of the sampled hospitals that were using HIT were using the same HIT implemented in the same manner. This is detrimental to the generalizability of their results. Desroches et al. (2010) argued that use of HIT was not sufficient to establish a definitive technology-performance link, however they offered no insights as to what additional information or measures would help establish that relationship. Romanow et al. (2018) show that HIT is an enabler of care coordination and patient communication when it is leveraged to support the underlying structure of the task. HIT features that facilitate these improvements include standardized order sets, clinical decision support and alerts, clinical results integration, and progress notes. Although these authors presented compelling arguments concerning the need to include consideration for how HIT is used and how frequently HIT is used in the hospital, HIT researchers have not adopted an approach that is consistent with these findings. Much of the research since 2018 considers only the use or presence of HIT (for example, Hydari et al., 2019; Karahanna et al., 2019).

Because the environment and processes required to provide healthcare for patients in a hospital are complex researchers will continue to be able to investigate the ways in which HIT affects the organizational outcomes for the hospital as well as the health outcomes for its patients. We expect that the research in these thematics will continue to expand as researchers look for ways to identify and quantify the value that is created from HIT.

5.0 Theories Used

As many of the studies have been performed using econometric techniques, the theories have been predominately focused on organizational behavior. Some theories that describe individual behavior have been used in studies that consider technology adoption, but these studies and thereby these types of theories are less prevalent in the literature. There is not much consistency in the theory bases used to study the effectiveness of HIT in the literature, this is likely because the technology-performance link has not been established.

5.1 Organizational Behavior

In explicating the manner in which HIT provides improvements to organizational outcomes, Devaraj and Kohli used the theories of business process reengineering (2000), technology-task-fit (2003), and process view of operations (2004) to focus their thinking about hospital operations and how HIT can affect revenues and patient mortality. The process view of operations also guided the research of Dobrzykowski and Tarafdar (2015), who looked at how HIT use improved care provided to the patient.

5.2 Economic Theories

Cost minimization was used by Menon and Kohli (2000) to investigate how investments in HIT can lead to improvements in malpractice insurance premiums, and also by Ayabakan (2014) to related intra-organizational information sharing to reductions in unnecessary repeated laboratory testing. Behavioral theory of the firm (Salge et al., 2015) to evaluate the effect of HIT investment decisions. Other researchers (DesRoches et al., 2010; Ederhof & Ginsburg, 2019) implicitly use cost minimization to guide their investigations of the potential economic impact of HIT use.

5.3 Other Theories

Devaraj and Kohli (2003) used task-technology-fit in their study of the impact of HIT on the revenues and mortality rates of hospitals that were members of the same private health system in Washington state. Lapointe and Rivard (2005) looked at the resistance to HIT use in a hospital and developed their multi-level model of resistance based on understandings gained through the resistance behavior literature. The theory of swift and even flow from operations management was used to related HIT investment to hospital organizational outcomes and mortality rates (Devaraj et al., 2013) and to evaluate the impact of HIT on telemedicine outcomes (Yeow & Goh, 2015). In considering the antecedents to realizing improvements in organizational outcomes and quality of care, Serrano and Karahanna (2016) viewed the process of acclimating to HIT through the lens of compensatory adaption to find that both technology capabilities and user capabilities are required to realize benefits form HIT. Technology-in-practice was used to guide the study into the process of HIT adoption in the operating room. The structure-process-outcome framework was used to evaluate an integrated HIT's ability to affect the quality of care of ambulatory patients (Pinsonneault et al., 2017). They found that the HIT enabled a higher quality of care in the follow-up period, and the HIT also tended to enhance the continuity of care for the patients. Insights from Bourdieu's forms of capital and the logic of digital options were used to investigate the antecedents to creating a digital advantage (Karahanna et al., 2019). Thompson et al. (2020) found that the use of HIT was important in increasing the cost and quality of care using the theory of temporal displacement of care to frame their study.

The prevalence in researchers' use of economic and organizational behavior theories is likely to continue until the technology-performance link is established. When the link is established, research will likely mature and consider topics such as antecedents for performance improvements. Additionally, the research is likely to continue to move away from theories that describe the adoption, diffusion and resistance to use until the proliferation of AI enabled HIT is deployed.

6.0 Methods

The study of HIT has been primarily conducted with econometric methods. This is reasonable as much of the data is panel data and the effects occur over time. Fixed effects modeling has been used to evaluate the effects of HIT on organizational outcomes (Devaraj & Kohli, 2000; Sharma et al., 2016), revenue and mortality rates (Devaraj & Kohli, 2003), and infant mortality (Miller & Tucker, 2011). In addition to the fixed effects modeling, other researchers (Menon & Kohli, 2013) have used Generalized Method of Moments (GMM) to provide instrumental variables to refine the fixed effects estimators, and difference-in-differences (Ayabakan et al., 2014; Hydari et al., 2019). Salge et al. (2015) used GMM to provide a more robust estimation as this approach allows for heteroscedasticity and autocorrelation consistent standard errors to be calculated. In fixed effects modelling there is an assumption that the entity, in this case the hospital is not changing across the duration of the panel. For the short time period studies (Devaraj & Kohli, 2000, 2003; Sharma et al., 2016), this is an appropriate assumption, however in studies that include data from a longer time span (Menon & Kohli, 2013; Miller & Tucker, 2014) this assumption should be confirmed, but was not in these studies. To analyze the data from their natural experiment, Pinsonneault et al. (2017) used multivariate least squares regression within a generalized estimating equation framework to account for the correlation between observations for the case of patients being seen by the same physician.

Other quantitative methods that have been used in the study of the effects of HIT on hospital operations include Full Information Maximum Likelihood (Menon & Lee, 2000), OLS (Devaraj et al., 2013; Kohli et al., 2012), PLS (Karahanna et al., 2019; Romanow et al., 2018), and t-tests for difference of means (Hydari et al., 2019). SEM was used to evaluate the antecedents to creating better care provider- patient communications (Dobrzykowski & Tarafdar, 2015). Stochastic Frontier Analysis was used to evaluate the effects of telemedicine on the input allocative efficiency of the healthcare process resulted in improvements in organizational outcomes, such as lower hospitalization rates and lower uncertainty in patient wait time (Yeow & Goh, 2015). Pinsonneault et al. (2015) used a prospective controlled cohort study to evaluate the ability of an integrated HIT to increase the continuity of care while reducing therapy duplication errors. They found support for these hypotheses but have likely under-reported the ability of a fully integrated HIT to improve quality of care; as there are other modalities in which a full featured and integrated HIT can improve quality of care, such as reducing errors in the prescription of care, and improved care coordination that is afforded through clinical decision support.

There is a trade-off that occurs when choosing data used for an analysis, data taken at the hospital is richer and can give more specific insights into issues, but the results of these studies are not necessarily generalizable (Devaraj and Kohli 200,2003; Kohli and Kettinger 2004; Yeow and Goh, 2015) and the datasets like the ones available from HCUP or CMS are not as rich, as a datapoint represents the hospital operation over one or multiple years. These data sets don’t lend themselves toward analysis that provide deep insights into the operations of the hospital.

As for qualitative research, Action Research was used to study resistance to HIT use (Kohli & Kettinger, 2004). Semi-structured interviews of clinicians were conducted by Lapointe and Rivard (2005) which led to their development of a multi-level model of resistance to HIT adoption. Xue and colleagues (2008) developed a number of case studies to investigate the HIT investment process. Ethnographic observations were taken in a study that looked at the adoption of mini-tablets used for access to electronic versions of documentation required during surgery rather than paper copies in the operating room (Sergeeva et al., 2017).

Design Science has also been used in the study of HIT. Predictive models were created to use data that is commonly collected by HIT to predict the likelihood and timing of readmissions for at risk patients diagnosed with Congestive Heart Failure (I. Bardhan et al., 2015),

7.0 Situational Factors

As research has primarily been attempting to definitively establish the technology-performance link, there has not been much attention paid to determining the moderators of HIT effects in the literature. Lapointe and Rivard (2005) looked at the forming of perceptions on HIT finding that it was a repeating, cyclical process. Although it is not directly commented on in the studies (Devaraj & Kohli, 2003; Ederhof & Ginsburg, 2019) demonstrate that organizational outcomes improve the longer that the HIT is in use.

8.0 Outcomes Studied

8.1 Organizational Outcomes

Menon et al. (2000) treated 18 years of longitudinal data from 55 hospitals in Washington State and found that HIT investment was related to increased hospital revenue. However, with the high standard deviation reported with the mean marginal revenue contribution estimator, this result is not convincing. Devaraj and Kohli (2000) also saw that the presence of HIT lead to higher revenues, but they observe that the improvements from HIT investments are seen after a lag period. For the deployment of Decision Support Systems, they found that a three-month lag existed between deployment and measurable benefits in cost and quality of care. In their 2003 treatment of the same 36 month data set that covered the operations from 8 hospitals, Devaraj and Kohli (2003) observed that system usage is a better predictor of organizational performance improvements than investment or presence of particular HIT. Kohli and Kettinger (2004) found that the care coordination afforded by HIT could improve cost of care. DesRoches and colleagues (2010) found similar results to those of Devaraj and Kohli's research from seven years earlier, that HIT adoption was not sufficient to see improvements in organizational outcomes. However, in their study they only considered two types of HIT applications – Computerized Physician Order Entry and Electronic Health Records. There are HIT systems in other areas of the hospital such as the laboratory and radiology that help inform clinicians in their decisions on care that are not included in the DesRoches study. The effect of HIT on the market value of non-publicly traded hospitals was studied by Kohli, Devaraj, and Ow (2012) they found support for their assertions that HIT would enhance the market value of these non-publicly traded hospitals. The ability of HIT to improve the quality of medication administration at medium-to-large acute care hospitals was studied by Appari et al. (2012). They found that the odds of adherence to quality of medication scores were appreciably higher for the hospitals that used HIT. Further, they found that the length of time that the HIT was in use was an important determinant of the magnitude of the improvement. HIT investments made to improve data safety and system resilience were found to be much more cost effective as proactive investments rather than in response to a data breach (Kwon & Johnson, 2014). Ayabakan and colleagues (2014) saw that HIT increased information sharing which resulted in a reduction in duplicate testing and thereby operating costs across a healthcare system. HIT capabilities as well as user capabilities are significant in realizing organizational performance improvements (Serrano & Karahanna, 2016). Ederhof and Ginsburg (2019) found that longer use of HIT was related to reductions in cost. HIT was shown to have the capacity for improving efficiency of tasks as well as allocation of resources (Devaraj et al., 2013; Thompson et al., 2020; Yeow & Goh, 2015).

8.2 Quality of Care, Patient Safety and Health Outcomes

Devaraj and Kohli (2003) observed that HIT use was related to lower mortality rates, but the primary source of the improvements came through business process reengineering, not from the presence of the HIT. One study showed an unexpected increase in mortality rate at a children's hospital immediately after HIT was implemented (Han et al., 2005). DesRoches and her colleagues (2010) saw that HIT usage could lead to improved hospital quality of care, however the positive results were seen only in hospitals that instituted policies encouraging system use. Improved quality of care in diabetes treatment was seen in hospitals with the use of EMR systems (Cebul et al. 2011), however, the same improvement in quality of care was not seen in ambulatory care (Linder et al., 2007). Researchers found evidence of a positive relationship between extent of HIT use and patient satisfaction, with non-academic hospitals seeing a larger benefit (Queenan et al., 2011). Menon and Kohli (Menon & Kohli, 2013) showed that HIT investment was related to improvements in quality of care and lower malpractice insurance premiums. Appari and Anderson (2013) saw that there were some improvements to quality that could be realized through HIT adoption, however, they observed quality of care decline when more advanced systems were implemented. Adler-Milstein and colleagues (2015) studied the impact of HIT adoption on various measures of quality of care, finding that the effects of the HIT were positive and significant for process adherence patient satisfaction, further that these effects were more pronounced with longer use. Researchers found that the implementation of HIT specific to clinical work processes was related to improved quality of care, but not cost improvements (Sharma et al., 2016). HIT was shown to increase care coordination and thereby patient satisfaction (Romanow et al., 2018). Devaraj and Kohli observed that HIT use was related to reductions in hospital mortality rates. The mortality rates were calculated by dividing total mortalities by operative procedures, this biases the rates to be higher as there are conditions such as pneumonia that do not generally require surgery but that can still cause patient death. Miller and Tucker (2014) showed that HIT usage was related to reduced infant mortality in US hospitals. Hyadri and colleagues (2019) showed that HIT use was related to decreased medical errors particularly for hospitals that were using them two or more years. Yuan, et al. (2019) observed that HIT use was associated with better process of care measure performance, but that it did not improve condition-specific readmission or mortality rates.

9.0 Conclusion

The outcomes studied, methods used, and the theoretical frameworks employed in the research of HIT reflect that the research has not matured greatly since the turn of the century. Much of the research in the early 2000s was conducted using a few custom created systems (Goldzweig et al., 2009). With commercially available HIT systems representing the vast majority of the HIT presently in use, there should be more homogeneity between the systems in use in the hospitals and the manner in which they provide value to the healthcare process. The Based on findings that investment in HIT (Devaraj & Kohli, 2003) and presence of HIT (Agarwal et al., 2010; Romanow et al., 2018) were insufficient to create the technology-performance link, the conversation in the literature should move forward to looking at how system maturity and use affect the value that can be received from HIT.

The study of the effectiveness of HIT is complicated by the complexity of the organizations, the complexity of the spectrum of care provided by a hospital, the complexity of the patients that they provide healthcare for, and the complexity of the processes involved in providing the healthcare to the patients.

CHAPTER III: STUDYING THE EFFECT OF THE USE OF ROUTINIZED HIT ON HOSPITAL COSTS

1.0 Introduction

Complexity in the healthcare environment stems from two primary sources, the patients (Safford et al., 2007) and the coordination of activities among many units and people within the units to provide care for the patients (Dobrzykowski & Tarafdar, 2015). Patient complexity, arising from patients' multiple clinical conditions as well as from social and economic factors including race, ethnicity and income levels, has a significant impact on patients' health as well as on hospital financial outcomes (Safford et al 2015, Peek, Baird, & Coleman, 2009). The racial disparity of health outcomes has been widely studied in the healthcare literature (DeSantis et al., 2017; Krieger, 2001; McLaren, 2021; Yedjou et al., 2019), and the health outcomes of poorer patients were seen to be worse (Barnett, et al., 2015). Moreover, complex patients generally have worse perceptions of their care and incur higher costs to provide that care (Krieger, 2001; Lynch & Smith, 2005). Healthcare researchers use the term "high-need, high-cost" (HNHC) patients which succinctly summarizes the established correlation between higher complexity and higher system utilization (Bilazarian, 2021) and thereby higher costs (Elixhauser et al., 1998). Some estimates for this relationship between complexity and cost are that 5% of the patient population accounts for 50% of the country's annual healthcare spending costs (Blumenthal, et al., 2016). The complexity of the patients that a hospital treats cannot be controlled or filtered by the hospital. Various federal laws such as Title VI of the Civil Rights Act of 1964 and the Age Discrimination Act of 1975, prevent hospitals from selecting patients with lower complexity to treat; therefore, the hospital must treat the patients that present for treatment. As higher complexity patients cost disproportionately more to treat, improvements in performance while treating these patients could provide the largest returns for the hospitals. Complex patients require more coordination and more communication among the members of the care team (Blumenthal et al., 2016). Caring for patients with multiple conditions (for example heart disease, hypothyroidism, and rheumatoid arthritis) in a hospital can involve many different people with specialized skills from multiple independent units working together to provide care. The coordination of care among these different units, and even the different individual caregivers who are working on shifts within the units, is among the many challenges a hospital faces in providing high quality care while maintaining costs. This challenge is particularly true for more complex patients with multiple chronic conditions and varied socio-economic backgrounds, who may need caregivers and specialists from multiple units to provide effective care for the variety of issues that these patients present (Blumenthal, et al., 2016). For example, a patient being treated for heart failure, could have fallen and fractured a hip and suffered renal insufficiency resulting from the sudden loss of heart function. Care for such patients requires the coordination of efforts and information among the cardiology, orthopedic, and nephrology units, which invariably involves additional costs.

The extant Healthcare Information Technology (HIT) literature that considers complexity predominantly views patient complexity as being wholly described by Case Mix Index (CMI), which is a metric that reflects the relative average cost for a hospital to treat its patients based on the illness and any additional comorbidities or other clinical complications (Karahanna et al., 2019). However, this operationalization of patient complexity does not directly consider demographic and socioeconomic factors that also affect the cost of providing care, or the ultimate health outcome for that care (Blumenthal et al., 2016; Safford et al., 2007). The greater uncertainty resulting from complexity in patients' characteristics and their care needs limits the health system's ability to plan and make decisions about activities in advance of their execution (Gardner et al., 2015). No studies were found that investigated the impact of the clinical, social, or economic dimensions of patient complexity on HIT enabled outcomes, nor was any Information Systems (IS) literature that addressed patient complexity beyond the consideration of CMI as a control variable. In this paper, we focus on the uncertainty that stems from the clinical, sociological, and economic condition of the patients.

