EXAMINING TWO DIMENSIONS OF TECHNOLOGY ADOPTION AND HOSPITAL PERFORMANCE

by

Joonghee Lee

A dissertation submitted to the Graduate Faculty of
Auburn University
in partial fulfillment of the
requirements for the Degree of
Doctor of Philosophy

Auburn, Alabama
August 7, 2021

Keywords: healthcare information technology, technology adoption, hospital performance

Approved by

Dianne Hall, Chair, Globe Life Professor of Information Systems and Business Analytics
David Paradice, Professor and Harbert Eminent Scholar of Business Analytics
Casey Cegielski, J.W. Woodruff, Sr. Professor of Information Systems Management
Kangbok Lee, EBSCO Associate Professor of Business Analytics

Abstract

This study examines the hospital performance implications of the different technology adoption behaviors in a hospital setting. Drawing on biodiversity concept in Ecology, this study includes two features (diversity and velocity) of technology adoption behavior to describe different ways of technology adoption. Diversity describes how different technologies are adopted in a hospital, while velocity describes the change of HIT diversity over time (i.e., the pace of technology addition). With longitudinal data on more than 3300 US hospitals spanning five years, this work explored technology adoption behaviors from an empirical taxonomic approach to determine whether the hospitals in the data could be distinguished by the two technology adoption dimensions. The clustering results show that three homogeneous classes of technology adoption behaviors exist according to these dimensions. Also, the study examines the association between the two dimensions and hospital performance. It used a dynamic panel model with GMM estimation to mitigate the bias from reverse causality. The results show the positive relationship between HIT diversity and hospital performance, while the velocity of HIT diversity change had a negative association with hospital performance.

Acknowledgments

Above all, I would like to thank God for always helping me and giving me the ability and patience to complete my doctoral journey. As always, my endless gratitude goes to my family. My eternal love goes to my wife, Aeri Song; her support for our family helped me find time to conduct my research. I also want to express my great appreciation to my mother for her never-ending belief in me. Furthermore, I have been strengthened by the belief that my father in heaven would be proud of me.

Many people at Auburn University have helped me become a scholar. I would first like to sincerely thank my chair, Dr. Dianne Hall, for her guidance. Her continuous support and encouragement have been invaluable throughout my doctoral studies; without her tireless efforts, I would not have succeeded. I would also like to thank Drs. David Paradice, Casey Cegielski, and Kangbok Lee for agreeing to serve on my committee and for their contributions to my dissertation. They gave me many challenging comments and constructive suggestions that greatly improved my study. In addition, I would like to thank Dr. Pei Xu for giving me an opportunity to collaborate on a research project that enhanced my skills and knowledge. I would also like to thank Drs. Ashish Gupta and Amit Mitra for the research knowledge and skills that I gained through their seminars. I also want to express my thanks to my colleagues—Jianliang Hao, Richard Ross, Jay Claiborne, James Locke, Yeasung Jeong, Jonathan Lee, and Wenting Jiang—for being part of my amazing experience at Auburn University. Lastly, I would like to thank the members of my church for supporting me.

I am very fortunate to know the countless people who have shaped me in different ways and helped me become who I am today. Thank you all for the parts that you have played in my journey.

Table of Contents

List of Tables

List of Figures

List of Abbreviations

EHR	Electronic Health Records
CPOE	Computerized Provider Order Entry
PD	Physician Documentation
BI	Business Intelligence
RFID	Radio-Frequency Identification
EMR	Electronic Medical Record
CDS	Clinical Decision Support
IS	Information System
RBV	Resource-Based View
HIMSS	Healthcare Information and Management Systems Society
CMS	Center for Medicare & Medicaid Services
HCAHPS	Hospital Consumer Assessments of Healthcare Providers and Systems
CMI	Case Mix Index
GMM	Generalized Method of Moments
CEM	Coarsen Exact Matching

CHAPTER 1

INTRODUCTION

Despite the amount of money spent within the healthcare industry, the quality of care in U.S. hospitals remains concerning. National healthcare expenditure in the U.S. was $3.8 trillion in 2019, and the U.S. Centers for Medicare and Medicaid Services projected that U.S. health care spending will grow at an average rate of 5.5 % per year for 2019 – 2028 and to reach nearly $6.2 trillion by 2028, which is outpacing the expected annual growth rate of 4.3 % in GDP (National Health Expenditure Accounts, 2019). Regarding these trends, the U.S. government legislated the Health Information Technology for Economic and Clinical Health Act in 2009 to encourage healthcare providers to adopt and use health information technology (HIT) and to improve care quality. With the increase of HIT throughout the U.S. healthcare system, along with the costs associated with its implementation and maintenance, a better understanding of how to adapt and exploit technology to improve hospital performance becomes an important consideration (Agarwal et al. 2010; Fichman et al. 2011; Kohli and Tan 2016; Lucas et al. 2013).

Given the importance of HIT to healthcare in general, numerous studies have attempted to discover what relationships exist between HIT adoption and hospital performance (Appendix B). Some studies have proved that HIT can improve the quality of care (e.g., lower mortality rates, reduce medical errors, improve patient safety, and increase patient satisfaction), hospital efficiency, and financial performance (e.g., lower costs, increase revenue, and increase productivity), but other studies have found that adoption yields marginal benefits (e.g., McCullough et al. 2010), and even has negative effects (e.g., Koppel et al., 2005). These conflicting findings question the role of information technology (IT) in the healthcare setting. However, such contradictory findings are not unique to HIT; authors have reported mixed results regarding general IT investments (Angst et al. 2011; Atasoy et al. 2018). These results suggest that the IT impact on organizational benefits is more nuanced than has previously been investigated and the methods used for measurement are important (Brynjolfsson and Hitt 1996, 2003; Sabherwal and Jeyaraj 2015). Moreover, most technology-value research in the healthcare setting focuses on whether a technology event (e.g., adoption, investment, or implementation) occurs or not and analyzes performance before and after the events. The challenge associated with this type of analysis is that how the adoption of technology is executed has not been considered and the analysis provides only a comparative result (i.e., hospitals adopting a technology perform better than those that do not).

This study examines the hospital performance implications of the different technology adoption behaviors in a hospital setting. The goal of this paper is not simply to test and discover the correlating value of information technologies within the healthcare context, but instead to explore different technology adoption behaviors. Further, it argues that the different ways of technology adoption can affect the results of the adoption. This study addresses the research question: *How do different ways of technology adoption impact hospital performance?*

To answer this question, this study includes two features of technology adoption behavior: diversity and velocity. Diversity describes how different technologies are adopted in a hospital, while velocity describes the change of HIT diversity over time (i.e., the pace of technology addition). This study leverages insights from biodiversity concepts in Ecology; ecologists partition biodiversity into alpha and beta diversities. Alpha diversity indicates how different species are in a single location, while beta diversity is a measure of the relative change in species composition between locations (Jost 2007). In this study, alpha diversity is the variety of HIT deployed in a hospital (i.e., HIT diversity) and beta diversity is the change in HIT diversity over time (i.e., velocity; pace of technology addition). Thus, this study understands the patterns of hospitals' technology adoption behaviors by considering the two dimensions of diversity and velocity. This study argues that hospitals that invest in diverse technology all at once are likely to have different results than ones that invest in technology over time or ones that perform major technology updates years after its deployment. Together, these patterns are likely to yield results different from those that appear when only one point in time is considered.

The premise of investigating the variations of adopting diverse HIT over time and hospital performance in this study is based on Resource Orchestration Theory (ROT) (Sirmon et al. 2011). The key idea of this theory is that the value of resources lies in accumulating, combining, and exploiting them over time. When applied to the context of this research, this study argues that there are potential performance-related properties associated with the adoption of diverse HIT and the composition change of deployed HIT over time. In investigating the conceptual model based on the empirical results of the taxonomy study and ROT, this work focuses on two aspects of hospital performance—patient satisfaction and the number of discharges—and explore whether the performance is affected by the two features of technology adoption.

In addition, this study uses a configurational approach to develop a taxonomy based on the two features of technology adoption because the diversity and velocity interface is largely unexplored. This variation of the two dimensions of technology adoption across hospitals seems to have never been systematically investigated; this approach is exploratory and demands little prior knowledge on the subject (Ketchen et al. 993). This study uses cluster analyses to classifies technology adoption behaviors of hospitals according to diversity and velocity dimensions empirically. It is an important aspect of any scientific investigation to classify the phenomena being studied. Observing differences among behaviors and classifying them must be effectively implemented before any attempt to discover "the universal laws which govern the behavior, functions, and processes of the objects under investigation" (McKelvey 1978, p. 1428). Simply put, the taxonomy development is a prerequisite to achieving a sound scientific method (McKelvey 1978, 1982). Based on this background, this work included a taxonomic study to investigate the two features of technology adoption and hospital performance. The specific research goals of this study are as follow:

- To empirically identify varieties of diversity and velocity configurations and develop a taxonomy.
- To explore the impacts of the two technology adoption dimensions on hospital performance in terms of patient satisfaction and discharges.

This study contributes to the literature in several ways. Considering the limited research on the patterns of technology adoption with the consideration of diversity and velocity, especially in healthcare, this study is the first to examine the effects of the different technology adoption patterns on hospital performance. In addition, this study contributes to reducing the research gaps found in the previous literature on HIT adoption. With few exceptions, most HIT adoption studies have focused on specific or limited technologies (e.g., Hydari et al. 2019; McCullough 2010), often within a specific functional area, such as clinical and administrative HIT (e.g., Sharma et al. 2016). The IT/performance link is more nuanced than has been uncovered, indicating that the assumption of IT positively affecting performance cannot be investigated by focusing on a single technology or type of technology (Choi et al. 2018;

Karahanna et al. 2019). In other words, it is a rich composite of technologies supporting an organization's various functions and processes that gives the organization a competitive advantage. Thus, examining the composition of multiple technologies rather than focusing on a specific technology elevates the research in a way that should clarify nuances among the technologies examined. Furthermore, the extant research has made little effort to understand the temporal dynamics of technology adoption in hospital settings and has not considered the temporal variation of hospitals' technology adoption behaviors (Appendix A). It might be more natural to view HIT from a longitudinal perspective because organizations are likely to not only adopt and use technology from one point in time but also to update or add to their technology at varying points in time. Scholars in management have argued that we need to understand how organizations function over time to understand the implications of organizational practices and behaviors better (Ancona et al. 2001; Lawrence et al. 2001). Specifically, the temporal lens considers sequencing (i.e., the order in which technologies are adopted over time), pacing (i.e., the speed of hospitals' technology adoption), and duration (i.e., the length of time that the technology has been in use in a hospital) (Ancona et al. 2001). Although a few studies examined the effects of HIT using a time lens, they focused on long-term/short-term effects (Bradley et al. 2018) and sequences (Angst et al. 2011). Previous literature has overlooked "pacing" regarding technology adoption in a hospital setting. Thus, the overarching contribution of this study is the enhancement of our understanding of hospitals' technology adoption behaviors by considering two features of technology adoption (diversity and velocity) and exploring how these are associated with performance in a hospital setting. From a practical standpoint, this study provides healthcare practitioners with insights relative to the values of considering diversity and velocity.