In justifying the more than $25 billion allocated to reimburse hospitals for procuring and implementing HIT, the HITECH Act cited that the widespread use of HIT would improve the quality of health care, prevent medical errors, reduce health care costs, increase administrative efficiencies, decrease paperwork, and expand access to affordable health care (HealthIT.gov, 2008). Health information technology (HIT) involves the processing, storage, and exchange of health information in an electronic environment. (www.hhs.gov). Research has found that enhanced communication and interactions across units are facilitated by the use of routinized HIT which helps to mitigate medical errors, improve patient safety, and reduce costs associated with extended waiting periods and unnecessary medical treatments (Orszag & Emanuel, 2010). The enhanced communication and interactions across units, facilitated by the use of routinized HIT, have been found to help mitigate medical errors, improve patient safety, and reduce costs associated with extended waiting periods and unnecessary medical treatments (Orszag and Emanuel, 2010). These improvements have not consistently been observed in prior research. Agarwal et. al (2010) observed that the evidence supporting HIT's effect on performance was mixed, that is still the case as current research shows mixed results. The presence of HIT has been observed to increase the occurrence of missed nursing care (Piscotty et al., 2015) show positive effects when supporting clinical activities, negative effects when supporting administrative activities, and no significant effect on strategic activities (Bhattacherjee et al., 2007), improve adherence to medication schedules, and increase the observed mortality rate for children who were transported for specialized care (Han et al., 2005).

Modern medicine is extremely complex. There are more than 14,000 different diagnoses in the current coding scheme, International Statistical Classification of Diseases and Related Health Problems (ICD-10). More than 6,000 prescription drugs, and more than 4,000 medical and surgical procedures. Treating patients often involves caregivers from multiple hospital units. Further, patients are complex, they do not have a uniform response to treatments due to issues such as comorbidities that complicate treatment as well as differences in socioeconomic, cultural, behavioral, and environmental circumstances (Safford et al., 2007). Patient complexity and the complexity in the processes required to treat the patient create uncertainty as to the correct course of treatment. Further, it hinders the ability of healthcare providers to plan and make decisions about treatments and medications in advance (Gardner et al., 2015). To address this uncertainty, hospitals have implemented HIT that allows them to process volumes of information. This allows them to better monitor patient conditions (Romanow et al., 2018) and coordinate their care (Dobrzykowski & Tarafdar, 2015).

The study of the effectiveness of HIT started by investigating the effects of investing in HIT with early studies showing that investment in HIT leads to higher revenue (Ayal & Seidman, 2009; Devaraj & Kohli, 2003; Menon et al., 2000), and lower costs (Borzekowski, 2009; Menon et al., 2000); however further studies (Adler-Milstein et al., 2015; Appari et al., 2013; Jones et al., 2010; Yuan et al., 2019) showed less positive and less certain results. Investment in new HIT does not ensure that benefits will be gained. Routinized use of HIT is defined as “the interplay between technology and patterns of clinical work embodied in routines” (J. M. Goh et al., 2011). The process of routinization occurs after the deployment of an IS (Cooper & Zmud, 1990) and occurs through an incremental accumulation of experiences with the information system (Luo & Ling, 2013). In their study on the routinization of HIT in healthcare, Goh and colleagues studied the nature and evolutions of the process of routinization (J. M. Goh et al., 2011). However, empirical research providing evidence that describes the effect of routinization of HIT on the performance of the hospital is lacking in the literature. The purpose of this paper is to investigate how routinized HIT impacts a hospital’s cost performance when treating complex patients.

We have created what we believe is a novel panel data set comprised of HIT usage and system maturity information from the HIMMS database, hospital operating characteristic data published by the CMS, income data from the IRS, and population characteristics collected by the US Census Bureau to describe the effects. The resultant unbalanced panel contains 18,967 total observations from the 5,101 U.S. acute care hospitals for the four years from 2014 to 2017. We conceptualize patient complexity as having clinical, sociological, and economic dimensions to evaluate the impact of complexity on cost of care and how the use of routinized HIT can affect this relationship.

Using the multidimensional conceptualization of complexity led us to some unexpected observations. We found that while the cost of care did increase with higher levels of clinical complexity, cost of care tended to decrease with increased sociological and economic complexity. Further, we observed that the moderating effect of the use of routinized HIT and clinical complexity tended to reduce cost of care, while the routinized use of HIT tended to increase the cost of care for hospitals that served populations with higher sociological or economic complexity.

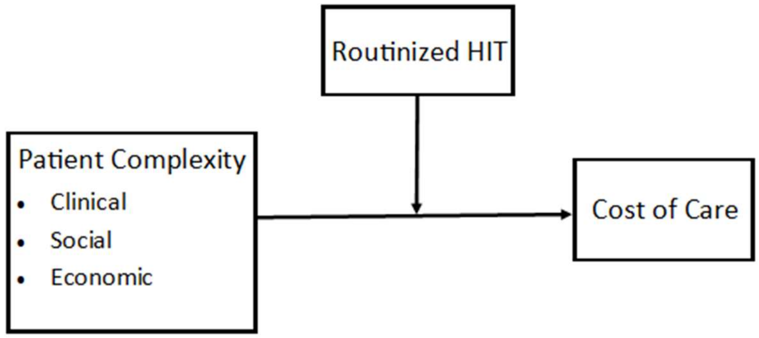
The remainder of the paper is organized as follows: we will discuss the theoretical background for the paper and develop hypotheses, we will then discuss the data set, the methods used to analyze the data, the results of the analysis, a discussion of the results, and end the paper with implications for research and practice, study limitations, and concluding remarks.

2.0 Theoretical Foundation

Hospitals operate in an uncertain environment. This uncertainty exists in the form of patient complexity, complexity in the process of coordinating care, and patients' non-uniform response to healthcare interventions. HIT has been implemented in hospitals to provide access to patient and treatment information, to coordinate care (Romanow et al., 2018), and to assist in clinical decision making (Kohli & Devaraj, 2004). In the information processing view of companies, organizations are structured around information and information flow to reduce uncertainty. Galbraith (1974) argued that to improve its performance in handling events that cannot be planned for in advance, organizations must adopt at least one of four information processing designs. These designs are to create slack resources, create self-contained tasks, invest in vertical information systems, and create lateral relations. In the hospital context, creating slack resources would mean hiring additional staff to assist in the information processing needs. An example of creating self-contained tasks would be apportioning care interventions so that a single person or team would have all the information needed and could accomplish the entire intervention. Investment in vertical information systems in the hospital would be the creation and deployment of integrated HIT systems that manage patient and care information in a way that facilitates patient care. The creation of lateral relations is similar to creating care teams that meet regularly. The first two of these information processing designs are intended to reduce the need for information processing as an organization handles unanticipated events, while the other information processing designs involve creating processes and mechanisms that increase the organization's capacity to acquire and process information, which is necessary for the increased demands of coordination and communication in managing complex tasks. Galbraith argued that unless an organization chooses one or some combination of these four information processing designs, it would have to accept lower performance.

While the study of HIT's impact on hospitals' performance remains on-going, the literature increasingly acknowledges that the use of HIT in the hospital is more important than the availability of HIT (Kohli & Tan, 2016; Setia et al., 2011). Routinized HIT creates processes and mechanisms that increase the capacity of the organization to acquire and process information. As the use of the HIT becomes routinized and embedded in the work processes of the healthcare providers, additional organizational benefits can be realized through improved organization and utilization of resources (J. M. Goh et al., 2011). The ability of HIT to influence a hospitals' cost performance in caring for complex patients is reliant upon their repeated use and assimilation into the work patterns of the caregivers, in other words the use of Routinized HIT. We investigate this relationship in this paper. The elements of the research model shown in figure 1 are explained in the sections below.

Figure 2 - Conceptual Model - Cost of Care.



2.1 The Role of Information in Healthcare

Galbraith (1974) proposed the information processing view of organizational design, later called the Organizational Information Processing Theory, which recognizes as a central tenet that the organization's reliance on efficient information processing has a direct relationship with the level of uncertainty of the task environment. "The greater the task uncertainty, the greater the amount of information that must be processed among decision makers during task execution in order to achieve a given level of performance." (Galbraith, 1974 pp. 28). Here, information processing includes gathering, interpreting, and synthesizing information to support decision making. Complex patients present multiple chronic conditions and come from varied socio-economic backgrounds, this creates a high-level of uncertainty for hospitals and makes pre-planning for their care challenging. Moreover, hospitals cannot control the complexity of the patients that they treat. In such dynamic and uncertain environments, hospitals must adopt mechanisms that increase information processing capabilities and coordinate action in order to achieve the level of cost efficiency required to remain financially viable (Galbraith, 1974).

Naylor, et al. (2011) identify that points of transition of patients, care providers and information contribute to high healthcare costs and low quality of care since the potential for errors or delays in the timely processing of information and the coordination of related tasks is much higher. Since complex patients with multiple chronic conditions (Blumenthal & Abrams, 2016; Rudin et al., 2016) exhibit different clinical problems, have diverse needs, and respond differently to different treatments (Willke et al., 2012), providing coordinated care for them is particularly challenging due to the unpredictability of outcomes from the dynamic interactions among their comorbidities (Wilson & Holt, 2001). Each patient presents a different set of comorbidities that may interact in different ways at different points in time (Hoogendoorn et al., 2016). Often these comorbidities are chronic conditions that interact with a variety of extraneous demographic and socioeconomic conditions that further impact the cost and quality of care for complex patients (Rudin et al., 2017). Treating complex patients through routine care programs that focus on individual conditions can result in uncertain quality of care.

While relatively fewer in number, complex patients incur high costs to a health system and are at high risk for poor health outcomes (Lipsitz, 2012). As a result, complex patients contribute a disproportionately high share of the nation's health care costs (Blumenthal, Bruce, Fulmer, John, & Jeffrey, 2016; Blumenthal & Abrams, 2016). Literature recognizes that complex patients need coordinated care from the multiple specialties and care services within the health system (Albert et al., 2015; Bodenheimer, 2008). Different units in the health system must interact with each other to perform the diverse range of operations required of the complex care management efforts needed to care for complex patients (Kannampallil et al., 2011; Tan et al., 2005). These activities are managed across the health system and rely on efficient information sharing for seamless delivery of effective care (Albert et al., 2015; Iezzoni et al., 2016). This relationship between patient complexity and the required response of the internal systems to deliver the required complexity of care, speaks to the critical role of effective information processing in delivering cost efficient and high-quality care for complex patients.

Hospitals invest a large amount of financial resources and care provider time to effectively manage care for complex patients. The delivery of healthcare, particularly for complex patients, is a highly interdependent task environment because the nature of coordination needs often change from one patient to another, as well as from one care episode to another. Clinical staff must improvise and adapt their actions and be responsive to each patient's emergent conditions. As high quality, safe and timely care for patients with chronic illness often requires services from multiple clinical and support departments, care providers must evaluate the specific needs of patients and adaptively coordinate their activities to address their patients' emergent needs. Greater uncertainty and complexity in patient characteristics and care needs limit the health system's ability to plan and make decisions about activities in advance of their execution (Gardner et al., 2015). Thus, healthcare organizations must increase their flexibility and adaptability and improve the coordination among the dynamically configured set of tasks across the health system, which is needed to provide effective care for the specific patient at fiscally viable levels of process efficiency. Mature HIT systems facilitate such coordination by providing the necessary information processing capability across the organization. Thus, we propose that, *use of routinized HIT will positively impact cost of care (H1).*

2.2 Patient Complexity

It has been established that more clinically complex patients generally have worse perceptions of their care and incur higher costs to provide that care (Krieger, 2001; Lynch & Smith, 2005). Our review of prior literature reveals that empirical research only considers clinical complexity as a measure of patient complexity, and it typically considers patient complexity as a control variable. The measure of patient complexity commonly seen in IS studies is Case Mix Index (CMI), which represents the relative effort and resources required to treat a patient with multiple clinical conditions (Carling et al., 2003). Little consideration is given in the IS and HIT literature on socio-economic factors that contribute to patient complexity, which may contribute to the mixed results seen in the prior literature. In this paper, we adopt a multidimensional view that includes clinical as well as socio-economic aspects that contribute to the complexity of patients and investigate the moderating effect of routinized HIT on the costs of treating complex patients. To the best of our knowledge, our investigation of the impact of a multidimensional conceptualization of patient complexity on hospitals' financial performance is novel in the HIT literature.

Clinical complexity is commonly conceptualized as comorbidities - the presence of two or more chronic conditions for a single patient. In healthcare and HIT research, clinical complexity is operationalized as the sum of chronic conditions a patient presents. This conceptualization treats conditions with discordant pathogeneses, where the comorbidities do not confound the treatment of each other (i.e. asthma and depression) in exactly the same ways as those with concordant pathogeneses, where the individual comorbidities do confound the course treatment (i.e. hypertension and heart disease). In this paper, we use a widely accepted definition of comorbidity - coexistence of two or more chronic conditions, where one is not necessarily more central than others (Zulman et al., 2014). Patients with multiple comorbidities, particularly where the conditions are chronic, tend to have frequent and intensive contact with the health care system (Eaton, 2015), thus there are more opportunities to monitor each of their conditions, to adjust treatment regimens, and to assess their general health maintenance needs (Higashi et al., 2007). At the same time, each additional condition generates opportunities for suboptimal management, including missed diagnoses, inadequate treatment, and access and communication barriers. This is even without the potential confounding of symptoms or misdiagnosis of underlying cause. If a patient has conditions that are discordant, there may be insufficient time or competing demands during a visit (Redelmeir et al., 1998; Kerr et al., 2008). Further, in this situation, the patient and their provider may disagree about which condition should be prioritized (Kerr et al., 2008; Zulman, et al. 2010). Additional challenges arise when patients have several clinicians involved in their care, increasing the likelihood of conflicting advice, redundant diagnostic tests and services as well as impractical or competing treatment regimens (Anderson, 2010). Therefore, we propose that *Clinical Complexity will negatively affect the cost of care (H2a)*.

While comorbidity generally refers to the presence of multiple clinical conditions, there is also growing recognition that a multitude of patient-level factors, independent of specific comorbid clinical conditions, may complicate care and affect outcomes for complex patients (Safford et al., 2007; Boyd et al, 2010; Nardi et al. 2007). For example, Safford et al. proposed a conceptual approach to complex patients that involves interactions between biological, socioeconomic, cultural, environmental, and behavioral forces as health determinants (Safford, 2007). Incorporating these dimensions into clinical assessments is likely to help ensure that care is aligned with patient's preferences, goals, and needs (American Geriatrics Society, 2012). This is a similar approach to the one proposed by Elixhauser et al. (1998). The HIT literature has not addressed other sources of patient complexity beyond clinical complexity.

The racial disparity in health outcomes has been widely observed and investigated in the literature (Levine et al., 2001; McLaren, 2021; Mensah et al., 2005; Mokdad et al., 2001; Yedjou et al., 2019). These studies show that health outcomes for minority populations are worse for conditions ranging from breast cancer to COVID-19. There are observed differences in accessibility, utilization and quality of care between majority and minority racial groups (Williams and Collins, 1995). There is also an array of cultural based predispositions with respect to receiving health care and even its underlying cause (Vaughn et al., 2009). Therefore, we propose that *Social Complexity will negatively affect the cost of care (H2b).*

Fitzpatrick et al. (2015) found that poorer patients were much more likely to be in the groups with the highest needs and highest costs for care. Again, as with social complexity, access to health care, and sporadic utilization of healthcare resources have also been cited as reasons behind the disparity in healthcare outcomes for economically disadvantaged patients. Williams and Collins (1995) argue that although racial factors influence health outcomes, economic inequality is the major driving force behind the widening health disparities. As such, we propose that *Economic Complexity will negatively affect the cost of care (H2c).*

2.3 Health IT Routinization

Much of the prior research concerning sustained use of technology has been concerned with the users' intentions of continuing to use a program or system (Bhattacherjee, 2001; Limayem et al., 2007). This research stream was significant when hospitals were transitioning from paper records to electronic records. The HIT systems that were implemented were custom in-house created systems that were often used in parallel with their paper counterparts (Haux, 2006). Today, the move to digital records has occurred with over 95% of all General Acute Care hospitals having implemented HIT (ONC, 2021). Healthcare providers use the information systems that hospital administration provides to complete their daily tasks in treating patients, whether that is a paper record or a full featured, fully integrated HIT environment; therefore, the approach of sustained use from these prior studies is not appropriate for our context.

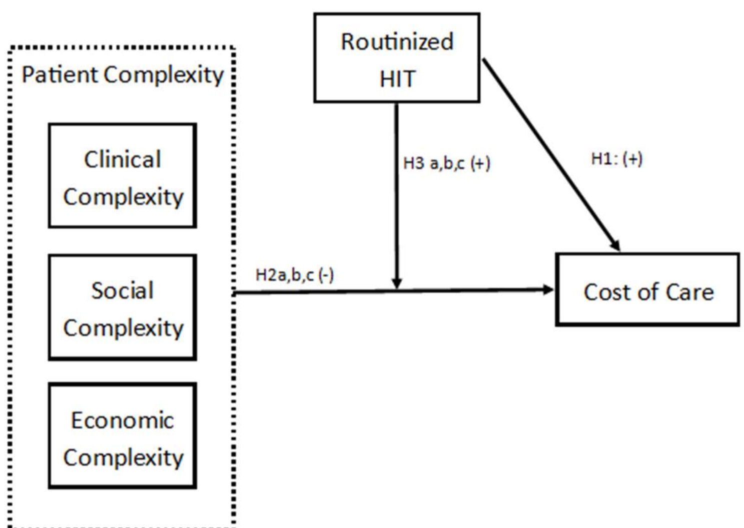
The implementation of Information Systems has been conceptualized as a 6 stage process: initiation, adoption, adaptation, acceptance, routinization, and infusion (Cooper & Zmud, 1990). Routinization occurs through the incremental accumulation of experience (Luo & Ling, 2013). Routinization was conceptualized as a stage that occurred after the adaptation and acceptance of the Information System in the organization. Routinization is characterized as a special form of system exploitation that requires little additional learning and promotes efficiency advantages as it becomes part of the daily work in the organization (Cooper & Zmud, 1990; Luo & Ling, 2013). In literature that investigates the process of realizing value from IS, routinization is described as a state where the IS has become normalized into the work process (Saga & Zmud, 1994). The definition of routinization has been further refined to mean the extent to which interfirm activities follow *regular* and *repetitive* patterns (M. S. Feldman, 2000). In a healthcare context, routinization has been defined as "*the interplay between technology and patterns of clinical work embodied in routines*" (J. M. Goh et al., 2011; K. T. Goh & Pentland, 2019). We will adopt this definition as our working definition of routinization.