The rest of this article is as follows: First, it presents a review of the literature on HITs and hospital performance, followed by a discussion of the exploratory study to develop a taxonomy. Specifically, this work documents the taxonomic procedure and presents the results, which include the taxonomy and outcomes of the configurations. It includes a confirmatory study to investigate the impact of HIT diversity and velocity on hospital performance with an econometric approach. This paper concludes with implications for academic research and managerial practice.

CHAPTER 2

LITERATURE REVIEW

Need to Further Examine Technology Adoption in Healthcare

Numerous, varied studies have investigated the value of IT in hospital settings (Table A1 in Appendix A). Despite the amount of extant literature, most technology-value research in the healthcare setting focused on whether a technology event (e.g., adoption, investment, or implementation) occurs or not, rather than the manner which the adoption of technology is executed. In addition, most studies focused on specific or limited technologies, often within a specific functional area and do not consider the temporal dynamics of technology adoption

The predominant focus within hospital IT research has been on specific or a limited number of technologies and/or a particular functional type of technology. For example, McCullough (2010) investigated the impact of HIT on care quality with a focus on electronic health records (EHR) and a computerized provider order entry (CPOE) and found significant improvements in hospitals' quality of care through using these technologies. More recently, Hydari et al. (2019) documented improvements in patient safety as a function of both CPOE and physician documentation (PD) adaption. By using these technologies, medical staff exchange information about patients electronically, enabling them to communicate faster and reduce communication errors (e.g., inaccurate reading of a physician's handwriting). Further, Oh et al. (2018) examined HIT applications (e.g. CPOE, business intelligence [BI], radio-frequency identification [RFID]) individually and found that HIT implementation is associated with a reduction in readmission risk. Implementation of HIT enables hospital managers to more optimally manage patient stays so that patients who require longer stays are not discharged preemptively (Oh et al. 2018).

While the extant results consistently support the value of HIT in improving outcomes, researchers have argued that it is not a single technology but a composite of technologies and a complementarity among them that truly supports and enhances the association between HIT and performance (Agarwal et al. 2010; Karahanna et al. 2019; Sharma et al. 2016). This is thought to stem from the adoption of HIT not as a standalone system but as bundles of technology (Sharma et al. 2016). For instance, electronic medical record (EMR) systems collect and manage a wide range of health and clinical data, such as patient and diagnostic information, prescriptions, and lab results, and CPOE allows physicians to enter orders for services and medications electronically. Hence, CPOE can facilitate coordination and communication across providers in conjunction with EMR (McCullough et al. 2016). Another example of how a composite of HITs can generate advantages beyond that for each HIT alone is the adoption of RFID and electronic data interchange (EDI) technologies. Bradley et al. (2018) documented improved supply chain cost efficiency along with personnel cost savings and a reduced readmission rate stemming from the adoption of RFID and EDI technologies. Specifically, they found that there is no statistically significant association between supply costs and readmission rates in hospitals using only RFID, but hospitals jointly using the RFID-EDI bundle have lower supply costs, personnel costs, and readmission rates. This bundle improves information flows so that hospitals have more accurate inventory records and can better communicate such information to various stakeholders. This results in a more efficient (and lower cost) supply chain and less time committed to non-patient care endeavors. These savings can then be turned to patient care, a value-added task (Bradley et al. 2018). Collectively adopting different technologies gives hospitals the ability to streamline the processes of patient care and hospital operations, which should improve hospital performance.

However, not all research has shown this relationship between composite technology use and improved performance. Using the IT portfolio approach, Angst et al. (2012) used the classifications of administrative and clinical HIT and found that the two types of HIT influence hospital processes differently. Clinical HIT helps medical staff comply with technical protocols so that they can provide proper and consistent service to patients, while administrative HIT adversely affects the doctor–patient relationship. Similarly, Sharma et al. (2016) created an additional category, and evaluated not only clinical HIT but also augmented clinical HIT. According to their study, neither classification is associated with cost performance, but each is associated with an improved quality of care. These technologies help medical staff adhere to technical standards and enhance the hospital’s ability to cater to the preferences of its patients. Moreover, the study results indicate that there is a complementary relationship between clinical HIT and augmented clinical HIT; these systems jointly affect hospital performance.

Some studies examined the adoption of a composite of multiple HITs (Burke et al. 2002; Jaana et al. 2006; Wang et al. 2005; Zhang et al. 2013), with the HITs categorized into strategic, administrative, and clinical bundles based on their functions, and examined the association between organizational and contextual factors and IT adoption in hospitals. They reveal that aggregate HIT adoption is associated with a variety of factors, such as hospital size, ownership status, teaching status, geographic locations, accreditation status, and market competition. Other researchers have studied multiple HIT but assessed the adoption of each HIT separately (Furukawa et al. 2008; Gabriel et al. 2014; McCullough 2008). These studies also examined the variation in HIT adoption. For example, Furukawa et al. (2008) studied the extent of the adoption of 8 HITs (e.g., EMR, clinical decision support [CDS], and CPOE).

A few studies have focused on the IT resource portfolio in the context of the business value of IT. For instance, Aral and Weill (2007) defined the IT resource portfolio as consisting of transactional, informational, strategic, and infrastructural IT. They examined how the type of IT resource is associated with firm performance. Additionally, Xue et al. (2012) provided evidence that an IT resource portfolio has different roles in supporting innovation and efficiency.

Some researchers used aggregate variables to measure HIT adoption, such as IT investment (Devaraj et al. 2013) and IT infrastructure level (Gardner et al. 2015; Queenan et al. 2011). Devaraj et al. (2013) used IT expenditure covering IT hardware, software, and service for patient care activities, and examined its impact on hospitals' financial performance. They reported that IT investment improves hospital operations, such as better diagnoses, scheduling, and coordination of patient care, which increases financial performance in hospitals. The IT expenditure measure captures the amount of budget allocated to IT resources, but it does not represent how different information technologies are used in hospitals. Queenan et al. (2011) examined the complementary role of IT infrastructure and found that patients are more likely to be satisfied with a hospital's service when it utilizes CPOE has a higher level of IT infrastructure. The higher level indicates that the hospital has better software, hardware, and network systems that increase the utilization of HIT (Queenan et al. 2011). Similarly, Gardner et al. (2015) examined the relationship between HIT infrastructure and hospital performance (e.g., patient satisfaction and care quality). They reported that HIT infrastructure positively affects the measures because it enables hospitals to collect, analyze, and leverage data for care delivery and operations (Gardner et al. 2015). IT infrastructure is generally regarded as the composite of tangible IT resources, such as the hardware, software, and network components required for the operation and management of an enterprise (Duncan 1995), broadening the perspective. Although previous studies (Gardner et al. 2015; Queenan et al. 2011) used the number of HITs available in hospitals as a proxy to measure the IT infrastructure, IT infrastructure differs conceptually from HIT diversity.

To obtain a more accurate measure of HIT impact, a deeper understanding of technology is required, particularly the interdependence that exists among HIT components (Agarwal et al. 2010). Previous research provides rich explanations for how an individual technology, the type of technology, the hospital's IT budget, and the set of tangible IT resources in hospitals are associated with hospital performance. However, there is no established research stream that identifies how hospitals allocate their budgets to IT resources and how diversified a hospital's IT resource portfolio is.

Another element that is missing in the literature is the view of HIT from a longitudinal perspective. Scholars in management have argued that we need to understand how organizations function over time to understand the implications of organizational practices and behaviors better (Ancona et al. 2001; Lawrence et al. 2001). The temporal lens considers sequencing (i.e., the order in which technologies are adopted over time), pacing (i.e., the speed of hospitals' technology adoption), and duration of changes (i.e., the length of time that the technology has been in use in a hospital) (Ancona et al. 2001). By taking on the temporal lens, we can understand the implications of HIT adoption in hospitals better because it more accurately reflects the realities of actual hospital practices of HIT adoption.

Healthcare technology has been evolving quickly, affecting virtually all aspects of healthcare, yet little research has addressed the issues associated with this evolution. The effects of the evolution have been addressed in terms of common areas of healthcare such as clinical nursing (e.g., Archibald and Barnard, 2018) and patient outcomes (e.g., Prahalad et al. 2018). Some evolution research is expanding to include technologies not previously widely considered in healthcare, such as blockchain to support record keeping (e.g., Roman-Belmonte et al. 2018) and the Internet of Things to support patient health and information distribution (e.g., Rodrigues et al. 2018). While this research focuses on the future of technology and its potential impacts, researchers still do not appear to be looking at technology's impact over time. Most extant literature focuses on whether a hospital adopts technology (often specific to its type or function) (e.g., Angst et al. 2012; Hydari et al. 2019; McCullough et al. 2010; Menachemi et al. 2006; Sharma et al. 2016), the extent to which a hospital allocates its budget to IT resources (e.g., Devaraj et al. 2013; Gardner et al. 2015; Queenan et al. 2011), and the impact of technology, albeit from a variety of contexts. However, these might not truly reflect a hospital's technology adoption given that organizations are likely to not only adopt and use technology continuously from one point in time but also to update or add to their technology at varying points in time. In an overview of the extant research regarding HIT, Agarwal et al. (2010) argued that technology has often not been clearly conceptualized and bounded. In particular, many researchers have examined individual technologies rather than integrated systems (Karahanna et al. 2019; Sharma et al. 2016). They note that there are about 100 different HIT applications, and this number has continued to grow over the last several years. They note as an example that "early investment in digitizing patient information may produce no obvious benefit to performance until the decision support component is added" (Agarwal et al. 2010, p. 802). Thus, taking snapshots of technology use limits our ability to understand the temporal dynamics of technology and the effects that the temporal dimension may be introduced.

Some studies have used time dimensions to examine the HIT's time-dependent effects. For example, Bradley et al. (2018) examined the time-dependent effects of the joint use of RFID and EDI by employing a dynamic modeling approach to estimate their long-term performance impact. They assumed that the effect of RFID–EDI might differ as function of the length of time that the technology has been in use in a hospital. They found that the persistence of these technology patterns over time brings positive results to hospitals, such as a reduction of supply costs and personnel expenses, and lower hospital readmission rates. This result suggests that hospitals need accumulated experience over time to fully leverage technologies and receive benefits; there is also a lag between the deployment of technology and the realization of its impact on organizational performance (Bradley et al. 2018). A learning curve is probably responsible for situations wherein employees (and potentially patients) must fully embrace and learn a technology to realize its potential for efficiency and effectiveness gains. In light of this, Angst et al. (2011) investigated the order in which medical technologies are transformed into information technologies through the process of converting them from stand-alone technologies to integrated information systems and examined whether certain configurations of sequences of integration yield additional value. They found that sequence matters and hospitals that integrated foundational technologies first—which, in this case, are known to be more complex—tend to perform better. Greater complexity of use is associated with a greater risk of implementation failure (Premkumar and Roberts 1999). Thus, one would expect simpler technologies to be integrated first. In addition, a foundational information system (IS) forms the infrastructure on which the other applications interface. Some studies have examined the length of time necessary for a hospital to receive a benefit following the implementation of technology (e.g., Devaraj and Kohli 2000, 2003; Menon et al. 2009). Although these studies examined the effects of HIT with a time lens, they focused on the long-term–short-term effects and sequences. This current study differs in that it focuses on the relationship between the rate of HIT diversity change in a hospital per unit of time and the level of patient satisfaction.

Employment of the temporal lens can contribute to resolving the inconclusiveness in the research stream of HIT adoption. Extant literature regarding HIT and hospital performance has yielded mixed results (Agarwal et al. 2010; Buntin et al. 2011) and reported either a positive outcome (e.g., Aron et al. 2011; Kohli and Devaraj 2003), marginal improvement (e.g., McCullough et al. 2010) or negative impact (e.g., Koppel et al. 2005) on hospital performance. Potential explanations for these conflicting results include limitations such as focusing on a single technology (Kohli and Devaraj 2004; Koppel et al. 2005), looking at final clinical outcomes such as readmission and morality that are intertwined with several patient characteristics that were not considered (DesHarnais et al. 1990), and missing an intermediate process leading to the final outcomes. To overcome these limitations, previous studies focused on a composite of HIT with the IT portfolio approach (Sharma et al. 2016) and used intermediate performance measures (Pinsonneault et al. 2017; Sharma et al. 2016). Sharma et al. (2016) examined how two key HIT bundles: clinical HIT (primarily used for patient data collection, diagnosis, and treatment) and augmented clinical HIT (used for integrating patient information and augmenting the decision-making capability of caregivers) jointly affect cost and process quality outcomes (conformance quality and experiential quality). Results show that both clinical and augmented clinical HIT enhance the ability to adhere to technical standards and to cater to patient preferences. In addition, Pinsonneault et al. (2017) documented that HIT improves hospitals' quality of care indirectly by increasing their continuity of care (i.e., the extent to which the care of an individual patient is maintained over time). HITs increase the frequency of interactions among healthcare partners in the care cycle and enhance the coordination of care delivery through shared care plans and treatment protocols, which leads to continuity of care. Another approach to overcome limitations is to use the complementary perspective. For example, Gardner et al. (2015) included two distinct means of processing information, including strategic and error processing, as complementarities with which HIT improve hospital performance. Error processing refers to the use of analytical tools such as the statistical analysis of data, process mapping, and error proofing to reduce hospital errors, and strategic processing is the extent to which objective data is collected, analyzed, and used for identifying competitive strengths and planning organizational direction (Gardner et al. 2015). The results provide empirical evidence that HIT infrastructure can serve as an effective mechanism for processing information leading to direct improvements in both care quality and patient satisfaction. Although previous research offers some resolution to the inconclusive empirical evidence with respect to the benefits of leveraging HIT in hospitals, its mixed results might stem from a lack of research rooted in the realities of the actual hospital practices of HIT adoption. Thus, the absence of temporal dynamics in technology adoption might influence the lack conclusive support for the association between HIT and performance.

From the above discussion, it is clear that most of the research in the field has focused on either specific or a limited number of technologies and/or a particular functional type of technology. Although the literature provides a rich explanation for the impact of HIT on hospital performance, there has been little to no effort to investigate how diversified a hospital's IT resource portfolio is and how hospitals develop a HIT portfolio over time via adoption and implementation. In particular, previous studies regarding the adoption of HIT have not sufficiently analyzed the temporal dynamics of technology and their effects. Most of the prior research focused on effect lag, although a few have touched on the sequence of technology adoption. Few, if any, have considered the effect of HIT when compared to its variety and pattern of adoption. Therefore, the temporal variable is likely to increase the understanding of the implications of HIT adoption (both variety and timing) as it more accurately reflects common patterns within a hospital setting.

Two Dimensions of Technology Adoption: Diversity and Velocity

To reduce the research gaps, this study leverages insights from biodiversity concepts in Ecology; ecologists partition biodiversity into alpha and beta diversities. Alpha diversity is a measure of single-location diversity (i.e., how different species are in a location), while beta diversity is a measure of the relative change in species composition between locations (i.e., the different species compositions among locations) (Jost 2007). These two diversity concepts can be applied in a hospital setting, where the level of HIT diversity represents alpha diversity and the change in HIT diversity over time (velocity) represents beta diversity.

HIT diversity is based on the concept of alpha diversity that is a measure of single-location diversity (i.e., how different species are in a location) (Jost 2007). Alpha diversity considers the number of living organisms and the variety of species. In other words, it is the set of relative frequencies for life in a species. Thus, alpha diversity is high, when a variety of species has a large population. If only one species is flourishing in a location, then alpha diversity is low. Taking this concept of alpha diversity, HIT diversity captures to what extent available HIT applications are live and operational in a given hospital based on the number of HIT applications and the various types of applications. Figure 1 presents a graphical illustration of alpha diversity and HIT diversity.

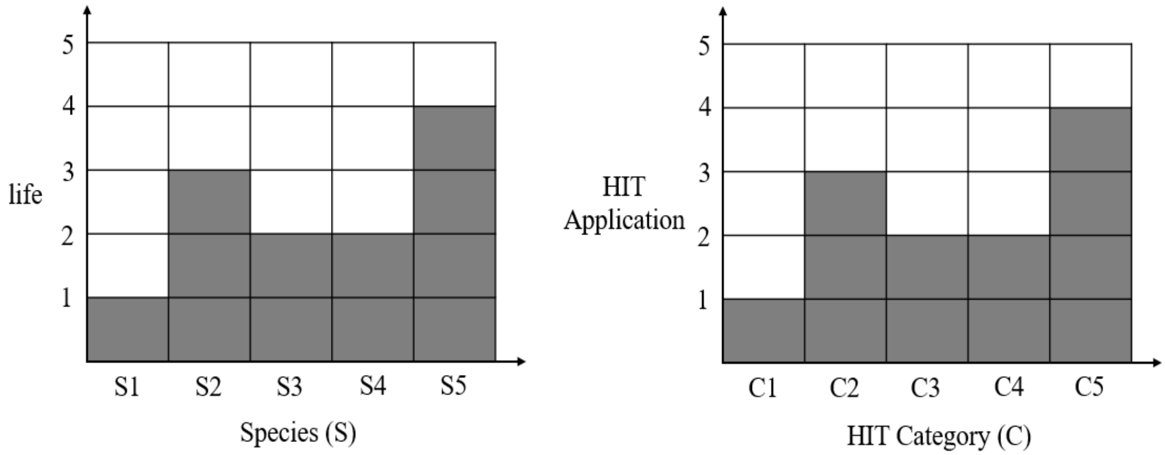

Figure 1. Graphical Description of Alpha Diversity (Left) and HIT Diversity (Right)

To measure hospital-level HIT diversity, this study adopted the Shannon index (Shannon 1948). This is widely used in ecology and genetics to measure how many different species exist in a given community (Jost 2007), and how evenly genes are distributed among tissues (Martínez and Reyes-Valdés 2008). The Shannon index for biodiversity is given as

$$Shannon\ Index\ (H_j) = -\sum_{k=1}^{s} P_k ln^{P_k}$$

where *j* indicates a location, P_k is the proportion (n/N) of individuals of one particular species *k* found (n) divided by the total number of individuals found (N), *ln* is the natural log, Σ is the sum of the calculations, and *s* is the number of species. This index implies that biodiversity is a mathematical measure of species diversity in a given location based on species richness (the number of species present) and species abundance (the number of individuals per species).

Based on the Shannon Index and concept of biodiversity, HIT diversity is mathematically defined as

$$HIT\ Diversity\ (D_j) = -\sum_{k=1}^{s} \frac{n_k}{30} log_2^{\frac{n_k}{30}}$$

where j indicates a hospital, n_k describes the individual HIT applications of a particular HIT category k deployed in j, Σ is the sum of the calculations, and s is the number of categories. In this measure, this study sets N to 30 and calculated P_k by dividing n_k by 30. It lists up HIT applications (Appendix A) based on the Electronic Medical Record Adoption Model (EMRAM) that is documented by HIMM Analytics. This model is designed to help ensure hospitals are on the right track when it comes to EHR deployment, leveraging the growing pool of analytics resources and coordinating care across a variety of settings. It suggests criteria to evaluate individual hospital's HIT adoption stages and suggests the HIT applications that should be adopted for each stage. Thirty HIT applications and 10 categories were found in the list. Thus, this study evaluates the level of HIT diversity based on this number. Also, D_j uses a logarithm of base 2. Although H_j uses the natural log, Shannon considered a binary message that consists of a string of zeroes and ones (Shannon 1948). In this case, he chose base 2 to measure the information needed to specify a series of binary bits (Shannon 1948). Technology adoption behaviors can be also viewed as a binary case, in that a hospital use a technology or not. Thus, HIT diversity measures how different technologies are deployed in a hospital based on the total number of HIT applications and the number of individual HIT applications per HIT category).

Velocity is based on the concept of beta diversity that is a measure of the relative change in species composition between locations (i.e., how different the species composition is among locations) (Jost 2007). This study used the different time points instead of locations, so velocity is the rate of change of a hospital's HIT diversity and is a function of time (i.e., how fast a hospital changes its level of HIT diversity over time). Thus, velocity is equivalent to the specification of the speed of a hospital's diversification of HIT within a given period. For example, one hospital can invest in diverse technologies all at once while another invests in technology over time and a third only performs a major technology update years after a deployment.

Why a Taxonomic Study of Technology Behavior is Crucial

> *"Animals cannot be discussed or treated in a scientific way until some taxonomy has been achieved"* (Simpson 1945 quoted by Mayr 1969, p. 19)
>
> *"The extent to which progress in ecology depends upon accurate identification and the existence of a sound systematic groundwork … without it the ecologist is helpless, and the whole of their work may be rendered useless"* (Elton 1947 quoted by Mayr 1969, p. 6)

Just substitute "the behaviors and functions of organizations" for *animal* in the foregoing quotes and it becomes clear how important the development of taxonomy and classification is for scientific organizational research. An important aspect of any scientific investigation involves classifying the phenomena being studies (Hawes and Crittenden 1984). This is often described as the systematics that focus on the development of taxonomies and the identification of homogeneous classes within the taxonomy (McKelvey 1978; Ross 1974). Observing differences among behaviors and classifying them must be effectively implemented before any attempt to discover "the universal laws which govern the behavior, functions, and processes of the objects under investigation" (McKelvey 1978, p. 1428). Simply put, systematics is a prerequisite to a sound scientific method (McKelvey 1978, 1982). In other words, researchers must investigate differences and similarities to enhance their understanding of the behaviors and functions of the entities under examination (Posey et al. 2013).