Goh et al. (2011) describe a process of changing work patterns that occurs by removing the affordances from a legacy system when it is replaced and gaining a new set of affordances when a new system is installed. The change in the performance of the hospital comes from the change in work processes when HIT is incorporated into the clinical routines of the hospital (J. M. Goh et al., 2011). There is also a time investment that is required to adapt to these new patterns and make them part of the clinical routine. Time is required to disrupt the patterns and routines that were afforded in the old context as well as to establish and embrace the patterns and routines afforded by the new HIT (Polites & Karahanna, 2013). This time requirement may also contribute to the mixed results seen in prior research that investigated the effects of HIT in hospitals (DesRoches et al., 2010; Devaraj & Kohli, 2000; Jha et al., 2009; Tsai & Jha, 2014). We propose that, *the use of routinized HIT will positively impact the relationships between Clinical Complexity (H4a), Social Complexity (H4b), and Economic Complexity (H4c) and cost of care.*

2.4 Research Model

Using the lens of the Organizational Information Processing Theory (Galbraith, 1974), we constructed the following model to test the hypotheses concerning the impact of Routinized HIT on the financial outcomes of the hospital while managing the uncertainty presented by multidimensional patient complexity. Included on the diagram in Figure 2 are our hypotheses and their expected direction of affect.

Figure 3 - Research Model - Cost of Care.



3.0 Data and Research Design

3.1 Data

The unit of analysis in this study is the U.S. acute care hospital. We collected secondary data from multiple sources for the four calendar years from 2014 to 2017 for the 5,101 U.S. acute care hospitals included in the CMS database as of 2017 resulting in an unbalanced panel containing 18,967 observations. The data is panel data as values for the same set variables were collected annually, however it is unbalanced as not all hospitals reported values in each of the reporting periods. Unbalanced panel data was used to maximize the observed variability in the data.

The data set from the CMS did not include data that would allow us to study the effects of socio-economic complexity, so we had to find ways that would allow us to approximate the social and economic attributes of the patients that the hospital treated while maintaining the hospital as the unit of analysis. As our collected data is at the individual health care facility, we approximated the sociological, and economic composition of the patient populations by taking measures for these parameters from the populations that the health care facilities serve. We used weighted averages for these values based on the ZIP codes of the patients treated by the hospital for each of the four years considered in the study. The exact number of patients treated by ZIP Code is annually reported by the CMS. The data source and the manner in which the socio-economic values were calculated are described in 3.3.2 and 3.3.3, below.

Information concerning IS usage and financial results were extracted from the Healthcare Information and Management Systems Society (HIMSS, previously the Dorenfest Institute for Health Information Technology Research) database. The HIMSS database is a nationally representative survey that includes meta data, IT usage metrics, and operational data from over

5000 hospitals. Operating expense information for each of the four years was converted to 2012 dollars using the CPI for hospital inpatient services, as compiled by the USDA Economic Research Services, to remove the effects of inflation. We extracted CMI and some of the controls from the CMS Impact File. Final adjusted values were used from the CMS Impact files when they were available from the CMS.

3.2 Cost of Care

In this study, we focus on the moderating role of the use of routinized HIT on the relationship between a multidimensional patient complexity and measures of a hospital's financial efficiency; therefore, we have selected Cost of Care as the appropriate dependent variable.

Cost of care is a commonly used measure of hospital effectiveness (DesRoches et al., 2010). In this study we normalized the total operating costs of the hospital by the number of active beds. Devaraj and Kohli (2000) found evidence of the positive effect of IT capital and labor on outcome measures among hospitals. However, other researchers did not observe this relationship between IT and firm performance (Barua et al., 1995; Strassman, 1990). We chose this measure of hospital effectiveness to examine the overall firm impacts of Routinized HIT. To calculate the cost of care, we convert each hospital's total inpatient operating charges for their fiscal years to 2012 U.S. dollars using the consumer price index for inpatient hospital services. We then divide these inflation-adjusted inpatient charges by the total number of active inpatient beds at the hospital reported for the time period. To produce a normally distributed form of the data we took the natural log of the Total Expense ($TE_{i,t}$) for each hospital, i, over each time period, t, divided by the number of beds at the hospital ($B_{i,t}$). So, Cost of Care ($BE_{i,t}$) is calculated by

Equation 1 - Cost of Care

$$BE_{i,t} = \ln\left(\frac{TE_{i,t}}{B_{i,t}}\right).$$

For our outcome variable, Cost of Care, the value is modeled based on:

Equation 2 - Empirical Model - Cost of Care

$$Cost\ of\ Care = \boldsymbol{\beta_k}\ \boldsymbol{Complexity_{it}} + \boldsymbol{\beta_l X_{it}} + \beta_1\ Routinized\ HIT_{it}$$
$$+ \beta_2(\ Routinized\ HIT\ x\ Complexity)_{it} +\ \gamma_i + \delta_t +\ \varepsilon_{it}$$

Where,

$\boldsymbol{\beta}_k$ = vector of estimators for measures of complexity

$\mathbf{Complexity}_{it}$ = vector of the three dimensions of patient complexity, Clinical Complexity, Social Complexity and Economic Complexity

$\mathbf{X}_{it}$ = vector of control variables for the hospital including, Hospital size, Teaching Intensity, Magnet Status, and Outlier Payments

Routinized HIT = measurement of length of time hospital has been using a mature HIT environment

γ_i = hospital fixed effect

δ_t = fixed effects of time

ε_{it} = observation specific error term

3.3 Independent Variables

In the framework for patient complexity proposed by Safford and colleagues (2007), they show that the "determinants of health include biology/genetics, socioeconomics, culture, environment/ ecology, behavior, and the medical system". In their vector model of patient complexity, they describe each of these determinants of health to be additive and variable from customer to customer. The Vector model of Complexity proposed by Safford and her colleagues is the only model that we found that provides insight into how the dimensions of complexity might interact and be combined. We have adopted the Vector Model of Patient Complexity as our model for patient complexity.

3.3.1 Clinical Complexity (CC)

The Case Mix Index (CMI) is the average relative Medicare Severity-Diagnosis Related Group (MS-DRG) weight of a hospital's inpatient discharges, calculated by summing the MS-DRG weight for each discharge and dividing the total by the number of discharges (www.cms.gov). The case-mix index is a gauge of the comparative cost needed to treat a patient group in a hospital within a time-period, usually a calendar year. An index of one indicates that it costs the national average amount of resources per patient to treat the hospital's specific patient group. A hospital that performs higher cost care or has more resource intensive operations, such as neurosurgery or cardiac surgery, has a higher CMI compared with another that performs less costly care. The CMI reflects the diverse clinical complexity and resource needs of all the patients in the hospital treated over a certain time-period. A higher CMI indicates a more complex and resource-intensive case load. Although the MS-DRG weights, provided by the Centers for Medicare & Medicaid Services (CMS), were designed for the Medicare population, they are applied here to all discharges regardless of payer. In most of the extant literature that considers the variability of patients, CMI is used as a control variable (I. Bardhan et al., 2015; I. R. Bardhan & Thouin, 2013; Setia et al., 2011) to adjust for the difference in complexity of patients treated by the hospital. Horn et al. (1985) showed that higher CMI was related to higher costs of treatment. We used the final adjusted CMIs reported by the CMS for each of the hospitals in our data to represent clinical complexity.

3.3.2 Sociological Complexity (SC)

The racial disparity of health outcomes has been widely studied in the healthcare literature (Yedjou et al., 2019; DeSantis et al., 2017). These studies show that the healthcare outcomes that minority populations achieve are inferior to those of the majority population. As Sociological complexity has not been addressed by the HIT literature, a measure of sociological diversity was made using the racial disparity, which was calculated by summing the percentages of minority populations for a given ZIP code and using these percentages in a weighted average calculation based on the ZIP Codes reported for the patients that were treated by the hospital for that year. The number of patients seen from a particular ZIP Code was multiplied by the percentage of minority population for the ZIP Code and summed across all ZIP Codes that had patients treated by the hospital. This sum was then divided by the total number of patients seen for that year by the hospital to arrive at the poverty level of the patients treated by the hospital.

3.3.3 Economic Complexity (EC)

Researchers have considered the impact of EC on health care costs and health outcomes. Barnett, et al (2015) saw that poorer patients had worse health outcomes. Su, et al.(2006) found that lower income patients had lower overall utilization of the healthcare system but incurred higher costs when they did seek care. Because the HIT literature has not addressed economic complexity, the measure of economic complexity was calculated by dividing the number of tax returns that had an Adjusted Gross Income (AGI) of less than $25k by the total number of returns submitted by ZIP Code for each of the four years considered in the study. The number of patients seen from a particular ZIP Code was multiplied by the percentage of returns with an AGI less than $25k for the ZIP Code and summed across all ZIP Codes that had patients treated by the hospital. This sum was then divided by the total number of patients seen for that year by the hospital to arrive at the poverty level of the patients treated by the hospital.

We modeled cost of care with and without interactions between the three dimensions of patient complexity. This allowed us to confirm that there were no interactions between the three dimensions of complexity. This finding is consistent with Safford et al.'s (2007) Vector Model of Complexity.

3.4 Routinized HIT

Information System Maturity Models have been conceptualized as an idealized set of hierarchical benchmarks that allow organizations to evaluate their capabilities (Poeppelbuss et al., 2011). In general, maturity models are constructed such that progressing through the maturity model brings increased benefit to the organization and that regressing to a prior stage is usually very difficult. (Solli-Sæther & Gottschalk, 2010). Maturity models became especially popular with the emergence of the Capability Maturity Model (CMM) in the late 1980s (Paulk et al., 1993). Iverson et al. (1999) described the purpose of maturity models as providing a set of requirements to support internal or external assessment, benchmarking and a roadmap for system or organizational improvements. HIT and organizational maturity are not concepts often studied in the HIT literature but they are concepts that should be considered as they impact the organization's ability to realize value from their HIT investments (CMMI Institute, 2022).

The Electronic Medical Record Adoption Model (EMRAM) developed by the Healthcare Information and Management Systems Society (HIMSS) is an eight stage (Stages 0-7) cumulative measure of the availability and use of various HIT within the organization (www.himss.org). According to HIMSS, "Measuring evidence-based data at each stage, organizations use EMRAM to optimize digital work environments, improve performance and financial sustainability, build a sustainable workforce, and support an exceptional patient experience. Leveraging information digitally improves patient safety and clinician satisfaction by reducing errors in care, length of stay for patients and duplicated care orders, and streamlining the access and use of data to inform care delivery." (https://www.himss.org/what-we-do-solutions/digital-health-transformation/maturity-models/electronic-medical-record-adoption-model-emram). In the EMRAM, Stage 6 is the first point where external validation by HIMSS certified auditors is required. For a hospital to achieve Stage 6 they must have all critical systems installed including full physician documentation, tracking of nurse order and task completion with clinical decision support (CDS) that at least performs rudimentary conflict checking and a second stage CDS related to evidence-based medicine protocols. Achievement of the EMRAM Stage 6 milestone indicates that a hospital is committed to improving patient safety, improving health outcomes, the move to a paperless health record, and overall integration of HIT in the operations of the hospital (Kilborn, 2019). We use the number of years after achieving EMRAM Stage 6 certification from the HIMMS trained auditor as the measure of time that a hospital has been working in a mature HIT environment. To the best of our knowledge, our use of EMRAM to represent the routinization of HIT in hospitals is both novel and timely considering the ten years since the CMS has mandated the use of HIT in hospitals.

3.5 Control variables

Our analysis includes four time-varying controls: hospital size, teaching intensity, magnet hospital status, and outlier payments. Hospital size is measured by natural log of the number of beds actively in use within the hospital. Teaching intensity is calculated as a ratio of medical residents per bed, teaching intensity is seen as having a direct impact on process quality and thereby cost of care (Theokary & Ren, 2011). Magnet hospital status, is an indication of hospitals that have nursing programs focused on “setting the standard for excellence through leadership, scientific discovery and dissemination and implementation of new knowledge” (www.nursingworld.org). Magnet hospitals are more likely to achieve routinization of HIT faster than non-magnet hospitals (Armstrong, et al., 2009). Outlier Adjustment Factor reflects exceptionally costly cases treated by the hospital during the time period which might bias the cost of care calculation (Jha et al., 2009). The Outlier Adjustment Factor is calculated and reported by the CMS. A factor for year is also included to capture any pertinent year effects.

A summary of the data is presented in Table 1 and the pairwise correlation table is presented as Table 2. The summary statistics are calculated across all the 18,967 observations between 2014 to 2017 covered in this study.

Table 1 - Summary Statistics -Cost of Care.

`	Median	Mean	Std Dev
1. Cost of care	654793.20	789785.57	691490.74
2. CMI	1.514	1.533	0.327
3. % Non-white	0.2167	0.2538	0.1609
4. Poverty Rate	0.638	0.632	0.073
5. Time HIT Routinized (Yrs)	0	0.769	1.596
6. Number of Beds	98	170.419	192.722
7. Teaching (Y/N)	0	0.10	0.31
8. Teaching Intensity	0	0.044	0.136
9. Magnet Hospital	0	0.089	0.284
10. Outlier Payments	0.008	0.027	0.076

(n= 18,967).

Table 2 - Pairwise Correlation Matrix - Cost of Care.

	1	2	3	4	5	6	7	8	9	10
1. Cost of Care	1									
2. CMI	0.36	1								
3. %non-white	0.019	0.12	1							
4. Poverty Rate	-0.29	-0.17	0.22	1						
5. Time Routinized (Yrs)	0.16	0.15	0.019	-0.18	1					
6. Hospital Size	0.075	0.47	0.24	0.0047	0.2	1				
7. Teaching (Y/N)	0.052	0.15	0.13	0.015	0.024	0.29	1			
8. Teaching Intensity	0.24	0.29	0.28	0.03	0.14	0.5	0.26	1		
9. Magnet Hospital (Y/N)	0.17	0.22	0.01	-0.18	0.15	0.36	0.1	0.21	1	
10. Outlier Payments	0.35	0.27	0.11	-0.061	0.0089	0.16	0.043	0.18	0.099	1

4.0 Analysis and Results

We used the plm package in R to analyze this un-balanced panel data. The plm package is a set of estimators and tests for panel data econometrics, as described in Hsiao (2022) and Croissant and Millo (2018). The data analysis included reviewing models that included interaction terms between the component dimensions of Patient Complexity. No significant interactions were seen in the moderated or unmoderated versions of the models for the outcome variable. This finding is consistent with the Vector Model of Complexity proposed by Safford and colleagues (2007). As the concepts for the dimensions of complexity are orthogonal in the Vector Model of Complexity, we are able to treat each dimension separately in independent hypotheses. Cost of Care was modeled with the multi-dimensional conceptualization of Patient Complexity and the control variables. A definite relationship between each of the dimensions of complexity and the outcome was seen prior to adding the effect of routinized HIT.

In considering the possibility of hospital level effects, we modeled cost of care using both fixed-effects and random effects estimators. A Durbin–Wu–Hausman test result indicates that modeling hospital-level the random effects estimators are most appropriate for this analysis ($\chi^2(13) = 7.984\text{e-}11$, $p \sim 1$). The parameters in a fixed effects model are all fixed or non-random quantities, where the parameters in a random effects model are all considered to be random (Greene, 2018).

Table 3 - Random Effects Estimates for Cost of Care Model.

	Without Routinized HIT	With Routinized HIT
Clinical Complexity (CC)	1.220*** (0.0237)	1.214*** (0.0245)
Social Complexity (SC)	-0.034*** (0.0065)	-0.040*** (0.0072)
Economic Complexity (EC)	-1.865*** (0.0569)	-1.744*** (0.0644)
Routinized HIT		0.069** (0.0210)
Hospital Size	-0.166*** (0.0056)	-0.178*** (0.0056)
Teaching Intensity	0.987*** (0.0371)	0.963*** (0.0372)
Magnet Hospital	0.155*** (0.0136)	0.147*** (0.0134)
Outlier Payments	0.715*** (0.0709)	0.789*** (0.0701)
Year: 2015	-0.032** (0.0115)	-0.404*** (0.0115)
Year: 2016	-0.326*** (0.0116)	-0.057*** (0.0117)
Year: 2017	0.030** (0.0117)	-0.007 (0.136)
CC*Routinized HIT		-0.079*** (0.0136)
SC*Routinized HIT		0.010*** (0.0035)
EC*Routinized HIT		0.042 (0.0298)
Adjusted R^2	0.3760	0.3930

CC: Clinical Complexity, SC: Sociological Complexity, EC: Economic Complexity
Robust Standard Errors in Parentheses
Signif. codes: *** p<0.01, ** p< 0.05,* p< 0.1

As expected, the clinical complexity showed a negative effect on cost of care in both models. The relationship between social complexity and cost of care as well as the one between economic complexity cost of care were opposite to the expected direction of effect. The direct effect of Routinized HIT was seen to increase the cost of care, while the indirect effect of Routinized HIT was to work against the primary effects of each of the dimensions of patient complexity. In other words, the moderating effect of Routinized HIT tended to decrease the cost of care for hospitals that treated more clinically complex patients while increasing the cost of care for hospitals that treat higher socially complex and economically complex patients.