Many disciplines have benefitted greatly from systematics. In particular, the natural sciences of biology, botany, ecology, and zoology could not have contributed to humanity to the degree that they have if it were not for initial taxonomic efforts. Although taxonomy is the branch of biology dealing with classification and nomenclature, other sciences such as physics, chemistry, and mineralogy have systematic studies as a significant feature of their past (Mckelvey 1982). As McKelvey (1982) states, chemistry saw significant progress following Mendeleev's creation of the periodic chart, and functional science in physics advanced significantly following Dalton and Bohr's conception of the atom. Despite taxonomy's youth relative to the aforementioned disciplines, taxonomic efforts have contributed to the growth of disciplines in business administration, such as IS, management, and marketing. Some IS scholars provided researchers and practitioners with a clear identification of this field and directions for available research and future work by using taxonomic approaches. For example, Mason and Mitroff (1973) suggested a research program in IS that uses a taxonomy of identifying general considerations for IS research. Larsen (2003) developed taxonomies of IS success antecedents that created two general categories. Further, many previous studies have developed taxonomies to improve the understanding of organizational behaviors and phenomena. For instance, Fiedler et al. (1996) developed a taxonomy that has implications for matching information technology and organizational structures based on the degree of centralization of computer processing, the capability to support communications, and the ability to share resources. In addition, Earl (2001) proposed a taxonomy of knowledge management strategies as a framework to understand the sorts of knowledge management initiatives or investments that are possible and to identify those that make sense in the context of specific goals, organizational character, and technological, behavioral, or economic biases. More recently, Posey et al. (2013) developed a taxonomy and theory of diversity for protection-motivated behaviors to understanding protective information security behaviors. Moreover, in the marketing field, research has applied taxonomies to comprehend how firms relate to their markets and their customers (Cannon and Perreault 1999; Coviello et al. 2002), how sellers manage key accounts (Homburg et al. 2002), how marketing contributes to the implementation of a business strategy (Slater and Olson 2001), and how the interface between marketing and sales units impact organizational performance (Homburg et al. 2008). These efforts provided a strong foundation and requisite guidance to the functional studies within their respective areas to develop universal theories about the phenomena. These efforts were vital for scientific progress because theoretical development is a methodical progression that must emerge from rigorous foundations (Gregor 2006).

As discussed above, the variation of the two dimensions of technology adoption across hospitals has never been systematically investigated. As the literature review in this study shows, most studies focused on specific or limited technologies (e.g., Hydari et al. 2019; McCullough 2010), often within a specific functional area, such as clinical and administrative HIT (e.g., Sharma et al. 2016), and they made little effort to understand the temporal dynamics of technology adoption in a hospital setting.

For these reasons, the area of technology adoption can benefit from taxonomic investigations. Accordingly, this study explores technology adoption behaviors using a taxonomic approach; it aims to determine whether the hospitals in the data can be distinguished by the two technology adoption dimensions of diversity and velocity.

Theoretical Background: Diversity, Velocity, and Hospital Performance

The resource-based view (RBV) (Barney 1991) has been used widely to explain the relationship between IT resources and organizational performance (Wade and Hulland 2004). This perspective suggests that the competitive performance of organizations is attributable to the organizations' idiosyncratic resources (Barney 1991). In other words, the potential for competitive advantage exists when resources are valuable, rare, and costly to imitate. Although this theoretical framework is popular, scholars argue that the theory is inadequate for explaining the differences among organizations. The essence of this criticism is that resource management is absent in RBV. Researchers have suggested that merely having valuable and rare resources is insufficient for gaining a competitive advantage; such resources must be effectively managed (Sirmon et al. 2008). ROT responds to this criticism and extends RBV by incorporating the resource management perspective (Sirmon et al. 2011).

ROT emphasizes managerial action and the resource-related processes; the underlying argument is that resources must be managed via managerial action for performances within organizations (Chirico et al. 2011). Sirmon et al. (2007) defined resource management as the three sequential processes of structuring, bundling, and leveraging organizational resources. Structuring is the process to develop an organization's resource portfolios by obtaining and accumulating resources. Bundling refers to the combined use of resources to form capabilities. Leveraging represents the degree to which organizations continue to exploit the bundled resources. Based on this theoretical perspective, this study explores hospitals' structuring of their technology resources, such that how they develop their IT resource portfolio by adopting diverse HITs over time at different paces.

CHAPTER 3

AN EXPLORATOTY STUDY FOR A TAXONOMY

Methods

Data Collection

This exploratory study employed multiple sources of data, including the Healthcare Information and Management Systems Society (HIMSS) database and the Center for Medicare & Medicaid Services (CMS) database. The HIMSS database provides hospital-level IT adoption. The longitudinal database contains information on the hardware and software adoption of healthcare providers across the U.S. Even though HIMSS data have limitations, the HIMSS database remains the most representative and detailed database for health IT adoption in the U.S. and is used in several studies (e.g., Atasoy et al. 2018; Gardner et al. 2015; Oh et al. 2018).

Cluster Variables and Additional Descriptors

Table 1 provides the study's variable list. The study included HIT diversity and the velocity of HIT diversity change as cluster variables. These variables were measured using secondary data provided by the HIMSS database from their 2008–2013 annual survey of U.S. hospitals, which is the most current data available. HIMSS surveys chief information officers and other IT executives annually to assess the adoption status of multiple HIT applications. Examples of HIT categories include EMR, financial decision support, human resources, health information management, cardiology, radiology, revenue cycle, and ambulatory status. The study focused on the proportion of information technologies that a given hospital has adopted as live and uses in daily operations. Technologies categorized by HIMSS as "automated" are those that have been adopted and are used to support a specific business process; adopted technologies are classified by HIMSS as either “live and operational” or “to be replaced.” Binary coding (0, 1) was used for not adopted or adopted status, respectively. In addition, the study measured the velocity of HIT diversity change over time (*velocity*) in a hospital. This captures the pace of a hospital’s HIT adoption over time. If a hospital’s HIT diversity values were $HITdiv_{2008} = 0.3$, and $HITdiv_{2013} = 0.6$ in 2008 and 2013, the *velocity* for this period is $\frac{(0.6-0.3)}{2013-2008} = 0.06$. However, if a hospital keeps the same level of HIT diversity over time, the *velocity* is 0.

In addition to the cluster variables, this work explored two outcome variables and seven control variables. It used patient satisfaction and discharges to measure hospital performance. Discharges occur when the patient is permitted to leave the hospital at the conclusion of inpatient treatment when the patient will no longer benefit from the hospital stay. Discharge delays indicate a lack of operational efficiency and are also estimated to account for up to 2% of inpatient days. The number of discharges is an objective measure that assesses the quality of hospital-care processes. In contrast, patient satisfaction is a subjective measure that reflects patients’ overall perception of the care quality and is an often-used proxy for hospital performance. To measure patient satisfaction, this study uses results from the Hospital Consumer Assessments of Healthcare Providers and Systems (HCAHPS) survey. Patient satisfaction was measured as the average of the patients’ willingness to recommend the hospital to friends and family and their overall rating of the hospital as reported during the survey. This approach has been used in prior published works on HIT and patient satisfaction (e.g., Gardner et al., 2015; Queenan et al., 2011). The HCAHPS survey asks recently discharged patients several questions, two of which assess overall satisfaction: (1) Overall, how would you rate this hospital on a scale from 0 to 10? and (2) Would you recommend this hospital to family and friends? A three-point scale is used to quantify the responses as follows: definitely yes, probably yes, and no. The satisfaction survey is independent of both the primary survey data and HIT infrastructure data. It is administered by the hospitals to their patients based on CMS requirements and the data is publicly reported through the same Hospital Compare website that provides the process of care data. Following the previous research (Queenan et al. 2011), this study involved averaging the two summarized values that are presented in the CMS database. In addition, given that all the values for the outcome variables are greater than zero, applying a log transformation enables the meeting of the distributional assumptions for regression more closely (Wooldridge 2016). Although patient satisfaction is an important indicator to show a hospital's care quality, it only measures the patient's perception of a hospital's service (i.e., it is a subjective measure).

When exploring whether the configurations of HIT diversity and velocity differ concerning hospital performance, the study controlled for hospital-level variables that are commonly used in publications on healthcare in the IS, operations management, and broader healthcare literature. Such variables include the Case Mix Index (CMI), governmental control, membership in a multi-hospital system, governmental ownership, profit status, a hospital's location, hospital's system affiliation, hospital size, and operating revenue.

Table 1 Variables for Cluster Analysis and Performance

Variable	Operationalization
Patient satisfaction	The log-transformation of the average of patients' willingness to recommend the hospital to friends and family and their overall rating of the hospital as reported in the survey
Discharges	The log-transformation of the number of discharges
HIT diversity	Calculated through Shannon entropy The diversity of HIT of a hospital i in year 2012 = $-\sum_{k=1}^{s} P_k log_2^{(P_k)}$, Where $p_k =$ the proportion of adopted HIT belonging to the category k
Velocity of HIT diversity change	$\frac{HITDiv_{2013} - HITDiv_{2008}}{2013 - 2008}$
Hospital size	The log-transformation of the number of general medical and surgical beds in a hospital.
Profit Status	A binary variable: 1 if a hospital's type of control is proprietary; otherwise, coded as 0.
Urban	A binary variable: 1 if urban, otherwise, coded as 0
Governmental Control	A binary variable: 1 if a hospital's type of control is governmental; otherwise, coded as 0
System	A binary variable: 1 if a member of multi-hospital system; otherwise, coded as 0
Case Mix Index	Average patient severity index in a hospital
Operating revenue	The log-transformation of revenues associated with the main operations of the hospital

Note: outcome and control variables are in 2013

Taxonomic Procedure

This study employed a three-stage clustering approach following previous studies (Homburg et al. 2008) to determine whether homogeneous classes of technology adoption behaviors exist by diversity and velocity. To obtain reliable results from a cluster analysis, it is important to address three core issues in clustering: (1) determining the number of clusters, (2) assigning observations to clusters, and (3) assessing the stability of cluster assignments.

The first step, to determine the appropriate number of clusters, involved both numeric indices and graphical methods. The study considered the indices that performed best in the simulation study by Milligan and Cooper (1985). It used the CH index (Calinski and Harabasz 1974), Duda index (Duda and Hart 1973), and Pseudo-t^2 (Duda and Hart 1973) in combination with the hierarchical clustering algorithm that Ward (1963) developed. In the comparative study of thirty indices to evaluate the number of clusters, these were among the top-performing criteria (Milligan and Cooper 1985). Ward's algorithm is sensitive to scaling, so the study standardized the clustering variables based on their range (Milligan and Hirtle 2003). These three criteria suggest the optimal number of clusters is three.

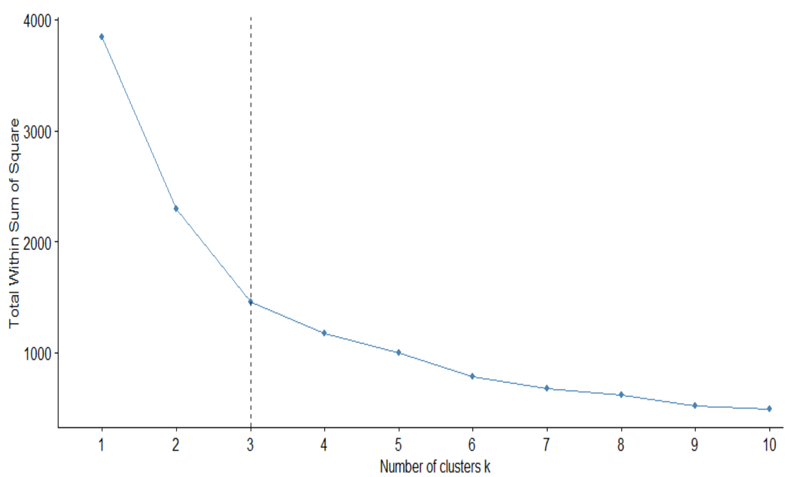

Figure 2 Scree Plot

The study used graphical methods to decide the optimal number of clusters. First, it used the elbow analysis (similar to a Scree plot) to determine the number of clusters. This method is accomplished by estimating the scree plot (Figure 2) and looking for the point at which the proportion of variance explained by each subsequent principal component drops off (James et al.

2013). In addition, the study used the Dindex (Lebart et al. 2000) and Hubert indexes (Hubert and Arabie 1985) as graphical methods. In these methods, the optimal number of clusters is identified by a significant peak in the plot of second differences values (Figure 3). The statistical indices and the results of visual inspection suggested that three is the relevant number of clusters within the data structure. Three total clusters emerged from these analyses.

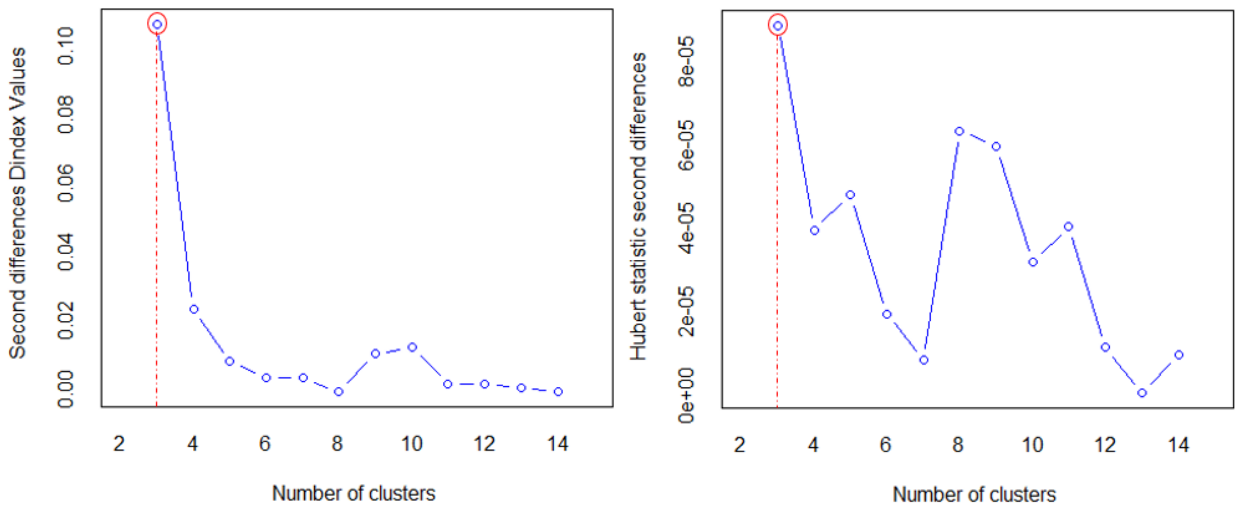

Figure 3 Dindex (Left) and Hubert (Right) statistic graphics

Following this determination, the study used a hybrid approach recommend by Punj and Stewart (1983), and Arabie and Hubert (1994) to assign observations to clusters. This method combined a k-means cluster analysis with Ward’s method. This procedure used Ward’s hierarchical method to determine starting points before conducting a cluster analysis with the k-mean algorithm. According to simulation studies on the performance of clustering algorithms, partitioning methods (e.g., k-means) yield excellent results if given a reasonable starting solution (Milligan and Cooper 1987). Further, Helsen et al. (1991) demonstrated that using the k-mean algorithm based on the starting point computed by Ward’s method is a powerful combination.

Lastly, the study used the cross-validation procedure proposed by McIntyre and Blashfield (1980) and recommend by Milligan and Cooper (1987) to assess the stability of the cluster assignment. James et al. (2013, p. 401) recommended: “clustering subsets of the data to get a sense of the robustness of the clusters obtained.” The study randomly split the original dataset in halves to create two subsets and applied the hybrid clustering approach to each subset. Then, it assigned each observation in the second subset to the closest cluster centroid obtained from the first subset based on the squared Euclidean distance. As a result, the second subset had two cluster assignments for each observation. Then, the study compared the consistency of the two cluster assignments by using Rand’s (1971) index. This index is scaled between 0 and 1, and 1 indicates perfect stability. The cross-validation yielded a Rand index of .964.

Results

The last step toward the taxonomy is to validate whether the clusters have meaningful interpretations (Rich 1992). Table 1 shows the cluster means for each of the cluster variables (diversity and velocity) and the descriptive variables that explore the outcomes of the clusters, their representation in hospital size, location, profit status, and so on. The descriptive variables were not used as active cluster variables. Thus, the study explored whether the clusters differ regarding the descriptive variables. Following the interpretation steps that Bunn (1993) suggested, the study compared the cluster means of the continuous variables using Waller and Duncan’s (1969) multiple-range t-test. Cluster means carrying the same superscript do not differ at a 5% significance level. Finally, the study ended by translating the statistical ranges into verbal descriptions (see Table 2).

Table 2. Statistical Cluster Description

	Total	Cluster 1	Cluster 2	Cluster 3
Percentage of Observations	100% (n = 1,924)	43% (n = 836)	32% (n = 614)	25% (n = 474)
Profit Status	100%	46%	36%	18%
Urban	100%	27%	48%	25%
Governmental Control	100%	40%	37%	24%
System	100%	38%	38%	24%
Hospital size		4.616[c]	5.22[a]	4.945[b]
Case Mix Index		1.299[c]	1.583[a]	1.51[b]
Operating revenue		18.375[c]	19.275[a]	18.956[b]
Patient satisfaction		4.417[c]	4.439[a]	4.431[b]
Discharges		4.444[b]	4.45[a]	4.453[a]
Diversity		1.156[b]	1.545[a]	1.536[a]
Velocity		.053[b]	.055[b]	.148[a]

Note: Reported values are mean values if not indicated otherwise. In each row, cluster means that have the same superscript are not significantly different ($p < .05$) on the basis of Waller and Duncan's (1969) multiple-range test. Means in the highest bracket are assigned the superscript "a," means in the next lower bracket are assigned the superscript "b," and so forth

Interpretation of Clusters

In interpreting the clusters, it is helpful to assign them names. The cluster names highlight empirically distinct aspects of different technology adoption behaviors and facilitate the discussion of the results. The first group of hospitals was named "Lazy Adopter" for its slow adoption of technologies. In this cluster, the HIT diversity level was also low. This indicates that hospitals in this group adopted fewer IT applications at a low speed over time. Cluster 2 was named "Steady Adopter." This cluster's HIT diversity level was high, while the velocity level was low. Hospitals in this group employed diverse HIT at a low speed over time. They gradually adopt various technologies. The third cluster was named "Greedy Adopter." Hospitals in this cluster had high levels of HIT diversity and velocity. They quickly adopted various technologies in a short period.

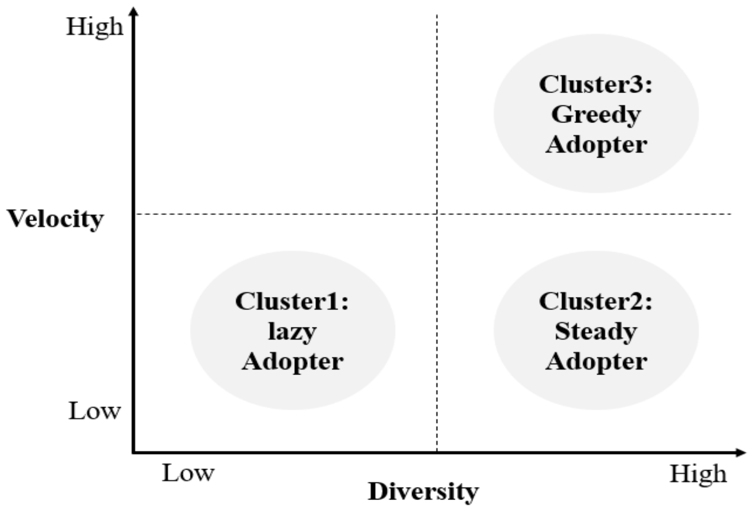

Figure 4 Verbal Cluster Description

Exploration of Outcomes

The bottom of Table 3 shows the outcomes achieved by the three clusters. The study used a perceptual measure (patient satisfaction) and an objective measure (discharges) to reflect hospital performance. The results include comments on the outcomes achieved by each cluster (see Table 3) and more general comments on the findings. The Lazy Adopter cluster was in the lowest range of clusters for the two outcome variables. The discharge of this cluster was consistently in the lowest category. The low HIT diversity level of the cluster might be the reason for this. In contrast, the Steady Adopter cluster achieved the highest levels of patient satisfaction. In particular, the Steady Adopter cluster showed a higher level of patient satisfaction compared to the Greedy Adopter cluster, though their diversity levels did not differ from each other. This result implies the negative impact of adopting diverse technologies in a short period on hospital performance. Notably, the Steady Adopter cluster was in the highest bracket for both patient satisfaction and discharge.

It is necessary to verify whether the between-cluster differences of the outcome variables remain significant when we control for other factors. The study employed two analysis of covariance (ANCOVA) models—one for patient satisfaction and one for patient discharge as the dependent variable (Table 4). The ANCOVA models comprised eight predictors: one class variable (cluster membership) and seven metric covariates (operating revenue, hospital size, CMI, hospital location, profit status, governmental control, and system). As Table 3 shows, the performance impact of the diversity and velocity configuration remained highly significant for all outcomes even after the inclusion of control variables. There was a significant association of cluster membership with the outcome variables.