5.0 Discussion of Results

This study examines the ability of use of routinized HIT to influence the relationship between a multi-dimensional view of patient complexity and outcomes for the hospital as measured by economic effectiveness and the patient's perception of care. The relationships that were observed and their implications as shown in Table 4.

Table 4 - Hypothesis Summary - Cost of Care.

	Hypothesis	Result	Implication
H1	Sustained use of routinized HIT will positively impact Cost of Care.	Unsupported	The direct effect of the Use of Routinized HIT was significant ($P<0.01$) and seen to increase the Cost of Care.
H2a	Clinical Complexity will negatively affect the Cost of Care of the hospital.	Supported	Hospitals could be optimizing the operations of their HIT to manage the effects of CC on expenses.
H2b	Social Complexity will negatively affect the Cost of Care of the hospital.	Unsupported	Hospitals that treat more socially diverse populations tend to have lower expenses per bed.

H2c	Economic Complexity will negatively affect the Cost of Care of the hospital.	Unsupported	Hospitals that treat populations with higher poverty rates tend to have lower expenses per bed.
H3a	The use of routinized HIT will positively impact the relationship between Clinical Complexity and Cost of Care.	Supported	The moderating effect of the Use of Routinized HIT was to decrease the expenses per bed for the hospitals that treated patients with higher clinical complexity.
H3b	The use of routinized HIT will positively impact the relationship between Social Complexity and Cost of Care.	Unsupported	The moderating effect of the Use of Routinized HIT was seen to be significant ($p<0.01$) and was shown to increase the expenses per bed for the hospitals that treated patients with higher social complexity.
H3c	The use of routinized HIT will positively impact the relationship between Economic Complexity and Cost of Care.	Unsupported	There was no evidence seen to support this relationship.

Although research suggests that the use of routinized HIT should improve healthcare effectiveness, and quality of care (Devaraj et al., 2013; J. M. Goh et al., 2011), the results of this analysis do not consistently support that statement. The care for patients that are more complex due to Clinical and/or Socio-economic factors do not always see these expected benefits. Although the research was primarily interested in the moderating effect of the routinized us of HIT it is also interesting to note that its direct effect was to increase Cost of Care (*H1*). The indirect effect of use of routinized of HIT overcomes the negative pressure from the direct effect for hospitals that have had more time using routinized HIT and/or treat patients with higher clinical complexity.

The model provided strong evidence that Clinical Complexity did increase Cost of Care. This result supports *H2a* and confirms observations seen in prior research (Lipsitz, 2012; Wilson & Holt, 2001). However, even though the estimators were seen to be significant for the relationships of Sociological Complexity and Economic Complexity and Cost of Care, they were in the opposite directions of the expectations. This means that *H2b* and *H2c* are not supported by the model. There has been a study (Hayes, 2016) that uses data from the Medical Expenditure Panel Survey, which is administered by the Agency for Healthcare Research and Quality, which observes that the minority races are underrepresented in the population of patients that are the most expensive to treat. More investigation may need to be conducted to determine the expected direction of the effect of Sociological Complexity on Cost of Care.

The moderating effect of the use of Routinized HIT on relationship between clinical complexity and Cost of Care (*H3a*) was seen to be significant ($p<0.01$), and it had a tendency to decrease the Cost of Care for the hospital. The moderating effect of the use of Routinize HIT did tend to work against the established relationship between SC and EC with Cost of Care, however, since the initial relationships were not in the expected direction of effect, these moderating effects were also in the opposite directions; therefore, *H3b* and *H3c* are unsupported. This is opposite the expected direction of effect and contrary to the expectations of the CMS, HIMSS, and the HITECH Act. The most unexpected implication of this observation is that there is not a lessening of this effect over time. This could imply that the HIT are bespoke systems, as the expectation for Configurable Off The Shelf (COTS) systems would be that the operating costs would decrease after system acceptance and through the routinization and infusion stage of system deployment. Use of routinized HIT did appear to reduce the effects of social complexity over time.

6.0 Conclusion

6.1 Contributions to Theory

Extant literature that considers the use of HIT is primarily concerned with investment in HIT or use of HIT, our study contributes to the conversation by explaining how the routinized use of HIT impacts a hospitals ability to manage complex patients efficiently. This research adds to the research streams on Routinized HIT and Routinized IS by providing empirical evidence that routinization of information systems does have an impact on the outcomes of an organization and it confirms the mixed results that have been seen previously (Agarwal et al., 2010). This research also adds to the HIT literature by operationalizing a multi-dimensional view of patient complexity. Other research has viewed only the clinical dimension of complexity and has used it as a control variable. We have brought understandings developed by healthcare researchers front and center into the HIT. Further, we have shown researchers a model that allows for the incorporation of additional dimensions of complexity into their models. Conceptualizing patient complexity in a richer manner than the traditional approach of using CMI as a control variable will give researchers a deeper understanding of the variability within the patient population and allow for better modeling of systems that involve healthcare outcomes. We also found no other research that leverages the CMS data to establish a portrait of the patient demographic profile based on the location of the patients treated rather than an equal average of the patients in the hospital's catchment area. The counterintuitive findings regarding the effect of sociological and economic diversity add to the literature on healthcare disparity. These findings suggest that there may be other factors that impact the cost of care at hospitals that serve patient populations with high sociological or high economic complexity. The findings concerning the indirect effects of routinized use of HIT suggest that hospitals have focused their attention on addressing clinical complexity in their HIT implementations and have not yet begun to use HIT to address the healthcare issues that arise from sociological and economic complexity.

6.2 Contributions to Practice

One of the more important implications that these results have for practitioners is that there are additional economic benefits that can and should be realized through their use of routinized HIT. The sign of the indirect effect of the use of routinized HIT on the relationship between economic complexity and cost of care could indicate that the push for hospitals to complete digital transformations is creating a digital divide for poorer patients. Although hospitals may see a short-term decrease in the expense to deliver information, there are long-term implications if all patients don't have access to these communications. For example, if a hospital sends a notification for a follow-up visit to the patient portal for a patient that does not have easy access to the internet, the patient may not receive the notification and miss the appointment as well as opportunities to reschedule.

6.3 Limitations and Conclusion

There are some limitations to this research, as well as additional questions that this research points toward. One of the largest limitations is the limit to the patient level data that can be gathered to add richness to the conceptualization of patient complexity while performing a hospital level study. The data set for this research was limited by the available data, so the 4-year window may not have been broad enough to accurately track the effects of the routinized HIT as hospitals incorporated the HIT use into their daily operations. There were only a handful of datapoints where a hospital had achieved their EMRAM Stage 6 certification 5 years or more prior to the dataset. This would reduce the influence of these datapoints in the calculation of the estimators. The observed economic effectiveness results along the economic dimension of patient complexity suggest that additional study may be warranted into the cause of the difference in costs, and whether or not this difference in economic effectiveness has an impact on the health outcomes for those patients or if there are strategies that were developed in these hospitals that allow for improved performance. Also, studies that track individual hospitals performance as they achieve EMRAM Stage 6 and routinize the use of HIT in their operations could give greater insight into the difference in performance across hospitals and point toward the antecedents of leveraging HIT use to achieve better healthcare outcomes for the hospitals and their patients. Further, the direction and magnitude of the indirect effects of the use of routinized HIT for hospitals that treat higher social complexity and economic complexity populations suggests a study focusing on the effect of use of routinized HIT on underserved areas.

CHAPTER IV: STUDYING THE EFFECT OF THE USE OF ROUTINIZED HIT ON HOSPITAL QUALITY OF CARE

1.0 Introduction

Hospital readmission rates and mortality rates have direct implications for patients and hospitals. Hospital readmission and mortality rates have long been considered indicators of quality of care and hospital performance, as well as having implications for hospital costs (Anderson et al., 1984; Gruneir et al., 2011; Lin et al., 2018). Beyond the quality of care provided to patients, factors such as inefficient care coordination and ineffective communication with patients contribute to higher readmissions (McCormack et al., 2013) and mortality rates (Hachem et al., 2014). Researchers have refuted the validity of using mortality rates as an indicator of quality of care (Goodacre et al., 2015; Thomas & Hofer, 1999), arguing that only mortality rates that are risk-adjusted for individual characteristics such as age, comorbidities, and diagnosis are valid as quality of care indicators. These arguments show that patient characteristics are important to consider when investigating interventions that might influence quality of care measures. In their 2008 report to Congress, the Medicare Payment Advisory Commission (MEDPAC) estimated that avoidable readmissions cost Medicare $12 billion annually (MEDPAC, 2008). The CMS estimated that since the beginning of the Hospital Readmission Reduction Program (HRRP) in October of 2012, hospitals have lost roughly $2 billion through reimbursement reductions by the Centers for Medicare and Medicaid Services (CMS) if they did not meet their target readmission rates (MedPAC, 2018). Mortality rates also affect patients' decision making and hospital utilization rates as these measures are available to the public on the Hospital Compare website (https://www.cms.gov/Medicare/Quality-Initiatives-

Patient-Assessment-Instruments/HospitalQualityInits/HospitalCompare), maintained by the CMS. Hospitals invest a large amount financial resources and care provider time to effectively manage readmission and mortality rates for complex patients.

Complexity in healthcare stems from two primary sources, the patients (Safford et al., 2007) and the coordination of activities among many units and people within the units to provide care for the patients (Dobrzykowski & Tarafdar, 2015). Patient complexity, arising from patients' multiple clinical conditions as well as from social and economic factors including race, ethnicity and income levels, has a significant impact on patients' health as well as on hospital financial outcomes (Safford et al 2007, Peek, Baird, & Coleman, 2009). The racial disparity of health outcomes has been widely studied in the healthcare literature (DeSantis et al., 2017; Krieger, 2001; McLaren, 2021; Yedjou et al., 2019), and the health outcomes of poorer patients were seen to be worse (Barnett et al., 2015). Moreover, complex patients generally have worse perceptions of their care and higher costs to provide that care (Krieger, 2001; Lynch & Smith, 2005). Healthcare researchers use the term "high-need, high-cost" (HNHC) patients which succinctly summarizes the established correlation between higher complexity and higher system utilization (Bilazarian, 2021) and thereby higher costs (Elixhauser et al., 1998). Some estimates for this relationship between complexity and cost are that 5% of the patient population accounts for 50% of the country's annual healthcare spending costs (Blumenthal, et al., 2016).

The complexity of the patients that a hospital treats cannot be controlled or filtered by the hospital. Various federal laws such as Title VI of the Civil Rights Act of 1964 and the Age Discrimination Act of 1975, prevent hospitals from selecting patients with lower complexity to treat; therefore, the hospital must treat the patients that present for treatment. Complex patients are at a higher risk for poor health outcomes (Lipsitz, 2012). Complex patients require more coordination and more communication among the members of the care team (Blumenthal et al., 2016). Caring for patients with multiple comorbid conditions (for example heart disease, hypothyroidism, and rheumatoid arthritis) in a hospital can involve many different people with specialized skills from multiple independent units working together to provide care. The coordination of care among these different units, and even the different individual caregivers who are working on shifts within the units, is among the many challenges a hospital faces in providing high quality care while maintaining costs (Senot, et al., 2016). This challenge is particularly true for more complex patients with multiple chronic conditions and varied socio-economic backgrounds, who may need caregivers and specialists from multiple units to provide effective care for the variety of issues that these patients present (Blumenthal, et al., 2016). For example, a patient being treated for heart failure, could have fallen and fractured a hip and suffered renal failure as a resulting from the sudden loss of heart function. Care for such patients requires the coordination of efforts and information among the cardiology, orthopedic, and nephrology units, which becomes a complex web of interdependent and sometimes competing interventions. For example, the management of chronic airways disease with corticosteroids may increase the likelihood of heart failure. The care of these competing health needs often lead to conflicting instructions, medication discrepancies, and lack of follow-up appointments with primary care providers after hospitalizations (Van Cleave et al., 2013). This creates uncertainty in the ultimate health outcome for the patient and tends to lead to higher hospital readmissions (Jencks, et al., 2009). The extant Healthcare Information Technology (HIT) literature that considers complexity predominantly views patient complexity as being wholly described by Case Mix Index (CMI), which is a metric that reflects the relative average cost for a hospital to treat its patients based on the illness and additional comorbidities or other clinical complications they may present (Karahanna et al., 2019). However, this operationalization of patient complexity does not account for socioeconomic factors that also affect the ultimate health outcome for the patient receiving the care (Blumenthal, Bruce, Fulmer, John, Jeffrey, et al., 2016; Safford et al., 2007). Greater uncertainty resulting from complexity in patient characteristics and care needs limit the health system's ability to plan and make decisions about activities in advance of their execution (Gardner, et al., 2014). In this paper, we focus on the uncertainty that stems from the clinical, social, and economic condition of the patients and how this uncertainty manifests in the quality of care patients receive.

In justifying the more than $30 billion allocated to reimburse hospitals to procure, implement and use HIT effectively in healthcare providers' operations, the Health Information Technology for Economic and Clinical Health (HITECH) Act espoused that the widespread use of HIT would improve the quality of care for patients, reduce or prevent medical errors, reduce health care costs, increase administrative efficiencies, decrease paperwork, and expand access to affordable health care (HealthIT.gov, 2008). Health information technology (HIT) involves the processing, storage, and exchange of health information in an electronic environment. (www.hhs.gov) typically through the use of electronic health records (EHRs). The federal investments made through the HITECH Act increased the rate of adoption of EHRs from 3.2% in 2008 to 14.2% in 2015. By 2017, 86% of office-based physician practices had adopted an EHR and 96% of non-federal acute care hospitals has implemented certified health IT (Office of the National Coordinator, 2018). As the hospitals have had their HIT systems in place for more than five years, using the HIT has become part of the process of providing care.

When the HIT becomes engrained into the routines of work, and its use is regular and repetitive the use is said to be routinized (Feldman, 2000). The use of routinized HIT facilitates and enhances communication and interactions across units which helps to mitigate medical errors, improve patient safety, and reduce costs associated with extended waiting periods and unnecessary medical treatments (Orszag and Emanuel, 2010). However, these improvements have not consistently been observed in prior research, which shows mixed results. The results of some studies supported the claim that HIT improved readmission rates (Muchiri et al., 2022; Yuan et al., 2019), have no impact on mortality rates (Yuan et al., 2019) and increase the observed mortality rate for children who were transported for specialized care (Han et al., 2005).

Modern medicine is extremely complex. There are more than 14,000 different diagnoses in the current coding scheme, International Statistical Classification of Diseases and Related Health Problems (ICD-10). More than 6,000 prescription drugs, and more than 4,000 medical and surgical procedures. Treating patients often involves care givers from multiple hospital units. Further, patients are complex, they do not have a uniform response to treatments due to issues such as comorbidities that complicate treatment as well as differences in socioeconomic, cultural, behavioral, and environmental circumstances that further exacerbate their conditions and health outcomes (Safford et al., 2007). Patient complexity and the complexity in the processes required to treat patients, create uncertainty as to the correct course of treatment and result in varying health outcomes. Further, this uncertainty due to patient complexity hinders the ability of healthcare providers to plan and make advance decisions about treatments and preferred courses of action (Gardner et al., 2015). To address this uncertainty, hospitals have implemented HIT that allows them to process volumes of information. This allows them to better monitor patient conditions (Romanow et al., 2018) and coordinate their care (Dobrzykowski & Tarafdar, 2015) in order to provide more effective care for their complex patients.

The study of the effectiveness of HIT started by investigating the effects of investing in HIT with early studies showing that investment in HIT leads to higher revenue (Ayal & Seidman, 2009; Devaraj & Kohli, 2000, 2003; Menon et al., 2000), and lower costs (Borzekowski, 2009; Menon et al., 2000); however further studies (Adler-Milstein et al., 2015; Appari et al., 2013; Jones et al., 2010; Yuan et al., 2019) show less positive and less certain results. However, investment in new HIT does not ensure benefits will be gained (DesRoches et al., 2010). The routinization of HIT is defined as "*the interplay between technology and patterns of clinical work embodied in routines*" (J. M. Goh et al., 2011). The process of routinization occurs after the deployment of an IS (Cooper & Zmud, 1990) and occurs through an incremental accumulation of experiences with the information system (Luo & Ling, 2013). In their study on the routinization of HIT in healthcare, Goh and colleagues studied the process of routinization (J. M. Goh et al., 2011) and proposed a virtuous cycle that led to adaptation which improved both the clinical routine and the HIT which led to improvements in efficiency and quality of care. However, there is little research that investigates the effects of routinized use of HIT. Specifically, research providing empirical evidence that describes the effect of routinization of HIT on the quality of care provided by hospitals is unavailable. The purpose of this paper is to addresses this gap in the literature by investigating the impact of routinized use of HIT on hospital performance as measured by 30-day readmission rate, and 30-day mortality rate for select chronic and non-chronic conditions.