Table 3 Exploratory ANCOVA Results for Cluster Performance

Dependent Variable		d.f.	Sum of Squares	Mean Sum of Squares	F	R^2
Patient Satisfaction	Model	9	1.078	.12	52.66***	.199
	Error	1877	4.271	.002		
	Cluster	2	.034	.017	7.51***	
	Operation revenue	1	.085	.085	37.4***	
	Size	1	.267	.267	117.18***	
	CMI	1	.252	.252	110.59***	
	Urban	1	.0003	.0003	.14	
	Profit	1	.176	.176	77.57***	
	Gov. control	1	.001	.001	.39	
	System	1	.0001	.0001	.03	
Discharges	Model	9	.416	.046	32.63***	.131
	Error	1868	2.649	.0014		
	Cluster	2	.026	.013	9.3***	
	Operation revenue	1	.044	.044	30.71***	
	Size	1	.196	.196	138.14***	
	CMI	1	.051	.051	35.67***	
	Urban	1	.014	.014	9.65***	
	Profit	1	.055	.055	38.77***	
	Gov. control	1	.009	.009	6.2**	
	System	1	.001	.001	.51	

*p < .10; **p < .05; ***p < .01

To conclude, the exploration of outcomes revealed one cluster (Cluster 2) whose patient satisfaction and discharges significantly differed from the other two clusters. Although the value of the Cluster 1 discharges did not significantly differ from Cluster 3, overall, this result suggests that there are superior technology adoption behavioral patterns toward which hospitals should strive.

CHAPTER 4

A CONFIRMATORY STUDY FOR A HYPOTHESIS TEST

The above exploratory study suggests a taxonomy based on technology adoption behaviors and three distinct groups. Additionally, the exploratory statistical analysis showed that there are significant differences among the three clusters. Specifically, the exploratory study suggests that "Steady Adopter" has better hospital performance than the other clusters do, which implies that employing diverse technologies at a slow (or moderate) speed results in positive outcomes. Although these results provide initial insights about the directionality of the relationships between the two dimensions and hospital performance, this evidence might not be strong enough to conclude a causal connection.

To draw a causal interpretation from an association, we must satisfy theoretical and statistical assumptions. First, we must assume causality at a theoretical level in a coherent manner, then develop a statistical model and test it (Shmueli and Koppius 2011). In other words, a set of hypotheses are derived from a logical theoretical argument (i.e., theoretical reasoning) and tested using statistical models and statistical inference (Shmueli and Koppius 2011). Theoretical reasoning is the conceptualization of how the response (i.e., a dependent variable) is generated through an intervention (i.e., an independent variable), which indicates a well-justified approximation reflecting the reality that we want to examine (Berk 2004). Generally, in the social sciences, it is common to use association-type statistical models such as regression models to see whether the association is significant. Although this practice is frowned upon by many statisticians under the common saying "correlation does not imply causation," the justification for using such models for causal inference is that given a significant association that is consistent with the theoretical argument, causality is inherited directly from the theoretical model (Shmueli and Koppius 2011).

However, a significant association that is consistent with the theoretical argument is not enough to establish a causal direction of the relationships among the variables. To make causal arguments, a regression model should be derived from an elaborate theory that specifies the causal interconnections of variables, functional form of the relationships, and statistical properties of error terms (e.g., independence or exogeneity) (Freedman 2010). However, social science theories, in general, do not provide the technical details for model specifications at the requisite level (Freedman 2010). The theories could suggest the relationships among the variables and the signs of the relationships, but there is a little that helps with the statistical properties of error terms, such as independence and exogeneity (i.e., how the errors may or may not be related to the intervention and a number of other essential features of the data generation process; Freedman 2010). In particular, the violation of the exogeneity assumption is a typical issue with observational studies. In social science, an intervention is not induced randomly in most cases. The intervention is, instead, a result of a conscious effort of humans or organizations, so it can potentially be a function of the unobservable features of humans and organizations (i.e., endogeneity). With the problem of endogeneity, conventional regression estimation methods such as Ordinary Least Square (OLS) can be biased (Wooldridge 2016). Therefore, studies must address the endogeneity issue in addition to developing hypotheses through theoretical reasoning to establish causal directions and make causal interpretations.

Hypothesis Development

This section covers the development of a set of hypotheses on HIT diversity and velocity and hospital performance. Figure 5 summarizes the key variables and hypotheses.

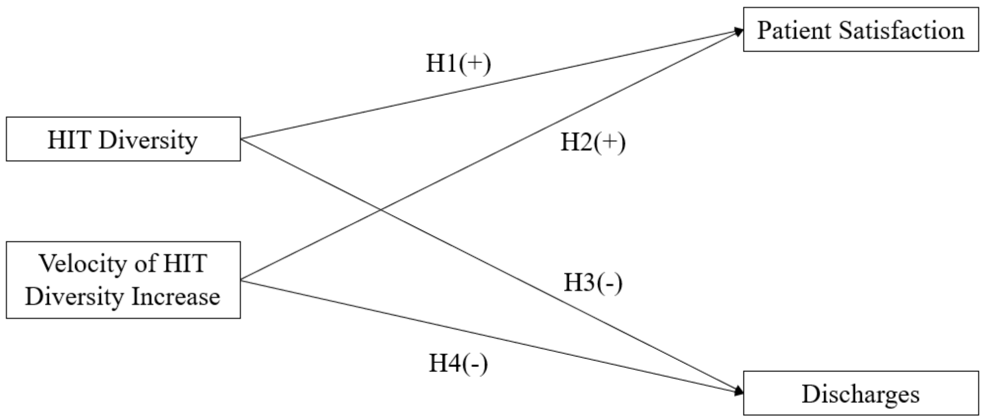

Figure 5. The theoretical model.

HIT Diversity and Hospital Performance

This study used patient satisfaction and discharge to measure hospital performance. Although patient satisfaction is a considerable measure for hospital performance, it is a perceptual measure assessed through the patient responses to a survey asking them to rate their satisfaction with their entire hospital stay. In addition, focus on a single performance measure fails to capture the potential tradeoffs between multiple performance measures (Chandrasekaran et al., 2012) while adopting HIT. Thus, this research used patient satisfaction (subjective measure) and discharge (objective measure) as proxies for hospital performance.

Linking HIT diversity to patient satisfaction requires an understanding of the determination of patient satisfaction. Customer satisfaction is the perception of the overall quality of the customer's experience with a product or service (Mithas et al. 2016); similarly, patient satisfaction is the extent to which a patient is pleased with the overall medical care received (Ancarani et al. 2011; Marley et al. 2004). Therefore, in most literature, results for customer satisfaction can be extrapolated to patient satisfaction. Prior literature in marketing research points to three antecedents of customer satisfaction: perceived quality, perceived value, and customer expectations (Fornell et al. 1996). Perceived quality represents a customer's experience of using products or services with two primary components: (1) customization, the degree to which the firm's offering is customized to meet heterogeneous customer needs; and (2) reliability, the degree to which the firm's offering is reliable, standardized, and free from deficiencies (Fornell et al. 1996). The second determinant of overall customer satisfaction is perceived value, referring to the perceived level of product and service quality given the price paid (Fornell et al. 1996). Finally, customer expectations refer to customer perspectives on prior consumption experiences as well as customer beliefs in the firm's ability to deliver quality in the future (Fornell et al. 1996).

There is no clear consensus regarding the relationship between HIT diversity and patient satisfaction, although extant IS research suggests they have a positive relationship (e.g., Mithas et al. 2016). Mithas et al. (2016) posited that IT could enhance the perceived quality of a firm's offering, which in turn has a positive effect on customer satisfaction. IT can enable a firm to capture customer-specific information, to use it to customize the firm's offerings for each customer, and to provide customers with a consistent experience (Mithas et al. 2016). Further, IT facilitates business process innovation by redefining and redirecting business relationships and core processes through new channels, leading to significant improvements in total customer experience (Tallon 2007).

Similar mechanisms appear to play a role in the determination of patient satisfaction with healthcare. Researchers have noted that quality is a key determinant of satisfaction (Dobrzykowski et al. 2015; Marley et al. 2004; Romanow et al. 2018). Prior researchers have suggested that HIT is positively associated with the care quality of the hospital, leading to increased patient satisfaction. Key arguments in the literature indicate that HIT implementation has the potential to enhance the ability to standardize best practices, improve interdepartmental communication, and provide information that can help prevent errors (Kuperman and Gibson 2003). IT can be employed to facilitate consistency (Pentland and Feldman 2008) in clinical processes across the spectrum of actions required to deliver care at high levels of quality. For example, Ozdas et al. (2006) found that decision-support tools linked to CPOE were associated with an increase in the percentage of patients who received proper care for a heart attack, one of the key conditions reported in care quality standards. HIT tools such as CPOE can also increase clarity and reduce uncertainty in physician notes and prescriptions. HIT tools such as computerized decision support systems (CDSS) can reduce uncertainty and ambiguity in treatments by providing supportive information for specific patient conditions. Queenan et al. (2011) found that both CPOE and aggregate HIT infrastructure are associated with higher overall patient satisfaction.

It makes sense that IT can reduce uncertainty throughout an organization by providing appropriate information to the right people at the right time (e.g., Galbraith 1973). Increased levels of uncertainty impact the type of information required, appropriate analysis, and application of that information (Gardner et al. 2015). Therefore, the more diverse the IT, the better it can function in times of both low uncertainty and low interdependence as well as at times when it is critical to provide multiple levels of support across different units.

The information sphere of healthcare is notably complex and diverse. A hospital has numerous patients with different characteristics including symptoms, diseases, and contraindicators. Further, a number of healthcare disciplines may be involved in the care of a given patient, meaning that other stakeholders from within and outside the hospital may require different information at different times to ensure positive outcomes for the patient (Fichman et al. 2011). The diversity of stakeholders combined with frequently unknown variables and outcomes results in a highly uncertain environment for which a variety of IT support is required. Some tasks are routine and independent with little information processing necessary; for these, a simple HIT system, such as automated reminders for medication distribution, is sufficient. As tasks increase in complexity, however, uncertainty rises and a different type of HIT may be necessary to process information and facilitate coordination, and other means may be employed to reduce uncertainty and improve outcomes (e.g., Tushman and Nadler 1978). In such cases, a more advanced system, such as a decision or expert support system, may be necessary in conjunction with collaborative or temporal systems. The increased information processing capacity of diverse HIT contributes to a purposeful management of information that can enhance organizational tasks (Galbraith 1973; Stock and Tatikonda 2008) and improve operational performance (Stratman 2007). Examples include improving interdepartmental communication, which helps reduce medical errors (Kuperman and Gibson 2003), providing consistent clinical service and proper care (Pentland and Feldman 2008), providing supportive information for specific patient conditions (Ozdas et al. 2006), and improving patient management (e.g., admissions, discharges, and billing), which can influence the overall patient experience (Gardner et al. 2015). In turn, patient care quality and patient satisfaction increases.