We have created what we believe is a novel panel data set comprised of HIT usage and system maturity information from the HIMMS database, hospital operating characteristic data published by the CMS, income data from the IRS, and population characteristics collected by the US Census Bureau to describe the effects. To our knowledge, this is the first data set that constructs patient characteristic data from the ZIP codes of the patients that are actually treated by the hospital rather than taking the catchment area of the hospital. The resultant unbalanced panel contains 18,967 total observations from 5,101 U.S. acute care hospitals for the four years from 2014 to 2017. As our data included auto-correlation, we used the Prais-Winstein procedure (Woolridge, 2010) to develop robust estimates of the effects of patient complexity and the use of routinized HIT on the hospital morbidity and readmission rates for chronic and non-chronic conditions. We found that the use of Routinized HIT does lead to lower mortality rates for patients treated for chronic - acute myocardial infarction (AMI), chronic obstructive pulmonary disease (COPD), and heart failure - and non-chronic conditions - coronary artery bypass graft (CABG), pneumonia, stroke. There was not support for the assertion that the use of Routinized HIT would improve readmission rates. We also found only mixed support for the effects of clinical and sociological complexity being related to higher readmission and mortality rates. Economic complexity was related to higher readmission and mortality rates for patients treated for chronic and non-chronic conditions.

The remainder of the paper is organized as follows: we will discuss the theoretical background for the paper and develop hypotheses, we will then discuss the data set, the methods used to analyze the data, the results of the analysis a discussion of the results, we will end the paper with implications for research and practice, study limitations, and concluding remarks.

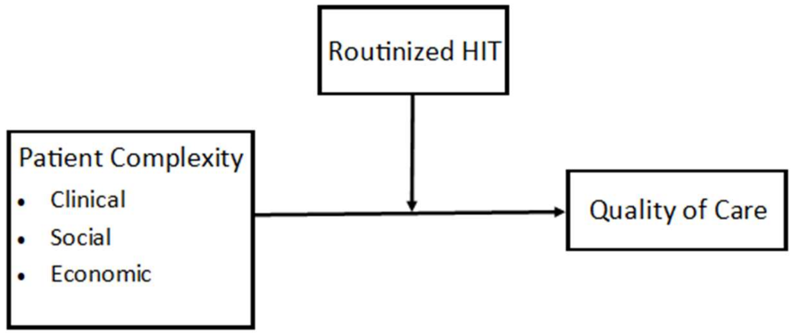
2.0 Theoretical Foundation

There have been many conversations in the extant health care literature concerning the treatment of patients with two or more chronic conditions (Higashi et al., 2007; Jencks, et al., 2009; Sampalli et al., 2012). These studies only consider the clinical component of patient complexity. The uncertainty created from patient complexity complicates the coordination of care, and can constrain the decisions made on how to treat the conditions by limiting the interventions that can be made (Van Cleave et al., 2013). Add to this patients' non-uniform response to healthcare interventions, variations in a patient's ability to pay for care (Barnett et al, 2015), and the varied attitudes toward hospitals. The complexity in treating a patient is comprised of more than just a listing of conditions. The hospital environment is also complex, with the care of patients often requiring treatment from multiple care teams, particularly with the trend of the US health care system to encourage physician specialization and single disease management programs (Van Cleave et al., 2013). This creates and environment that requires access to more information and information sharing across care teams (Naylor et al., 2011).

HIT has been implemented in hospitals to provide access to patient and treatment information, to coordinate care (Romanow et al., 2018), and to assist in clinical decision making (Kohli & Devaraj, 2004). In the information processing view of companies, organizations are structured around information and information flow to reduce uncertainty. Galbraith (1974) argued that to improve its performance in handling events that cannot be planned for in advance, organizations must adopt at least one of four information processing designs. These designs are to create slack resources, create self-contained tasks, invest in vertical information systems, and create lateral relations. In the hospital context, creating slack resources would mean hiring additional staff to assist in the information processing needs. An example of creating self-contained tasks would be apportioning care interventions so that a single person or team would have all the information needed and could accomplish the entire intervention. Investment in vertical information systems in the hospital would be the creation and deployment of integrated HIT systems that manage patient and care information in a way that facilitates patient care. The creation of lateral relations is similar to creating care teams that meet regularly. The first two of these information processing designs are intended to reduce the need for information processing as an organization handles unanticipated events, while the other information processing designs involve creating processes and mechanisms that increase the organization's capacity to acquire and process information, which is necessary for the increased demands of coordination and communication in managing complex tasks. Galbraith argued that unless an organization chooses one or some combination of these four information processing designs, it would have to accept lower performance.

While the study of HIT's impact on hospitals' performance remains on-going, the literature increasingly acknowledges that the use of HIT in the hospital is more important than the availability of HIT (Kohli & Tan, 2016; Setia et al., 2011). Routinized HIT creates processes and mechanisms that increase the capacity of the organization to acquire and process information. As the use of the HIT becomes routinized and embedded in the work processes of the healthcare providers, additional organizational benefits can be realized through improved organization and utilization of resources (J. M. Goh et al., 2011). The ability of HIT to influence a hospitals' quality in caring for complex patients is reliant upon their repeated use and assimilation into the work patterns of the caregivers, in other words the use of Routinized HIT. We investigate this relationship in this paper. The elements of the conceptual model shown in figure 1 are explained in the sections below.

Figure 4 - Conceptual Model - Quality of Care.



2.1 The Role of Information in Healthcare

Galbraith (1974) proposed the information processing view of organizational design, later called the Organizational Information Processing Theory, which recognizes as a central tenet that the organization's reliance on efficient information processing has a direct relationship with the level of uncertainty of the task environment. "The greater the task uncertainty, the greater the amount of information that must be processed among decision makers during task execution in order to achieve a given level of performance." (Galbraith, 1974 pp. 28). Here, information processing includes gathering, interpreting, and synthesizing information to support decision making. Complex patients present multiple chronic conditions and come from varied socio-economic backgrounds, this creates a high-level of uncertainty for hospitals and makes pre-planning for their care challenging. Moreover, hospitals cannot control the complexity of the patients that they treat. In such dynamic and uncertain environments, hospitals must adopt mechanisms that increase information processing capabilities and coordinate action in order to achieve the level of cost efficiency required to remain financially viable (Galbraith, 1974).

Naylor, et al. (2011) identify that points of transition of patients, care providers and information contribute to high healthcare costs and low quality of care since the potential for errors or delays in the timely processing of information and the coordination of related tasks is much higher. Since complex patients with multiple chronic conditions (Blumenthal & Abrams, 2016; Rudin et al., 2016) exhibit different disease conditions, have diverse needs, and respond differently to different treatments (Willke et al., 2012), providing coordinated care for them is particularly challenging due to the unpredictability of outcomes from the dynamic interactions between their comorbidities (Wilson & Holt, 2001). Each patient presents a different set of comorbidities that may interact in different ways at different points in time (Hoogendoorn et al., 2016). Often these comorbidities are chronic conditions that interact with a variety of extraneous demographic and socioeconomic conditions that further impact the cost and quality of care for complex patients (Rudin et al., 2017). Treating complex patients through routine care programs that focus on individual conditions can result in uncertain quality of care.

While relatively fewer in number, complex patients incur high costs to a health system and are at high risk for poor health outcomes (Lipsitz, 2012). As a result, complex patients contribute a disproportionately high share of the nation's health care costs (Blumenthal, Bruce, Fulmer, John, & Jeffrey, 2016; Blumenthal & Abrams, 2016). Literature recognizes that complex patients need coordinated care from the multiple specialties and care services within the health system (Albert et al., 2015; Bodenheimer, 2008). Different units in the health system must interact with each other to perform the diverse range of operations required of the complex care management efforts needed to care for complex patients (Kannampallil et al., 2011; Tan et al., 2005). These activities are managed across the health system and rely on efficient information sharing for seamless delivery of effective care (Albert et al., 2015; Iezzoni et al., 2016). This relationship between patient complexity and the required response of the internal systems to deliver the required complexity of care, speaks to the critical role of effective information processing in delivering cost efficient and high-quality care for complex patients.

Hospitals invest a large amount financial and care provider-time resources to effectively manage care for complex patients. The delivery of healthcare, particularly for complex patients, is a highly interdependent task environment because the nature of coordination needs often change from one patient to another, as well as from one care episode to another. Clinical staff must improvise and adapt their actions and be responsive to each patient's emergent conditions. As high quality, safe and timely care for patients with chronic illness often requires services from multiple clinical and support departments, care providers must evaluate the specific needs of patients and adaptively coordinate their activities to address their patients' emergent needs. Greater uncertainty and complexity in patient characteristics and care needs limit the health system's ability to plan and make decisions about activities in advance of their execution (Gardner et al., 2015). Thus, healthcare organizations must increase their flexibility and adaptability and improve the coordination among the dynamically configured set of tasks across the health system, which is needed to provide effective care for the specific patient at fiscally viable levels of process efficiency. Mature HIT systems facilitate such coordination by providing the necessary information processing capability across the organization. Thus, we propose that, *use of routinized HIT will positively impact quality of care, as measured by mortality rates for chronic (H1a), and non-chronic conditions (H1b); readmission rates for patients treated for chronic (H1c), and non-chronic conditions (H1d); as well as hospital wide readmission rates (H1e).*

2.2 Patient Complexity

It has been established that more clinically complex patients generally have higher costs to treat and worse perceptions of the care they receive (Krieger, 2001; Lynch & Smith, 2005). Our review of prior literature reveals that empirical research only considers clinical complexity as a measure of patient complexity, and it typically considers patient complexity as a control variable. The measure of patient complexity commonly seen in IS studies is Case Mix Index (CMI), which represents the relative effort and resources required to treat a patient with multiple clinical conditions (Carling et al., 2003). Little consideration is given in the IS and HIT literature on socio-economic factors that contribute to patient complexity, which may contribute to the mixed results seen in the prior literature. In this paper, we adopt a multidimensional view that includes clinical as well as socio-economic aspects that contribute to the complexity of patients and investigate the moderating effect of routinized HIT on the costs of treating complex patients. To the best of our knowledge, our investigation of the impact of a multidimensional conceptualization of patient complexity on hospitals' quality of care is novel in the HIT literature.

Clinical complexity is commonly conceptualized as comorbidities - the presence of two or more chronic conditions for a single patient. In healthcare and HIT research, clinical complexity is operationalized as the sum of chronic conditions a patient presents. This conceptualization treats conditions with discordant pathogeneses, where the comorbidities do not confound the treatment of each other (i.e. asthma and depression) in exactly the same was as those with concordant pathogeneses, where the individual comorbidities do confound the course treatment (i.e. hypertension and heart disease). In this paper, we use a widely accepted definition of comorbidity - coexistence of two or more chronic conditions, where one is not necessarily more central than others (Zulman et al., 2014). Patients with multiple comorbidities, particularly where the conditions are chronic, tend to have frequent and intensive contact with the health care system (Van Cleave et al., 2013), thus there are more opportunities to monitor each of their conditions, to adjust treatment regimens, and to assess their general health maintenance needs (Higashi et al., 2007). At the same time, each additional condition generates opportunities for suboptimal management, including missed diagnoses, inadequate treatment, and access and communication barriers. This is even without the potential confounding of symptoms or misdiagnosis of underlying cause. If a patient has conditions that are discordant, there may be insufficient time or competing demands during a visit (Redelmeir et al., 1998; Kerr et al., 2008). Further, in this situation, the patient and their provider may disagree about which condition should be prioritized (Kerr et al., 2008; Zulman, et al. 2010). Additional challenges arise when patients have several clinicians involved in their care, increasing the likelihood of conflicting advice, redundant diagnostic tests and services as well as impractical or competing treatment regimens (Anderson, 2010). Therefore, we propose that *Clinical Complexity will negatively affect the quality of care, as measured by mortality rates for patients treated for chronic conditions (H2a), and non-chronic conditions (H2b) as well as readmission rates for patients treated for chronic conditions (H2c), non-chronic conditions (H2d) and hospital-wide readmissions (H2e).*

While comorbidity generally refers to the presence of multiple clinical conditions, there is also growing recognition that a multitude of patient-level factors, independent of specific comorbid clinical conditions, may complicate care and affect outcomes for complex patients (Safford et al., 2007; Boyd et al, 2010; Nardi et al. 2007). For example, Safford et al. proposed a conceptual approach to complex patients that involves interactions between biological, socioeconomic, cultural, environmental, and behavioral forces as health determinants (Safford, 2007). Incorporating these dimensions into clinical assessments is likely to help ensure that care is aligned with patient's preferences, goals, and needs (American Geriatrics Society, 2012). This approach is similar approach to the one proposed by Elixhauser et al. (1998). The HIT literature has not addressed other sources of patient complexity beyond clinical complexity.

The racial disparity in health outcomes has been widely observed and investigated in the literature (Levine et al., 2001; McLaren, 2021; Mensah et al., 2005; Mokdad et al., 2001; Yedjou et al., 2019). These studies show that health outcomes for minority populations are worse for conditions ranging from breast cancer to COVID-19. There are observed differences in accessibility, utilization and quality of care between majority and minority racial groups (Williams and Collins, 1995). There is also an array of cultural based predispositions with respect to receiving health care and even its underlying cause (Vaughn et al., 2009). Therefore, we propose that *Sociological Complexity will negatively affect the quality of care, as measured by mortality rates for patients treated for chronic conditions (H3a), and non-chronic conditions (H3b) as well as readmission rates for patients treated for chronic conditions (H3c), non-chronic conditions (H3d) and hospital-wide readmissions (H3e).*

Fitzpatrick et al. (2015) found that poorer patients were much more likely to be in the groups with the highest needs and highest costs for care. Again, as with social complexity access, utilization have also been cited as reasons behind the disparity in healthcare outcomes for economically disadvantaged patients. Williams and Collins (1995) argue that although racial factors influence health outcomes, economic inequality is the major driving force behind the widening health disparities. As such, we propose that *Economic Complexity will negatively affect the quality of care, as measured by mortality rates for patients treated for chronic conditions*

(H4a), and non-chronic conditions (H4b) as well as readmission rates for patients treated for chronic conditions (H4c), non-chronic conditions (H4d) and hospital-wide readmissions (H4e).

2.3 Routinization

Much of the prior research concerning sustained use of technology has been concerned with the users' intentions of continuing to use a program or system (Bhattacherjee, 2001; Limayem, et al., 2007; Hsiao, 2019). However, in the hospital environment, the healthcare providers use the information systems that administration provides to complete their daily tasks in treating patients, whether that is paper record or a full-featured EMR; therefore, the approach of sustained use from these prior studies is not appropriate for our context.

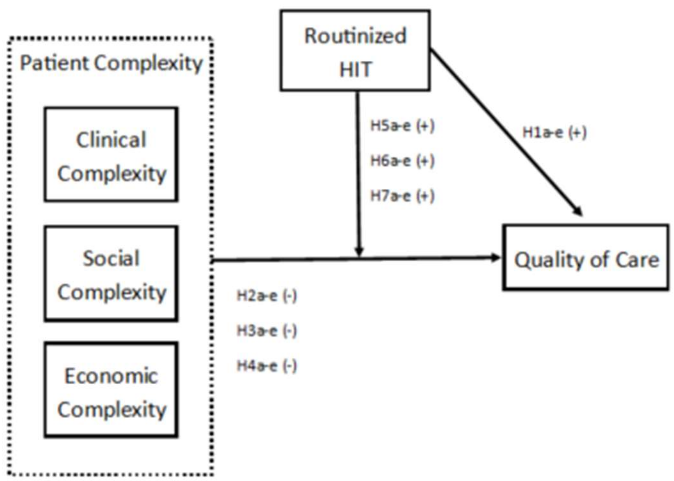
The Implementation of Information Systems has been conceptualized as a 6 stage process: initiation, adoption, adaption, acceptance, routinization, and infusion (Cooper & Zmud, 1990). Routinization occurs through the incremental accumulation of experience (Luo & Ling, 2013). Routinization was conceptualized as a stage that occurred after the acceptance and go-live of the Information System and was characterized as a special form of system exploitation that required little additional learning and one that promotes efficiency advantages in daily work (Cooper & Zmud, 1990; Luo & Ling, 2013). In literature that investigates the process of realizing value from IS, routinization is described as a state where the IS has become normalized into the work process. (Saga & Zmud, 1994). The definition of routinization has been further refined to mean the extent to which interfirm activities follow *regular* and *repetitive* patterns (Feldman, 2000). In a healthcare context, routinization has been defined as "*the interplay between technology and patterns of clinical work embodied in routines*" (Goh et. al, 2011, Goh and Pentland, 2019). We will adopt this definition as our working definition of routinization.

Goh et al (2011) describe a process of changing work patters that occurs by removing the affordances from a legacy system when it is replaced and gaining a new set of affordances when a new system is installed. The change in the performance of the hospital comes from the change in work processes required to incorporate the HIT into the clinical routine (J. M. Goh et al., 2011). There is also a time investment that is required to adapt to these new patterns and make them part of the clinical routine. Time is required to disrupt the patterns and routines that were afforded in the old context as well as to establish and embrace the patterns and routines afforded by the new HIT (Polites & Karahanna, 2013). This time requirement could explain the mixed results seen in prior research that investigated the effects of HIT in hospitals (DesRoches et al., 2010; Devaraj & Kohli, 2000; Jha et al., 2009; Tsai & Jha, 2014). Therefore, we propose that, *the use of routinized HIT will positively impact the relationships between Clinical Complexity and the mortality rates for patients treated for chronic conditions (H5a), non-chronic conditions (H5b) as well as positively impacting the readmission rates for the patients treated for chronic conditions (H5c), non-chronic conditions (H5d), and hospital-wide readmissions(H5e). Similarly, we expect that the use of routinized HIT will positively impact the relationships between Sociological Complexity and the mortality rates for patients treated for chronic conditions (H6a), and non-chronic conditions (H6b) as well as positively impacting the readmission rates for patients treated for chronic conditions (H6c), non-chronic conditions (H6d), and hospital-wide readmissions (H6e). Also we expect that the use of routinized HIT will positively impact the relationships between Economic Complexity and the chronic conditions (H7a), and non-chronic conditions (H7b) as well as positively impacting the readmission rates for patients treated for chronic conditions (H7c), non-chronic conditions (H7d), and hospital-wide readmissions (H7e).*

2.4 Research Model

Using the lens of the Organizational Information Processing Theory, we constructed the following model to test the hypotheses concerning the impact of Routinized HIT on the financial outcomes of hospital expense and patient perception of care while managing the uncertainty presented by multidimensional patient Complexity. Included on the diagram are the hypotheses and their expected direction of affect.

Figure 5 - Research Model - Quality of Care.



3.0 Data and Research Design

3.1 Data

The unit of analysis in this study is the U.S. acute care hospital. We collected secondary data from multiple sources for the four calendar years from 2014 to 2017 for 5,011 U.S. acute care hospitals included in the CMS database as of 2017 resulting in an unbalanced panel containing 18,967 observations. The data is panel data as values for the same set of variables was collected annually, however it is unbalanced as not all hospitals had qualifying data in each of the reporting periods. As per CMS guidelines, only measures that are based on a sample of at least 25 patients for a given condition are included in the study. Unbalanced panel data was used to maximize the observed variability in the data.

Information concerning IS usage was extracted from the Healthcare Information and Management Systems Society (HIMSS, previously the Dorenfest Institute for Health Information Technology Research) database. The HIMSS database is a nationally representative survey that includes meta data, IT usage metrics, and operational data from over 5000 hospitals. The readmission and mortality rate data were collected from the Hospital Quality Initiative (HQI) data set published by the CMS.

The data set from the CMS did not include data that would allow us to study the effects of socio-economic complexity, so we had to find ways that would allow us to approximate the social and economic attributes of the patients that the hospital treated while maintaining the hospital as the unit of analysis. As our collected data is at the individual health care facility, we approximated the social, and economic composition of the patient populations by taking measures for these parameters from the populations that the health care facilities serve. We used weighted averages for these values based on the ZIP codes of the patients treated by the hospital for each of the four years considered in the study. The exact number of patients treated by ZIP Code is annually reported by the CMS. The data source and the manner in which the socio-economic values were calculated are described in 3.3.2 and 3.3.3, below.

3.2 Independent Variables

3.2.1 Complexity

Safford and colleagues (2007) argue that "determinants of health include biology/genetics, socioeconomics, culture, environment/ ecology, behavior, and the medical system". In their vector model of patient complexity, they describe each of these determinants of health to be additive and variable from patient to patient. The Vector model of Complexity proposed by Safford and her colleagues is the only model that we found that provides insight into how the dimensions of complexity might interact and be combined. We have adopted the Vector Model of Patient Complexity as our model for patient complexity.

3.2.1.1 Clinical Complexity

The Case Mix Index (CMI) is the average relative Medicare Severity-Diagnosis Related Group (MS-DRG) weight of a hospital's inpatient discharges, calculated by summing the MS-DRG weight for each discharge and dividing the total by the number of discharges (www.cms.gov). The case-mix index is a gauge of the comparative cost needed to treat a patient group in a hospital within a time-period, usually a calendar year. An index of one indicates that it costs the national average amount of resources per patient to treat the hospital's specific patient group. A hospital that performs higher cost care or has more resource intensive operations, such as neurosurgery or cardiac surgery, has a higher CMI compared with another that performs less costly care. The CMI reflects the diverse clinical complexity and resource needs of all the patients in the hospital treated over a certain time-period. A higher CMI indicates a more complex and resource-intensive case load. Although the MS-DRG weights, provided by the Centers for Medicare & Medicaid Services (CMS), were designed for the Medicare population, they are applied here to all discharges regardless of payer. In most of the extant literature that considers the variability of patients, CMI is used as a control variable (I. Bardhan et al., 2015; I. R. Bardhan & Thouin, 2013; Setia et al., 2011) to adjust for the difference in complexity of patients treated by the hospital. Horn et al. (1985) showed that higher CMI was related to higher costs of treatment. We used the final adjusted CMIs reported by the CMS for each of the hospitals in our data to represent clinical complexity.

3.2.1.2 Sociological Complexity

The racial disparity of health outcomes has been widely studied in the healthcare literature (Yedjou et al., 2019; DeSantis et al., 2017). These studies show that the healthcare outcomes minority populations achieve are inferior to those of the majority population. As Sociological complexity has not been addressed by the HIT literature, a measure of sociological diversity was made using the racial disparity, which was calculated by summing the percentages of minority populations for a given ZIP code and using these percentages in a weighted average calculation based on the ZIP Codes reported for the patients that were treated by the hospital for that year. The number of patients seen from a particular ZIP Code was multiplied by the percentage of minority population for the ZIP Code and summed across all ZIP Codes that had patients treated by the hospital. This sum was then divided by the total number of patients seen for that year by the hospital to arrive at the racial composition of the patients treated by the hospital.

3.2.1.3 Economic Complexity

Researchers have considered the impact of EC on health care costs and health outcomes. Barnett, et al (2015) saw that poorer patients had worse health outcomes. Su, et al.(2006) found that lower income patients had lower overall utilization of the healthcare system but incurred higher costs when they sought care. Because the HIT literature has not addressed economic complexity, the measure of economic complexity was calculated by dividing the number of tax returns had an adjusted gross income (AGI) of less than $25k by the total number of returns submitted by ZIP Code for each of the four years considered in the study. The number of patients seen from a particular ZIP Code was multiplied by the percentage of returns with an AGI less than $25k for the ZIP Code and summed across all ZIP Codes that had patients treated by the hospital. This sum was then divided by the total number of patients seen for that year by the hospital to arrive at the poverty level of the patients treated by the hospital.

We modeled cost of care with and without interactions between the three dimensions of patient complexity. This allowed us to confirm that there were no interactions between the three dimensions of complexity. This finding is consistent with Safford et al.'s (2007) Vector Model of Complexity.

3.2.2 Routinized HIT

Information System Maturity Models have been conceptualized an idealized set of hierarchical benchmarks that allow organizations to evaluate their capabilities (Poeppelbuss et al., 2011). In general, maturity models are constructed such that progressing through the maturity model brings increased benefit to the organization and that regressing to a prior stage is usually very difficult. (Solli-Sæther & Gottschalk, 2010). Maturity models became especially popular with the emergence of the Capability Maturity Model (CMM) in the late 1980s (Paulk et al., 1993). Iverson et al. (1999) described the purpose of maturity models as providing a set of requirements to support internal or external assessment, benchmarking and a roadmap for system or organizational improvements. HIT and organizational maturity are not concepts often studied in the HIT literature but they are concepts that should be considered as they impact the organization's ability to realize value from their HIT investments (CMMI Institute, 2022).

The Electronic Medical Record Adoption Model (EMRAM) developed by the Healthcare Information and Management Systems Society (HIMSS) is an eight stage (Stages 0-7) cumulative measure of the availability and use of various HIT within the organization (www.himss.org). According to HIMSS, "Measuring evidence-based data at each stage, organizations use EMRAM to optimize digital work environments, improve performance and financial sustainability, build a sustainable workforce, and support an exceptional patient experience. Leveraging information digitally improves patient safety and clinician satisfaction by reducing errors in care, length of stay for patients and duplicated care orders, and streamlining the access and use of data to inform care delivery." (https://www.himss.org/what-we-do-solutions/digital-health-transformation/maturity-models/electronic-medical-record-adoption-model-emram). In the EMRAM, Stage 6 is the first point where external validation by HIMSS certified auditors is required. For a hospital to achieve Stage 6 they must have all critical systems installed including full physician documentation, tracking of nurse order and task completion with clinical decision support (CDS) that at least performs rudimentary conflict checking and a second stage CDS related to evidence-based medicine protocols. Achievement of the EMRAM Stage 6 milestone indicates that a hospital is committed to improving patient safety, outcomes, the move to a paperless health record and overall integration of HIT in the operations of the hospital (Kilborn, 2019). We use the number of years after achieving EMRAM Stage 6 certification from the HIMMS trained auditor as the measure of time that a hospital has been working in a mature HIT environment. To the best of our knowledge, our use of EMRAM to represent the routinization of HIT in hospitals is both novel and timely considering the ten years since the CMS has mandated the use of HIT in hospitals.

3.3 Outcomes

The data set includes readmission and mortality rate data for the following conditions: acute myocardial infarction (AMI), coronary artery bypass graft (CABG), chronic obstructive pulmonary disease (COPD), heart failure (HF), pneumonia (PN), and stroke (STK). Additionally, we included the data for hospital wide readmissions (HOSP). We extracted CMI and some of the controls from the CMS Impact File. At the end of the reporting period, the CMS adjusts the weights of the values used to calculate the CMI based on the values submitted by all hospitals. They calculate their reimbursement withholdings based on these final adjusted values. Final adjusted values were used from the CMS Impact files when they were available from the CMS. The mortality and readmissions data reported to the CMS are three-year rolling summations. This means that the values reported in 2014 include data from 2012-2014, and the values reported in 2017 include data from 2015-2017.

3.3.1 Mortality Rate

The risk adjusted 30-day mortality rates (mortality rate) are published by the CMS. They are the rate at which patients die within 30 days of admission for six chronic and non-chronic conditions. The chronic conditions are acute myocardial infarction (AMI), chronic obstructive pulmonary disease (COPD), and heart failure (HF). The non-chronic conditions are coronary artery bypass graft (CABG), pneumonia (PN), and stroke (STK). The mortality rate accounts for medical care the patient received in the prior year, as well as the number of AMI and HF admissions at each hospital. The model uses this information to adjust for differences in each hospital's patient mix.

3.3.2 Readmission Rate

The 30-day readmission rates are computed as part of the Hospital Readmissions Reduction Program (HRRP). The HRRP is one of the four Hospital Inpatient Quality Programs managed by the CMS. The HRRP is a value-based program intended to improve the US healthcare system through performance targets and enforced through reductions in CMS reimbursements (https://qualitynet.cms.gov/inpatient/hrrp). Hospitals with high readmission rates will incur a decrease in their overall reimbursements from the CMS by up to 3% based on their performance with respect to HRRP. Since the start of the program on Oct. 1, 2012, hospitals have experienced nearly $1.9 billion of penalties, including $528 million in 2017 (AHA Staff, 2018). The readmission rate is the rate at which patients are readmitted into the hospital within 30 days of admission for six chronic and non-chronic conditions. The chronic conditions are acute myocardial infarction (AMI), chronic obstructive pulmonary disease (COPD), and heart failure (HF). The non-chronic conditions are coronary artery bypass graft (CABG), pneumonia (PN), and stroke (STK). Additionally, we included the data for hospital wide readmissions (HOSP) in our data set.

For each of the Outcomes (Mortality or Readmission Rate) the value is modeled based on the following equation:

Equation 3 - Quantitative Model - Quality of Care

$$Outcome = \boldsymbol{\beta_k}\ \boldsymbol{Complexity_{it}} + \boldsymbol{\beta_l X_{it}} + \gamma_i + \delta_t + \beta_1\ Routinized\ HIT_{it}$$
$$+ \beta_2(\ Routinized\ HIT\ x\ Complexity)_{it} + \varepsilon_{it}$$

Where,

$\boldsymbol{\beta}_k$ = vector of estimators for measures of complexity

$\mathbf{Complexity}_{it}$ = vector of the three dimensions of patient complexity, Clinical Complexity, Social Complexity and Economic Complexity

$\mathbf{X}_{it}$ = vector of control variables for the hospital

γ_i for hospital fixed effect

δ_t = fixed effects of time

ε_{it} = observation specific error term

3.4 Control variables

Our analysis includes four time-varying controls: hospital size, teaching intensity, magnet hospital status, and outlier adjustment factor. Hospital Size as measured by the natural log of the number of beds actively in use within the hospital. Teaching Intensity is calculated as a ratio of medical residents per bed as process quality and thereby expense per bed is affected by the teaching intensity of a hospital (Theokary & Ren, 2011) it is indicative of . Magnet hospital status, which is an indication of hospitals that have nursing programs focused on "setting the standard for excellence through leadership, scientific discovery and dissemination and implementation of new knowledge" (www.nursingworld.org) magnet hospitals are more likely to achieve routinization of HIT faster than non-magnet hospitals (Armstrong, et al., 2009). Outlier Adjustment Factor, which reflects exceptionally costly cases treated by the hospital during the time period which might bias the expense per bed calculation (Jha et al., 2009). The Outlier Adjustment Factor is calculated and reported by the CMS. A factor for year is also included to capture any pertinent year effects.

Table 5 - Summary Statistics - Quality of Care

	Median	Mean	Std Dev
1. AMI Mortality	13.9	13.9862	1.2649
2. AMI Readmission	16.7	16.803	1.03
3. COPD Mortality	7.8	7.928	1.0857
4. COPD Readmission	20	20.0867	1.2646
5. HF Mortality	11.8	11.8913	1.487
6. HF Readmission	21.8	21.9056	1.5492
7. CABG Mortality	3.1	3.2782	0.8442
8. CABG Readmission	14.5	14.5382	1.3617
9. PN Mortality	13.9	13.9628	2.97
10. PN Readmission	16.9	16.992	1.2614
11. STK Mortality	14.7	14.8082	1.652
12. STK Readmission	12.5	12.5809	1.0969
13. Hospital-wide Readmission	15.3	15.3432	0.8439
14. Clinical Complexity	1.5139	1.5336	0.3278
15. Social Complexity	0.2167	0.2538	0.1609
16. Economic Complexity	0.6382	0.6322	0.0732
17. Routinized HIT	0	0.7693	1.5958
18. Hospital Size	98	170.4129	192.725
19. Teaching Status	0	0.1038	0.305
20. Teaching Intensity	0	0.0436	0.1363

21. Magnet Status	0	0.0645	0.2457
22. Outlier Payments	0.0079	0.0266	0.076

(n=18,966).

Table 6 - Pairwise Correlations - Quality of Care

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22
1	1																					
2	0.14	1																				
3	0.21	-0.16	1																			
4	0.039	0.32	-0.049	1																		
5	0.32	-0.16	0.46	-0.066	1																	
6	0.06	0.46	-0.17	0.44	-0.15	1																
7	0.32	0.062	0.2	0.0098	0.21	0.04	1															
8	0.15	0.39	-0.06	0.16	-0.045	0.24	0.2	1														
9	0.1	-0.14	0.35	-0.069	0.36	-0.059	0.15	-0.22	1													
10	-0.021	0.35	-0.12	0.41	-0.16	0.47	-0.022	0.13	0.042	1												
11	0.27	-0.07	0.31	-0.02	0.36	-0.13	0.14	0.035	0.16	-0.057	1											
12	-0.01	0.37	-0.23	0.34	-0.26	0.46	-0.027	0.18	-0.17	0.4	-0.12	1										
13	0.0026	0.5	-0.18	0.48	-0.22	0.64	0.014	0.24	0.047	0.6	-0.085	0.52	1									
14	-0.095	-0.14	-0.002	-0.15	-0.091	-0.17	-0.22	-0.17	-0.051	-0.05	0.11	-0.047	-0.064	1								
15	-0.013	0.18	-0.16	0.11	-0.31	0.22	-0.066	0.013	-0.058	0.19	-0.21	0.31	0.23	0.12	1							
16	0.24	0.19	0.054	0.12	0.065	0.21	0.17	0.14	0.067	0.15	0.11	0.15	0.2	-0.1	0.18	1						
17	-0.11	-0.072	-0.033	-0.042	-0.037	-0.047	-0.11	-0.091	0.018	0.0003	0.013	-0.047	-0.013	0.18	-0.052	-0.15	1					
18	-0.01	0.07	-0.11	0.098	-0.19	0.065	-0.2	-0.042	-0.1	0.14	0.025	0.18	0.2	0.42	0.21	0.071	0.2	1				
19	-0.085	0.01	0.037	0.05	-0.023	-0.017	0.0022	-0.014	-0.016	0.028	0.022	0.037	0.05	0.047	0.064	0.03	-0.005	0.14	1			
20	-0.11	0.14	-0.18	0.09	-0.24	0.15	-0.19	-0.036	-0.14	0.2	0.045	0.24	0.35	0.44	0.21	-0.04	0.18	0.46	0.15	1		
21	-0.062	0.041	-0.076	0.018	-0.07	-0.065	-0.12	0.033	-0.19	0.0077	0.033	0.066	0.18	0.0075	0.024	-0.11	0.075	0.27	0.034	0.2	1	
22	-0.083	0.0012	-0.09	-0.02	-0.12	-0.013	-0.18	-0.034	-0.096	0.021	0.024	0.027	0.045	0.44	0.18	-0.13	0.071	0.29	0.0093	0.36	0.15	1

Significance levels: $p \leq 0.01$ if $|r| > 0.02$

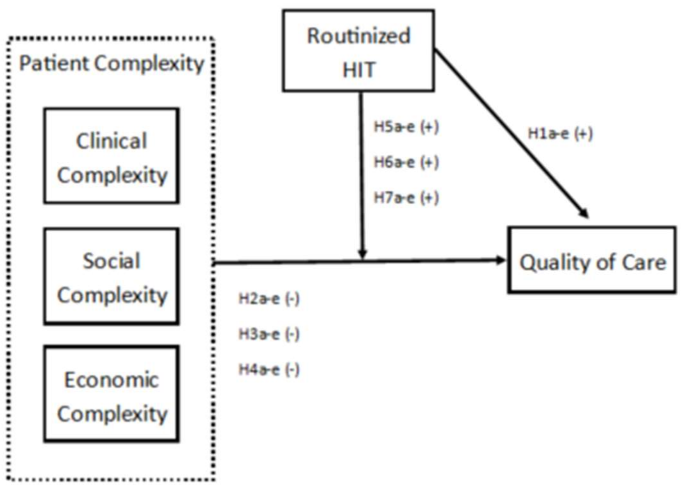
4.0 Analysis

4.1 Analytical Approach

We used the panelAR package in R-Studio to analyze this un-balanced panel data. The panelAR package is a set of estimators and tests for panel data econometrics in the presence of AR(1)-type autocorrelation. The AR(1)-type autocorrelation is addressed in using a two-step Prais-Winstein feasible generalized least squares (FGLS) procedure (Woolridge, 2010), where the autocorrelation coefficients can be panel specific (Judge, et al., 1985). Additionally, we used panel-weighed least squares in the error calculation to adjust for heteroskedasticity and to further address the effects of autocorrelation. Other research (Senot et al., 2016) has addressed the inherent autocorrelation in the CMS data occurring because the data is collected by the CMS as a rolling three-year summation, by using panels from years that do not overlap. This results in a data set that is not affected by the inherent autocorrelation present in data sets constructed with panel data from consecutive years. In our research, this approach would be problematic as it would convolute our representation of the patient demographic data, therefore we used the panel specific autocorrelation coefficients afforded to us through the Prais-Winstein FGLS procedure.