Therefore, this study considers the following hypotheses:

Hypothesis 1 (H1). *HIT diversity is positively associated with patient satisfaction.*

Hypothesis 2 (H2). *HIT diversity is positively associated with discharges.*

Velocity and Hospital Performance

Numerous IT business value studies suggest that IT can be more effective when accompanied by other firm resources; this nuance should be further investigated by taking contingent approaches to further explain the IT–value relationship (Melville et al. 2004; Nevo and Wade 2010). Diversity is one characteristic of IT to be considered; however, research that simply considers IT diverse or not adds little understanding. Given that IT is not generally acquired and used fully immediately on implementation, IT diversity should be examined along a timeline.

Several motives support the above line of reasoning. Viewing technology as a static entity ignores the HIT artifact itself and minimizes the richness and complexity of the HIT–value link (Angst et al. 2011). Technology analysis should involve a temporal component instead of the standard "snapshot-in-time" approach. Further, both the location of the IT and the speed at which the IT changes are likely to impact value. Accordingly, this study focused on the types of technology within the hospital at a specific point in time (alpha diversity) as well as the change in that composition over time (beta diversity). For example, hospitals might adopt a composite of technologies at different speeds, as seen in the table below. Hospital 1 adopted several technologies at once and then did not add new technology. Hospital 2 increased the level of HIT diversity incrementally, while Hospital 3 increased the level of HIT diversity more rapidly compared to the other two hospitals in this example. In other words, Hospital 3 adopted more technologies in the same period.

Table 4. Example of different pace of technology addition

	2008	2009	2010	2011	2012	2013
Hospital 1	10	10	10	10	10	10
Hospital 2	1	2	3	4	5	6
Hospital 3	1	2	4	7	11	16

These different paces of HIT adoption might have different impacts on hospital performance. Although the extant research primarily supports the use of IT to improve performance, they ignore the way the technology adoption is executed. In fact, studies have proposed that adopting many technologies may not have the desired effect on performance, and a high rate of adoption in a short time may lead to a negative impact, largely resulting from uncertainty (Galbraith 1973; Shannon 1948). Diverse IT is sometimes used to mean complex IT, but such IT complexity is generally viewed as undesirable and detrimental to organizational performance because of its difficulty of maintenance, proneness to design flaws, and vulnerability to adverse incidents, among others (Xue et al. 2012). New technologies can drastically change both existing infrastructure and processes but do not automatically improve performance. Adopting many different HITs over a short period can increase uncertainty, particularly regarding trust, use, and integration (Galbraith 1973; Shannon 1948). For example, EMRs are considered to be a highly complex technology innovation that supports evidence-based decisions but also changes how patient records are obtained, shared, and processed within and across hospital units (Queenan et al. 2011). To benefit from technologies, hospitals must learn how to implement and use this technology most effectively. This learning must continue as hospitals move through the life cycles of various emerging medical technologies and make investments in equipment and employee training. However, when new technologies are adopted over a short period, the uncertainty of the hospital increases, which may cause difficulties for smoothing organizational changes or promoting the learning process. Thus, the rapid adoption of diverse technologies over a short period is likely to increase the IT complexity, resulting in negative effects concerning organizational performance.

Hypothesis 3 (H3). *The velocity of HIT diversity change is negatively associated with patient satisfaction.*

Hypothesis 4 (H4). *The velocity of HIT diversity change is negatively associated with discharges.*

Methods

Variable Operationalization and Descriptive Statistics

Table 5 provides the operationalization for variables in this study. These are the same variables used in the exploratory study. However, this time, the study used a panel structure to control time-invariant unobservable variables and address endogeneity. Therefore, all variables have time dimensions. To measure hospital performance, the study used two outcome variables, patient satisfaction, and patient discharge. Patient satisfaction is a subjective and perceptual measure and discharges are an objective measure. The independent variables in this study are the level of HIT diversity and the velocity of HIT diversity change.

Consistent with prior studies, this work also included a collection of commonly used hospital-level control variables. It controlled for the CMI (Sharma et al. 2016), location (Gardner et al. 2015; Karahanna et al. 2019), governmental control (Bradley et al. 2018; Queenan et al. 2011), and membership in a multi-hospital system (Bradley et al. 2018; Queenan et al. 2011). CMI is a composite measure of the severity of a patient's illness and the complexity of service procedures offered to patients (Bradley et al. 2018; Sharma et al. 2016). A higher level of CMI requires that a hospital allocate and deploy more resources (e.g., more suppliers and human resources) for service delivery (Angst et al. 2011; Sharma et al. 2016), which is likely to affect clinical outcomes. The study further controlled for governmental ownership (i.e., 1 if a hospital is controlled by a governmental entity, 0 otherwise), profit status (1 for-profit, 0 otherwise), and the hospital's location (1 urban, 0 otherwise), because results from prior studies (Goldstein and Iossifova 2012) suggest that such characteristics are associated with hospital performance.

Table 5. Variable Operationalizations

Variable	Notation	Operationalization
Patient satisfaction	$Lnps_{it}$	The log-transformation of the average of patients' willingness to recommend the hospital to friends and family and their overall rating of the hospital as reported in the survey
Discharges	$Lndisch_{it}$	The log-transformation of the number of discharges
HIT diversity	$HITDiv_{it}$	Calculated through Shannon entropy The diversity of HIT of a hospital *i* in year *t* $= -\sum_{k=1}^{s} P_k log_2^{(P_k)}$, where $p_k =$ the proportion of adopted HIT belonging to the category *k*
Velocity of HIT diversity change	$Velocity_{it}$	$HITDiv_{it} - HITDiv_{it-1}$
Hospital size	$Size_{it}$	The log-transformation of the number of general medical and surgical beds in a hospital.
Profit Status	Prf_{it}	A binary variable: 1 if a hospital's type of control is proprietary; otherwise, coded as 0.
Urban	$Urban_{it}$	A binary variable: 1 if urban, otherwise, coded as 0
Governmental Control	$Gvrm_{it}$	A binary variable: 1 if a hospital's type of control is governmental; otherwise, coded as 0
System	Sys_{it}	A binary variable: 1 if a member of multi-hospital system; otherwise, coded as 0
Case Mix Index	CMI_{it}	Average patient severity index in a hospital
Operating revenue	$Lnor_{it}$	The log-transformation of revenues associated with the main operations of the hospital

The study also controlled for a hospital's system affiliation (i.e., a hospital is coded as 1 if it is part of a multi-hospital system and is coded as 0 otherwise). Multi-hospital systems represent a set of affiliated hospitals governed within a corporate framework (Chen et al. 2013). System-affiliated hospitals tend to have greater access to necessary resources and realize performance advantages by leveraging economies of scale as well as economies of scope through the multi-hospital system (Bradley et al. 2018).

Table 6. Variable descriptive statistics across all yearly hospital observations

Quantitative Variables	Mean	Std. dev.	Min	Max
Patient satisfaction	4.416	.064	3.901	4.599
Discharges	4.419	.056	3.951	4.605
HIT Diversity	1.244	.292	.116	1.782
Velocity	.079	.139	0	1.094
Hospital size	4.816	.852	.693	9.744
Operating revenue	18.65	1.128	13.901	22.156
CMI	1.446	.288	.707	3.488
Categorial Variables	**Proportion**	**Std. dev.**	**Min**	**Max**
Urban	.723	.447	0	1
Governmental Control	.158	.365	0	1
System	.515	.500	0	1
Profit Status	.224	.417	0	1

Table 6 presents the summary statistics of the variables used in this study. For each variable, the mean (or proportion) and standard deviation are reported. It appears that, on average, the patient satisfaction level was about 4.4 with a standard deviation of .064, and discharges were 4.4 with a standard deviation of .056. The average HIT diversity level for hospitals was 1.24, and the velocity was .079, indicating that hospitals increase HIT diversity by an average of .079 for each year. In addition, 70% of hospitals were in urban areas, 16% were controlled by the government, 52 % were members of a multi-hospital system, and 22% were profitable. Table 7 contains pairwise correlations for all continuous variables.

Table 7. Variable Correlation Matrix

Quantitative Variables	1.	2.	3.	4.	5.	6.
1. Patient satisfaction	-					
2. Discharge	.581	-				
3. HIT Diversity	.143	.216	-			
4. Velocity	-.025	-.042	.127	-		
5. Hospital size	-.045	-.108	.458	-.032	-	
6. Operating revenue	.102	.056	.512	-.039	.087	-
7. CMI	.260	.167	.372	-.024	.585	.707

Model Estimation

This study used the model represented by Equation (1) to test the hypotheses. More specifically, the coefficients of β_1 and β_2 capture the average effect of HIT diversity and the velocity of HIT diversity change on hospital performance for hospital *i* at time *t*, where dt is a time-specific fixed effect, αi is a hospital-specific fixed effect, and PERF indicates patient satisfaction and the number of discharges.

$$PERF_{it+1} = \beta_0 PERF_{it} + \beta_1 HITDiv_{it} + \beta_2 Velocity_{it} + \beta_3 Size_{it} + \beta_4 Prf_{it} + \beta_5 Urban_{it} + \beta_6 Gvrm_{it} + \beta_7 Sys_{it} + \beta_8 CMI_{it} + \beta_9 Lnor_{it} + d_t + \alpha_i + v_{it} \quad (1)$$

Evaluating the effect of the use of diverse HIT on hospital-level performance outcomes is likely to be subject to identification issues and endogeneity, as is typically the case with observational studies. The rationale for the inclusion of hospital-specific effects is based on the nature of the hospitals in the sample. The group of hospitals that use HIT is non-random since it can potentially be a function of anticipated outcomes. While HIT leads to a positive outcome, such as a higher level of patient satisfaction, it can also be argued that a hospital is more likely to use HIT when the expected outcome is high, which is a reverse causality problem. To mitigate the reverse causality, this study used the generalized method of moments (GMM) approach (Hansen 1982), which is a panel regression estimator, to consistently estimate the dynamic models proposed in Equation (1). It used a GMM estimator of the kind developed by Arellano and Bond (1991). More specifically, it used the xtabond2 command in STATA14 to estimate the dynamic panel model via a robust two-step estimation, which has a higher accuracy and a lower bias than the alternative one-step estimator after correcting for the downward bias in standard error (Bond and Windmeijer 2005). Consistent with prior studies (e.g., Senot et al. 2016; Bradely et al. 2018), this study included the GMM approach based on the characteristics of the sample, namely, (1) a small T (8 periods), large N (3327 hospitals) panel, (2) a linear functional relationship between the predictors and outcome variables, (3) a dynamic outcome variable (e.g., patient satisfaction) with autocorrelation, (4) a predictor of interest (i.e., HIT diversity and Velocity) that could be endogenous, (5) a need to control for hospital fixed effects, and (6) heteroscedasticity. Moreover, GMM is an attractive dynamic panel data estimation technique (Baltagi 2008) for analyzing hospital-fixed effects when lagged dependent variables display time persistence. GMM produces consistent estimates in a dynamic regression model with both endogenous explanatory variables and the presence of measurement error (Di Liberto et al. 2008), as is likely the case with our measures of hospital performance. The GMM estimator also improves upon population-averaged estimators as it controls for the bias induced by the omission of hospital-specific effects and endogeneity.