4.2 Results

Figure 6 - Research Model - Quality of Care.



4.2.1 Mortality Rate

The standard errors are corrected for heteroscedasticity and clustered at the hospital level.

Chronic Conditions

Table 7 - Prais-Winstein FGLS Estimators - Mortality Rates for Chronic Conditions.

	AMI	COPD	HF
Clinical Complexity (CC)	-0.4421 (0.051)***	0.7752 (0.0431)***	0.1482 (0.0455)***
Social Complexity (SC)	-0.0711 (0.0435)	-0.2804 (0.0432)***	-1.7835 (0.0552)***
Economic Complexity (EC)	2.4315 (0.0665)***	0.4027 (0.0865)***	0.8961 (0.1052)***
Routinized HIT	-0.057 (0.0352)	-0.0496 (0.0312)	-0.0783 (0.0383)***
Hospital Size	-0.0368 (0.0114)***	-0.0178 (0.0102)***	-0.1225 (0.0108)***
Teaching Intensity	-0.516 (0.0476)***	-1.0122 (0.0521)***	-1.2998 (0.0628)***
Magnet Hospital	-0.0765 (0.0194)***	-0.078 (0.0197)***	-0.1472 (0.0264)***
Outlier Payments	0.2409 (0.1661)	-0.2923 (0.1099)***	0.1236 (0.1203)
Year: 2015	-0.0548 (0.0107)***	0.3046 (0.0103)***	0.4008 (0.0115)***
Year: 2016	0.0803 (0.0108)***	-0.0119 (0.0119)	0.0008 (0.0133)
Year: 2017	-0.4717 (0.0111)***	0.3182 (0.011)***	0.2072 (0.0143)***
CC*Routinized HIT	-0.0338 (0.0232)	-0.0282 (0.0177)	0.0790 (0.0239)***
SC*Routinized HIT	-0.0676 (0.0237)***	-0.1148 (0.0238)***	-0.2331 (0.0283)***
EC*Routinized HIT	0.01199 (0.0515)***	0.1791 (0.0475)***	0.2117 (0.0589)***

CC: Clinical Complexity, SC: Sociological Complexity, EC: Economic Complexity

Robust Standard Errors in Parentheses

*Signif. codes: *** p<0.01, ** p< 0.05,* p< 0.1*

The direct effect of the use of Routinized HIT was to decrease mortality rates for the chronic conditions. There was some support for hypothesis *H1a*. The sign of the effect was negative in each case and the effect was seen to have p<0.01 for HF. We found mixed support for hypothesis *H2a*. Clinical complexity was seen to be significant for each of the three chronic conditions. The direction of effect was positive for COPD and HF. However, the direction of effect was seen to be negative for AMI, indicating that the hospitals may have better standard practices in place to deal with comorbidities that commonly appear with AMI. Hypothesis *H3a* is supported. The relationship between SC and the mortality rates for the chronic conditions did tend to be significant, however it was in the opposite direction than theory expected. We did see support for hypothesis *H4a.* The effect was significant ($p<0.01$) and positive for each of the three chronic conditions. We found mixed support for hypothesis *H5a.* The moderating effect for the use of Routinized HIT on the relationship of CC to mortality rate for the chronic conditions tended to reduce mortality rates, however this moderating effect was significant and positive for HF. The model estimators do support hypothesis *H6a*. The moderating effect of the use of Routinized HIT was seen to be significant (all p values less than 0.01) and reducing the mortality rate for each of the chronic conditions. Hypothesis *H7a* was unsupported. The moderating effect was seen to be significant (all p values less than 0.01), however the effect was to increase mortality rates for the hospitals that treated populations with higher prevalence of poverty.

Non-Chronic Conditions

Table 8 - Prais-Winstein FGLS Estimators - Mortality Rates for Non-Chronic Conditions.

	CABG	PN	STK
Clinical Complexity (CC)	-0.7421 (0.0805)***	0.1654 (0.1090)	0.585 (0.0635)***
Social Complexity (SC)	-0.1283 (0.0678)*	-0.1140 (0.1098)***	-2.1131 (0.0585)***
Economic Complexity (EC)	1.5183 (0.1228)***	2.4591 (0.2272)***	2.9433 (0.1058)***
Routinized HIT	-0.0667 (0.0340)*	-0.3052 (0.0737)***	-0.2395 (0.04)***
Hospital Size	-0.1467 (0.0165)***	-0.0293 (0.012)**	-0.0433 (0.011)**
Teaching Intensity	-0.1765 (0.0544)***	-1.5708 (0.0834)***	0.7793 (0.0833)***
Magnet Hospital	-0.1192 (0.0175)***	-0.355 (0.035)***	-0.0775 (0.0279)**
Outlier Payments	-0.8069 (0.177)***	-0.8585 (0.1598)***	1.1745 (0.2326)***
Year: 2015	0.1225 (0.0119)***	4.8889 (0.0182)***	0.0927 (0.0134)***
Year: 2016	0.067 (0.0144)***	0.0713 (0.0211)***	0.0128 (0.0159)
Year: 2017	0.1376 (0.016)***	4.6011 (0.0226)***	-0.1939 (0.017)***

CC*Routinized HIT	-0.0759 (0.0277)**	0.024 (0.0357)*	0.3269 (0.0318)***
SC*Routinized HIT	0.0495 (0.0236)*	-0.1704 (0.0385)***	-0.1668 (0.0335)***
EC*Routinized HIT	0.0839 (0.0483)**	0.4768 (0.075)***	0.2225 (0.0647)***

CC: Clinical Complexity, SC: Sociological Complexity, EC: Economic Complexity

Robust Standard Errors in Parentheses

*Signif. codes: *** p<0.01, ** p< 0.05,* p< 0.1*

There was mixed support for the relationship between CC and mortality rates for the non-chronic conditions (*H2b*). The relationship between SC and the mortality rate was seen to be significant but in the opposite direction to the expectation from theory (*H3b*), and the relationship was significant and as expected between EC and mortality rates for the non-chronic conditions (*H4b*). The direct effect of Routinized use of HIT tended to provide benefit in the form of reducing the mortality rate for each of the modeled non-chronic conditions; therefore, *H1b* was supported. As for the moderating effect of the use of Routinized HIT there was mixed support for hypothesis *H6b*, but no clear support for the positive effect along the CC dimension of complexity *(H5b)* or the EC dimension of complexity *(H7b).* For this set of conditions, the Indirect Effects tended to have more effect than the Direct Effects. The effect of EC was much higher than the other effects and tended to dominate the net effect of the other factors. EC was the strongest predictor of mortality rate across all of the hospital data for these non-chronic conditions with patients having higher EC also having higher mortality rates. Hospitals that used HIT in a routinized manner and treat higher clinical complexity CABG patients tend to have lower mortality rates. However, hospitals that treat higher EC patients and have routinized HIT tend to have higher mortality.

4.2.2 Readmission Rate

We included a measure for the overall readmission rate of the hospital (HOSP) in this result set that was not included in the Morbidity data. The Prais-Winstein FGLS estimators for this system are shown in Table 9. Again, we used panel-weighed least squares in the error calculation to adjust for heteroskedasticity and to further address the effects of autocorrelation.

Chronic Conditions

Table 9 - Prais-Winstein FGLS Estimators - Readmission Rates for Chronic Conditions.

	AMI	**COPD**	**HF**
Clinical Complexity (CC)	-1.0981 (0.0451)***	-1.7998 (0.0516)***	-2.1466 (0.0608)***
Social Complexity (SC)	0.7732 (0.0328)***	0.5388 (0.0549)***	1.5718 (0.056)***
Economic Complexity (EC)	1.0194 (0.0837)***	0.0739 (0.1139)	1.6936 (0.1161)***
Routinized HIT	0.1580 (0.0227)***	0.1265 (0.0364)***	-0.0428 (0.0374)
Hospital Size	0.0799 (0.0093)***	0.3798 (0.0127)**	0.2364 (0.013)***
Teaching Intensity	0.952 (0.0531)***	0.6954 (0.0638)***	2.0011 (0.0822)***
Magnet Hospital	-0.0013 (0.0122)	-0.1259 (0.0263)***	-0.4327 (0.0276)***
Outlier Payments	0.1619 (0.1097)	-0.0489 (0.0956)	-0.8372 (0.1417)***
Year: 2015	-0.1051 (0.0090)***	-0.2493 (0.0118)***	-0.0252 (0.0127)**
Year: 2016	0.0375 (0.0102)***	0.0487 (0.0141)***	0.1014 (0.0146)***
Year: 2017	-0.6326 (0.0095)***	-0.3816 (0.0151)***	-0.2141 (0.0141)***
CC*Routinized HIT	-0.1639 (0.0185)***	-0.1069 (0.0233)***	-0.0525 (0.0287)
SC*Routinized HIT	0.0095 (0.0141)	0.0933 (0.0278)***	0.1268 (0.0302)***
EC*Routinized HIT	-0.1300 (0.033)***	-0.2147 (0.0579)***	-0.0312 (0.0525)

CC: Clinical Complexity, SC: Sociological Complexity, EC: Economic Complexity

Robust Standard Errors in Parentheses

*Signif. codes: *** p<0.01, ** p< 0.05,* p< 0.1*

There was mixed support for Hypothesis *H1c*, as the, as the direct effect of the use of Routinized HIT was seen to reduce the readmission rates for HF, while increasing the readmission rates for AMI and COPD. Higher Clinical Complexity tended to be related to lower readmission rates, so *H2c* was unsupported. The model did show the expected relationships between both Sociological Complexity (*H3c*) and Economic Complexity (*H4c*). Both these hypotheses were supported by the model. The support for the hypothesis regarding the moderating effect for the use of Routinized HIT was mixed along the Clinical Complexity dimension (*H5c*). The evidence did support hypothesis *H7c*, which expected the moderating effect of the use of Routinized HIT to reduce readmission rates for hospitals that treat patient populations with higher Economic Complexity. However, the moderating effect was not supported along the Sociological dimension of Complexity (*H6c*).

For the chronic conditions, the Indirect Effects tended to have more effect than the Direct Effects. Looking at AMI, the hospitals that had higher routinized use of HIT tended to have higher readmission rates, but lower mortality rates. This could be from a better set of discharge instructions and patients having a better understanding of what constitutes a need to return to the hospital. Also, there is a lower readmission rate for the hospitals that have routinized use of HIT, but without an appreciable change in mortality rate for high CC patients treated for AMI. Conversely, for patients treated for either HF or COPD at hospitals with higher routinized use of HIT, we observed a tendency for lower readmission rate and higher mortality rates for patients with high EC.

Non-Chronic Conditions

Table 10 - Prais-Winstein FGLS Estimators - Readmission Rates for Non-Chronic Conditions.

	CABG	PN	STK
Clinical Complexity (CC)	-1.4339 (0.1307)***	-1.3445 (0.0511)***	-0.9739 (0.0446)***
Social Complexity (SC)	0.0554 (0.086)	0.9672 (0.0595)***	1.5086 (0.0351)***
Economic Complexity (EC)	2.1407 (0.1314)***	1.2672 (0.1229)***	0.7705 (0.0679)***
Routinized HIT	0.1944 (0.0612)***	-0.0422 (0.0285)	-0.0432 (0.0304)
Hospital Size	-0.1078 (0.0255)***	0.3188 (0.0127)***	0.1356 (0.0104)***
Teaching Intensity	0.2752 (0.1053)***	1.1089 (0.0764)***	1.4832 (0.0606)***
Magnet Hospital	-0.0538 (0.0311)*	-0.1969 (0.0258)***	0.0009 (0.0196)
Outlier Payments	1.2818 (0.2968)***	-0.3875 (0.1775)**	-0.6016 (0.1504)***
Year: 2015	-0.5127 (0.0209)***	0.2244 (0.0122)***	-0.1849 (0.0093)***
Year: 2016	0.0539 (0.02)***	0.0653 (0.0145)***	0.0384 (0.0103)***
Year: 2017	-1.0453 (0.0255)***	0.0998 (0.0149)***	-0.4924 (0.0108)***
CC*Routinized HIT	-0.1968 (0.0505)***	0.0045 (0.0218)	-0.0250 (0.0212)
SC*Routinized HIT	0.0089 (0.0393)	0.1208 (0.0247)***	0.1360 (0.0203)***
EC*Routinized HIT	-0.1232 (0.0825)	-0.0501 (0.0436)	-0.0439 (0.0454)

CC: Clinical Complexity, SC: Sociological Complexity, EC: Economic Complexity

Robust Standard Errors in Parentheses

*Signif. codes: *** p<0.01, ** p< 0.05,* p< 0.1*

There was mixed support for the claim that the routinized use of HIT reduced readmission rates for non-chronic conditions (*H1d*). The relationship between Clinical Complexity and the readmission rate was seen to be significant (all p values less than 0.01), however the direction of the effect was not what theory predicted (*H2d*), however there was support for the hypotheses concerning the relationship between Sociological Complexity and readmission rate (*H3d*), as well as the one between Economic Complexity and readmission rates

(*H4d*). The moderating effect was in the opposite direction from the hypothesis along the Sociological dimension of Complexity (*H6d*). There was mixed support along the Clinical dimension (*H5d*) and some support for the hypothesis for the moderating effect along the Economic dimension (*H6d*).

It was surprising to observe that the direct effect Routinized Use of HIT tended to correspond to increased Readmission Rates. It was also unexpected to see a trend of lower readmission rates for patients with higher CC. The moderating effect of Routinized use of HIT tended to add support for lower Readmission Rates for CABG patients, however the moderating effect tends to increase the readmission rates for hospitals with Routinized Use of HIT for pneumonia and stroke patients. As with the readmission rates for the patients treated for chronic conditions, the patients treated for non-chronic conditions tended to have higher readmission rates at the hospitals that treated patients with higher EC. The overall moderating effect of the routinized use of HIT was to decrease the readmission rates for CABG, but to increase the readmission rates, particularly at hospitals that treated patients that had higher levels of SC.

Hospital-wide Readmissions

Table 11 - Prais-Winstein FGLS Estimators - Hospital-Wide Readmission Rates.

	Hospital Wide Readmissions
Clinical Complexity (CC)	-1.1001 (0.0080)***
Social Complexity (SC)	0.7678 (0.0035)***
Economic Complexity (EC)	1.1167 (0.0678)***
Routinized HIT	0.0203 (0.0230)
Hospital Size	0.1444 (0.0039)***
Teaching Intensity	2.031 (0.0458)***
Magnet Hospital	-0.1382 (0.0161)***

Outlier Payments	0.2716 (0.0631)***
Year: 2015	0.3626 (0.0074)***
Year: 2016	0.0482 (0.0083)***
Year: 2017	0.1495 (0.0085)***
CC*Routinized HIT	-0.0622 (0.0161)***
SC*Routinized HIT	0.0756 (0.0171)***
EC*Routinized HIT	-0.0769 (0.0351)**

CC: Clinical Complexity, SC: Sociological Complexity, EC: Economic Complexity

Robust Standard Errors in Parentheses

*Signif. codes: *** p<0.01, ** p< 0.05,* p< 0.1*

The direct effect of the use of Routinized HIT was seen to increase the Hospital Wide readmission rate, thus there was no support for hypothesis *H1e*. Although the relationship between CC and Hospital Wide readmission rate was significant it was in the opposite direction of effect than the theory predicted (*H2e*). However, the other dimensions of complexity were significant (p<0.01) and in the expected directions (*H3e, H4e*). The hypothesis for the moderating effect was supported along the Sociological dimension of complexity (*H6e*); however, it was seen to be significant but in the opposite direction along both the Clinical (*H5e*) and Economic dimensions (*H6e*).

5.0 Discussion and Conclusion

This study examines the ability of routinized use of HIT to influence the relationship between a multi-dimensional view of patient complexity and outcomes for the hospital as measured mortality and readmission rates for chronic and non-chronic conditions. The relationships that were observed are summarized in Tables 12 and 13.

Table 12 - Hypotheses and Results

	Hypothesis	*Result*
H1a	*The use of routinized HIT will positively impact quality of care, as measured by mortality rates for chronic conditions.*	*Supported*
H1b	*The use of routinized HIT will positively impact quality of care, as measured by mortality rates for non-chronic conditions.*	*Supported*
H1c	*The use of routinized HIT will positively impact quality of care, as measured by readmission rates for chronic conditions.*	*Unsupported*
H1d	*The use of routinized HIT will positively impact quality of care, as measured by readmission rates for non-chronic conditions.*	*Unsupported*
H1e	*The use of routinized HIT will positively impact quality of care, as measured by hospital-wide readmission rates.*	*Unsupported*
H2a	*Clinical Complexity will negatively affect the quality of care, as measured by mortality rates for patients treated for chronic conditions.*	*Mixed*
H2b	*Clinical Complexity will negatively affect the quality of care, as measured by mortality rates for patients treated for non-chronic conditions*	*Mixed*
H2c	*Clinical Complexity will negatively affect the quality of care, as measured by readmission rates for patients treated for chronic conditions.*	*Mixed*

H2d	*Clinical Complexity will negatively affect the quality of care, as measured by readmission rates for patients treated for non-chronic conditions.*	*Unsupported*
H2e	*Clinical Complexity will negatively affect the quality of care, as measured by hospital-wide readmission rates.*	*Unsupported*
H3a	*Sociological Complexity will negatively affect the quality of care, as measured by mortality rates for patients treated for chronic conditions.*	*Unsupported*
H3b	*Sociological Complexity will negatively affect the quality of care, as measured by mortality rates for patients treated for non-chronic conditions*	*Unsupported*
H3c	*Sociological Complexity will negatively affect the quality of care, as measured by readmission rates for patients treated for chronic conditions.*	*Unsupported*
H3d	*Sociological Complexity will negatively affect the quality of care, as measured by readmission rates for patients treated for non-chronic conditions.*	*Supported*
H3e	*Sociological Complexity will negatively affect the quality of care, as measured by hospital-wide readmission rates.*	*Supported*
H4a	*Economic Complexity will negatively affect the quality of care, as measured by mortality rates for patients treated for chronic conditions.*	*Supported*

H4b	*Economic Complexity will negatively affect the quality of care, as measured by mortality rates for patients treated for non-chronic conditions*	*Supported*
H4c	*Economic Complexity will negatively affect the quality of care, as measured by readmission rates for patients treated for chronic conditions.*	*Supported*
H4d	*Economic Complexity will negatively affect the quality of care, as measured by readmission rates for patients treated for non-chronic conditions.*	*Supported*
H4e	*Economic Complexity will negatively affect the quality of care, as measured by hospital-wide readmission rates.*	*Supported*
H5a	*The use of routinized HIT will positively impact the relationships between Clinical Complexity and the mortality rates for patients treated for chronic conditions.*	*Mixed*
H5b	*The use of routinized HIT will positively impact the relationships between Clinical Complexity and the mortality rates for patients treated for non-chronic conditions.*	*Mixed*
H5c	*The use of routinized HIT will positively impact the relationships between Clinical Complexity and the readmission rates for patients treated for chronic conditions.*	*Supported*

H5d	*The use of routinized HIT will positively impact the relationships between Clinical Complexity and the readmission rates for patients treated for non-chronic conditions.*	*Mixed*
H5e	*The use of routinized HIT will positively impact the relationships between Clinical Complexity and the hospital-wide readmission rate.*	*Unsupported*
H6a	*The use of routinized HIT will positively impact the relationships between Sociological Complexity and the mortality rates for patients treated for chronic conditions.*	*Supported*
H6b	*The use of routinized HIT will positively impact the relationships between Sociological Complexity and the mortality rates for patients treated for non-chronic conditions.*	*Mixed*
H6c	*The use of routinized HIT will positively impact the relationships between Sociological Complexity and the readmission rates for patients treated for chronic conditions.*	*Unsupported*
H6d	*The use of routinized HIT will positively impact the relationships between Sociological Complexity and the readmission rates for patients treated for non-chronic conditions.*	*Unsupported*
H6e	*The use of routinized HIT will positively impact the relationships between Sociological Complexity and the hospital-wide readmission rate.*	*Supported*

H7a	*The use of routinized HIT will positively impact the relationships between Economic Complexity and the mortality rates for patients treated for chronic conditions.*	*Unsupported*
H7b	*The use of routinized HIT will positively impact the relationships between Economic Complexity and the mortality rates for patients treated for non-chronic conditions.*	*Unsupported*
H7c	*The use of routinized HIT will positively impact the relationships between Economic Complexity and the readmission rates for patients treated for chronic conditions.*	*Supported*
H7d	*The use of routinized HIT will positively impact the relationships between Economic Complexity and the readmission rates for patients treated for non-chronic conditions.*	*Supported*
H7e	*The use of routinized HIT will positively impact the relationships between Economic Complexity and the hospital-wide readmission rate.*	*Unsupported*

Table 13 - Quality of Care - Results Summary Grid.

	Mortality Rates		Readmission Rates		
	Chronic	Non-Chronic	Chronic	Non-Chronic	Hospital Wide
1. Direct effect of Routinized HIT	S	S	U	U	U
2. Clinical Complexity (CC)	M	M	U	U	U
3. Sociological Complexity (SC)	U	U	U	S	S
4. Economic Complexity (EC)	S	S	S	S	S
5. Routinized HIT x CC	M	M	S	M	U
6. Routinized HIT x SC	S	M	U	U	S
7. Routinized HIT x EC	U	U	S	S	U

There were several unexpected outcomes found in the analysis of the results. There was support for the hypotheses that the use of Routinized HIT would improve patient mortality rates (*H1a, H1b*), however, none of the readmission rate hypotheses (*H1c, H1d, H1e*) were supported. There was no clear effect of Clinical Complexity on either Mortality or Readmission Rates for the hospital (*H2a-e*). Similarly, the trend for the effect of Sociological Complexity (*H3a-e*) was also weak, with evidence only seen to support its effect on Hospital-wide, and non-chronic condition readmission rates. Of the three dimensions of patient complexity, only Economic Complexity (*H4a-e*) was consistently supported. There was also only sporadic support for the moderating effect of the use of Routinized HIT. This could be due to the inconsistent patterns in the primary effects of Clinical and Sociological Complexity.

The general trend for mortality rates was that the mortality rates were decreased at the hospitals that had achieved routinized use of HIT. There was an increase in mortality rates for patients that had higher EC for both chronic (AMI, COPD, and HF) and non-chronic conditions

(CABG, pneumonia, and stroke). Again, additional research with patient specific data would be required to uncover the cause of this departure from the general trend of mortality rate reduction.

Overall, the tendency was for hospitals that have achieved Routinized Use of HIT to have higher readmission rates across each of the dimensions of patient complexity. This is an unexpected trend that warrants further investigations. There are several potential causes for this trend that have been identified in prior research such as patient specific characteristics like insurance type (Bernatz et al., 2015) or Hospital Acquired Conditions (Raines et al., 2015) that were not captured in our primarily administrative data set. Anderson, et al. (1999) found that only about half of the hospital readmissions they considered were diagnosed with the same condition as the primary diagnosis of the initial admission.

These observed trends for Readmissions and Mortality in the hospitals that have achieved Routinized use of HIT are opposite the overall trends for all hospitals that report to the HRRP. In a study that covered 2008-2018, the 30-day readmission rate for all hospitals dropped roughly 8% and the mortality rate increased by nearly 9% (Psotka, et al., 2020).

In the models, there were several instances where the time after the hospital had achieved Routinized use of HIT became the dominating factor in the mortality rate models. This was also the case for all the readmission rate models. The time effect tends to dominate the model after 2-3 years past achieving EMRAM Stage 6 Certification.

5.1 Contributions to Theory

This research adds to the literature by describing the need for and demonstrating a multi-dimensional view of patient complexity. This we have contributed to the IS and HIT literature by providing a multidimensional conceptualization of patient complexity. Further, we have operationalized the concept, and provided measures for the three dimensions of patient complexity that were included in this research. Conceptualizing patient complexity in a richer manner than the traditional approach of using CMI as a control variable will give researchers a deeper understanding of the variability within the patient population and allow for better modeling of systems that involve healthcare outcomes. In this paper we have established the need to look beyond the use or investment in HIT to create a link to performance of the HIT at the hospital. We have conceptualized Routinized HIT and have provided also provided a measure. We also found no other research that leverages the CMS data to establish a portrait of the patient demographic profile based on the location of the patients treated rather than an equal average of the patients in the hospital's catchment area. The counterintuitive findings regarding the effect of sociological and economic diversity add to the literature on healthcare disparity. These findings suggest that there may be other factors that impact the cost of care at hospitals that serve patient populations with high sociological or high economic complexity.

5.2 Contributions to Practice

One of the more important implications that these results have for practitioners is that there are additional benefits that can and should be realized through their use of HIT. The relationship between Routinized HIT use and improved reduced mortality was consistent as a direct effect which improved the longer the system was in routinized use. The direct effect of routinized use of HIT was to increase the readmission rate. However, it was the tendency of the indirect effect of Routinized use of HIT was to reduce the readmission rates along the Clinical and Economic dimensions of patient complexity and increase the readmission rate along the Sociological dimension. This could point to opportunities to realize improvements in readmission rate by improving the HIT generated discharge instructions to patients, particularly for hospitals that serve more socially diverse populations.

5.3 Limitations and Conclusion

We do acknowledge that there are some limitations to this research, as well as additional questions that this research points toward. One of the largest limitations is the limit to the patient level data that can be gathered to add richness to the conceptualization of patient complexity while performing a hospital level study. The data set for this research was limited by the available data, so the 4-year window may not have been broad enough to accurately capture the effects of the routinized HIT. There were only a handful of datapoints where a hospital had achieved their EMRAM Stage 6 certification 5 years or more prior to the dataset. This would reduce the influence of these datapoints in the calculation of the estimators. The readmissions included in the data for the study are not necessarily in relation to the condition for which the patient was initially treated (CMS). Additionally, since reductions in Readmissions are prioritized by the CMS over reductions in deaths, the CMS may be incentivizing the gaming of the system through coding and patient management rather than improvements in hospital quality of care (Psotka, et al., 2020). Also, studies that track individual hospitals performance as they achieve EMRAM Stage 6 and routinize the use of HIT in their operations could give greater insight into the difference in performance across hospitals and point toward the antecedents of leveraging HIT use to achieve better healthcare outcomes for the hospitals and their patients.

CHAPTER V: SUMMARY

The initial goal for the research was to investigate the value of HIT. In the review of the literature we found that the presence of HIT alone was not sufficient to ensure improvements in hospital or patient outcomes (DeSantis et al., 2017; Devaraj & Kohli, 2003; Romanow et al., 2018). The studies that looked at the performance of HIT on profits (Devaraj & Kohli, 2000; Menon et al., 2000), expenses (Appari et al., 2012; Ayabakan et al., 2014; Kohli & Kettinger, 2004), mortality rates (Devaraj & Kohli, 2003; Han et al., 2005), and quality of care (Cebul et al., 2011; DesRoches et al., 2010; Linder et al., 2007) showed mixed results. The research had not conclusive established a technology to performance link for any of these outcomes. Agarwahl et al. (2010), described the evidence as equivocal with respect to HIT's ability to impact performance and "non overwhelmingly positive" when attempting to link HIT to efficiency of care measures.

The HIT and IS literature considered patient complexity only to be the complexity in treatment due to the patient's diagnosed conditions as represented by the case mix index (CMI) for the hospital. Most of the literature that we reviewed used CMI as a control variable to account for the patient and case-load mix for the hospital when studying other variables of interest. We saw that in the healthcare literature there were patient factors such as socioeconomic status (Barnett et al., 2015; Krieger, 2001; McLaren, 2021; Yedjou et al., 2019), that influence the difficulty of the hospital to provide care for the patient and the ability of the patient to achieve a positive health outcome (Blumenthal & Abrams, 2016). We adopted the Vector Model for Complexity to address the deficiency that we saw in previous treatments of patient complexity.

The HIT research began with studies that investigated the presence of HIT on outcomes (Devaraj et al., 2013; Devaraj & Kohli, 2000; Menon & Lee, 2000). The studies that did find positive, conclusive evidence were predominately made using a one of the few custom-built and tailored to the operations of the hospital where it exists (Agarwal et al., 2010). The inconsistent and inconclusive results of studies that attempted to link technology to performance in a large study prompted some researchers to look further into the way in which HIT was used. There is a stream of HIT literature that argues that measures for HIT investment or for presence of HIT were not sufficient in explaining the connection between HIT technology and the outcomes it influences. Devaraj and Kohli (2000) put this question in the title of their study, "Performance impacts of information technology: Is actual usage the missing link?". The influence of HIT use rather than HIT investment was further confirmed by (Romanow et al., 2018). They found that value from HIT was realized when it was used in ways to support the structure of the clinical tasks. As it was 13 years since the passing of the HITCECH Act, it was appropriate and timely to consider how HIT had been incorporated into the work processes of providing care for patients. As the HIT becomes routinized, the hospital becomes more able to create value from its use (J. M. Goh et al., 2011).

From these understandings we developed the research model and the goals of the research, the goals for the research became to investigate the ability of the use of routinized HIT to affect a hospital's cost effectiveness and quality of care. One important measure of effectiveness for a hospital is economic effectiveness. To measure economic effectiveness, we chose expense per bed. This measure is a proxy for hospital operating costs (I. R. Bardhan & Thouin, 2013). It aggregates cost savings from improvements in clinical decisions such as reduced unnecessary laboratory testing, or overuse of imaging. As measures for quality of care we chose mortality rate and readmission rate. These measures are important measures for hospitals, patients, and healthcare administrators (Goodacre et al., 2015; Hachem et al., 2014).

In the study on hospital cost effectiveness, we used econometric methods to find that the use of routinized HIT was related to higher costs; however, it enabled hospitals to treat more clinically complex patients at lower costs. This implies that the implementations for the clinical support systems are reducing duplicated or unnecessary procedures, but that the systems may not be configured in a way that supports the structure of the clinical tasks (Romanow et al., 2018). Surprisingly, we saw that hospitals that serve more diverse populations and populations with lower incomes tended to have lower costs. We also found that the use of routinized HIT does not facilitate improved costs for the treatment of patients that are more socially diverse or have lower incomes.

This research adds to the research streams on Routinized HIT and Routinized IS by providing empirical evidence that routinization of information systems does have an impact on the outcomes of an organization, and it confirms the mixed results that have been seen previously (Agarwal et al., 2010). These findings suggest that there may be other factors that impact the cost of care at hospitals that serve patient populations with high sociological or high economic complexity. The findings concerning the indirect effects of routinized use of HIT suggest that hospitals have focused their attention on addressing clinical complexity in their HIT implementations and have not yet begun to use HIT to address the healthcare issues that arise from sociological and economic complexity. One of the more important implications that these results have for practitioners is that there are additional economic benefits that can and should be realized through their use of routinized HIT. The sign of the indirect effect of the use of routinized HIT on the relationship between economic complexity and cost of care could indicate that the push for hospitals to complete digital transformations is creating a digital divide for poorer and perhaps older patients.

In the study that investigated the potential impact of the use of routinized HIT on quality of care, we used the Prais-Winstein FGLS procedure to correct for autocorrelation present in the data to find the use of routinized HIT did tend to reduce mortality rates, but it did not tend to reduce hospital readmission rates. Although the findings for the Clinical and Sociological Complexity were mixed, there was significant and consistent support for the positive moderating effect of the use of routinized HIT for the readmission rates for patients with lower incomes treated for chronic and severe non-chronic conditions. This tendency for lower readmission rates for patients with lower incomes was not seen for hospital wide readmission rates. The counterintuitive findings regarding the effect of clinical complexity, and sociological complexity – clinical complexity is not related to higher readmission rates and sociological complexity is not necessarily related to higher mortality rates - add to the literature on healthcare literature. These findings suggest that there may be other factors that impact the cost of care at hospitals that serve patient populations with high sociological or high economic complexity.

Through these studies we have presented the need for and have demonstrated a multi-dimensional view of patient complexity. Further, we have operationalized the concept, and provided measures for the three dimensions of patient complexity that were included in this research. Conceptualizing patient complexity in a richer manner than the traditional approach of using CMI as a control variable will give researchers a deeper understanding of the variability within the patient population and allow for better modeling of systems that involve healthcare outcomes. Also, we established the need to look beyond the use or investment in HIT to create a link to performance of the HIT at the hospital. We have conceptualized Routinized HIT and have provided also provided a measure. EMRAM Stage 6 is an externally validated indication that the hospital has HIT implemented and in productive use throughout their operations. For a hospital to achieve Stage 6 they must have all critical systems installed including full physician documentation, tracking of nurse order and task completion with clinical decision support (CDS) that at least performs rudimentary conflict checking and a second stage CDS related to evidence-based medicine protocols. Achievement of the EMRAM Stage 6 milestone indicates that a hospital is committed to improvements patient safety, outcomes, the move to a paperless health record and overall integration of HIT in the operations of the hospital (Kilborn, 2019). We also found no other research that leverages the CMS data to establish a portrait of the patient demographic profile based on the location of the patients treated rather than an equal average of the patients in the hospital's catchment area.

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