Results

Effect of HIT diversity and Velocity on Hospital Performance

This study conducted both autocorrelation and the Hansen (1982) test to check the model specification. First-order was significant based on the Arellano–Bond test for AR (1), thereby rejecting the null hypothesis ($p < 0.01$) that there is no first-order serial correlation. However, the study failed to reject the test for the second-order serial correlation's AR (2), which supports the validity of using lags 2 and longer as GMM instruments (Arellano and Bond 1991). Further, the result of the Hansen (1982) test showed a failure to reject the null hypothesis ($p > 0.05$), which attests to the validity of the instruments. Taken together, these results offer further support for the selected model specification.

Table 8. The effects of HIT diversity and Velocity on Hospital Performance

	DV = lnps_{t+1}	DV = $\mathrm{lndisch}_{t+1}$
Number of instruments	30	35
Lagged DV	$.801^{***}$ (.089)	$.192^{**}$ (.093)
HIT Diversity	**$.018^{***}$ (.006)**	**$.031^{***}$ (.007)**
Velocity	**.014 (.013)**	**$-.026^{***}$ (.009)**
Hospital size	$-.006^{**}$ (.003)	$-.025^{***}$ (.006)
Profit status	.0003 (.003)	$-.006^{***}$ (.002)
Urban	.0004 (.001)	$-.008^{***}$ (.002)
Governmental control	-.0002 (.001)	$-.01^{***}$ (.002)
System	.0004 (.001)	.001 (.001)
CMI	$.014^{*}$ (.007)	$.031^{***}$ (.007)
Operating revenue	.001 (.001)	.009 (.006)
Number of observations	9756	9699
Number of groups	3068	3051
Wald χ^2 statistic	6839.28^{***}	$6.89 \times 10^{7\ ***}$
AR (1)	-8.53^{***}	-3.69^{***}
AR (2)	1.53	.85
Hansen test (*p*-value)	.219	.112

Notes: ***$p < 0.01$; **$p < 0.05$; *$p < 0.1$; heteroscedasticity consistent asymptotic standard errors in parentheses; AR(1) is a serial correlation test of order 1 using residuals in first differences, asymptotically standard normal; Wald is a test for the joint significant test of all the explanatory variables.

H1 and H2 posited that the positive relationship between the use of diverse HIT and hospital performance. As shown in Table 8, the results indicate that HIT diversity has a positive and statistically significant association with patient satisfaction ($\beta = .018$, $p < 0.01$) and discharge ($\beta = .031$, $p < 0.01$). Taken together, these findings suggest that using diverse HITs is positively associated with hospital performance, which offers an approximately 1.8% increase in patient satisfaction and a 3.1% increase in discharges. Thus, there is support for H1 and H2.

H3 and H4 posited that the rapid adoption of diverse HIT in a short period is associated with lower hospital performance. As shown in Table 8, the results indicate that the velocity of HIT diversity change has a negative and statistically significant association with discharges ($\beta = -.026$, $p < 0.01$). Although the relationship between the velocity of HIT change and patient satisfaction is not supported, overall, these results indicate that adopting many HITs in a short period can negatively affect hospital performance. The coefficient of the velocity of HIT diversity change shows that HIT diversity decreases patient discharges by approximately 2.6%. Thus, these results do not support H3, but do support H4.

Post-Hoc Analysis of Effects of Velocity Change on Hospital Performance

To understand the implications of the velocity dimension of technology adoption for hospital performance better, the study explored the impact of velocity change on hospital performance. In this post-hoc analysis, changing HIT diversity over time at different rates may have different impacts on hospital performance. Newton's second law of motion is that the force (f) on an object is equal to the mass (m) of that object multiplied by the acceleration (a) of the object: $f = ma$ (Newton 1802). This physical law can be interpreted as there being a force of zero when an object moves at a constant velocity (i.e., a is equal to zero). In other words, if an object is accelerating, then there is a force on it. This law of physics is substituted into the organizational behavior of adopting technologies. In the context of this study, if a hospital increases the level of HIT diversity at an almost constant rate, the perceived strength of organizational changes following the adoption of technologies may be reduced, which can result in a positive outcome compared to hospitals that accelerate their change in HIT diversity over time.

Given that this study focuses on hospitals that increase their level of HIT diversity at an almost constant speed or accelerate it, they can be divided into two hospital groups: *uniform motion* and *acceleration*. First, the analysis involved calculating the velocity of HIT diversity change from 2008 to 2010 (V_1) and from 2010 to 2012 (V_2) (i.e., $V_1 = \frac{HIT\ Div_{2010} - HIT\ Div_{2008}}{2}$, $V_2 = \frac{HIT\ Div_{2012} - HIT\ Div_{2010}}{2}$). Then, it compared the two velocity values (i.e., $V_2 - V_1$). If the difference is between -.05 and .05, a hospital is included in the uniform motion group. If the value of velocity change is greater than .05, the hospital is included in the acceleration group. If the value of velocity change is less than -.05, the hospital is included in the deceleration group. The standard deviation of the velocity change is .014. Considering rounding, the velocity is constant if the absolute value of the velocity change is less than .05.

This post-hoc analysis employed coarsen exact matching (CEM) because decisions on the increase or reduction of the speed of HIT diversity change are not random. CEM is a nonparametric technique that allows matching in blocks and has been found to perform better than propensity score matching (Iacus et al. 2011). To compare *uniform motion* and *acceleration* groups, the analysis involved constructing the acceleration treatment dummy, equal to 1 when a hospital's velocity change falls above .05. Hospitals that had a value of velocity change less than -.05 were removed. The analysis matched hospitals' operation revenue, size, CMI, location, governmental ownership, profit status, and system affiliations in 2008. It also verified that the multivariate imbalance score after matching ($\mathcal{L}_1^{\text{After}}$ = .771) is lower than that before matching ($\mathcal{L}_1^{\text{Before}}$ = .438). This result indicates that the covariates are balanced between the treatment and control groups.

Table 9 presents OLS regressions to estimate the average effect of the acceleration of velocity change. This analysis included control variables in 2008 and used dependent variables in 2013. Estimates show that *acceleration* has a negative and statistically significant association with patient discharge (β = -.006, $p < 0.05$). However, the relationship between *acceleration* and patient satisfaction was not significant. Overall, these results indicate that adopting many HITs at an almost constant rate can positively affect hospital performance.

Table 9. Regressions of Acceleration and Uniform Motion Using CEM

	DV = lnps_{2013}	DV = lndisch_{2013}
Acceleration	**-.005 (.004)**	**-.006** (.003)**
Operating revenue	.021*** (.006)	.012** (.005)
Hospital size	-.037*** (.007)	-.033*** (.005)
CMI	.07*** (.014)	.035** (.01)
Urban	-.004 (.007)	-.008** (.005)
Profit status	-.037*** (.008)	-.018*** (.005)
Governmental control	-.002 (.007)	-.002 (.005)
System	.007 (.005)	.008*** (.004)
Constant	4.13*** (.089)	4.35*** (.063)
No. of Observations (hospitals)	718	718
R^2	.179	.142

Notes: ***p < 0.01; **p < 0.05; *p < 0.1; robust standard errors in parentheses; Reference group: uniform mover

CHAPTER 5

DISCISSION AND CONCLUSION

This research produced interesting results for both researchers and practitioners. By developing a taxonomy with the two features of technology adoption, diversity and velocity, and testing the impacts of the two features on hospital performance, this study differs from other research that focused on specific or limited technologies, often within a specific functional area, and makes up for the lack of studies applying a longitudinal approach.

Primary Findings

This work explored technology adoption behaviors from an empirical taxonomic approach to determine whether the hospitals in the data could be distinguished by the two technology adoption dimensions: diversity and velocity. The clustering results show that three homogeneous classes of technology adoption behaviors exist according to these dimensions. The first cluster group was named “Lazy Adopter” because they slowly adopted technologies and their diversity level was low; the second cluster was named “Steady Adopter.” This cluster’s HIT diversity level was high, while their velocity level was low. The third cluster was named “Greedy Adopter.” Hospitals in the third cluster had high levels of both HIT diversity and velocity. They quickly adopted various technologies in a short period. In addition, ANCOVA analyses conducted with two outcome variables, patient satisfaction and discharge, verified whether the between-cluster differences of the outcome variables remained significant when controlled for other factors. According to the ANCOVA results, the performance impact of the diversity and velocity configuration remained highly significant for all outcomes, even after the inclusion of control variables. Further, the exploration of outcomes suggested that Cluster 2 (Steady Adopter) is superior to Clusters 1 (Lazy Adopter) and 3 (Greedy Adopter).

The study included confirmatory hypotheses tests to make a causal interpretation from the association between the two dimensions and hospital performance. It used a dynamic panel model with GMM estimation to mitigate the bias from reverse causality. The results show the positive relationship between HIT diversity and hospital performance, while the velocity of HIT diversity change had a negative association with hospital performance. These results suggest that a hospital could benefit by using diverse HITs, but the positive outcomes can be offset if hospitals adopt technologies in a very short period. Thus, there is a trade-off between diversity and velocity.

Lastly, the study involved a post-hoc analysis to understand the implications of the velocity dimension of technology adoption for hospital performance more deeply. It explored the impact of velocity change on hospital performance. This posthoc analysis involved creating two groups, (1) accelerator and (2) uniform motion (i.e., accelerating the level of HIT diversity or increasing it at an almost constant speed), and comparing their hospital performance with CEM. Estimates showed that *acceleration* had a negative and statistically significant association with patient discharge ($\beta = -.006$, $p < 0.05$). However, the relationship between *acceleration* and patient satisfaction was not significant. Overall, these results indicate that adopting many HITs at an almost constant rate can positively affect hospital performance.

Implications and Limitations

As a key contribution, the current research deepens our understanding of the technology adoption behavior of organizations in a hospital setting by considering two features of technology adoption. The literature on HIT adoption has focused on either specific or a limited number of technologies and/or a particular functional type of technology (e.g., Angst et al. 2012; Hydari et al. 2019; Sharma et al. 2016; Zhang et al. 2013). In addition, previous studies regarding the adoption of HITs have not sufficiently analyzed the temporal dynamics of technology and its effects. Only a few studies have focused on effect lag and the sequence of technology adoption. However, the previous literature did not consider another temporal lens, "pacing" (i.e., how fast organizations adopt diverse technologies in a certain period).

The current research bridges this critical gap in the literature by adopting two diversity concepts (alpha and beta) from ecology. It proposed and demonstrated the unique value of the composition of multiple technologies and the temporal aspect of technology adoption behavior. In line with the wealth of literature on technology adoption, there is no disputing the clear findings that HITs play a positive role in improving hospital performance. Instead, the findings support the argument that adopting a rich composite of technologies gives a hospital more benefits than using a single technology (Karahanna et al. 2019). This finding implies that hospitals should consider the connections and compositions of IT applications to leverage the benefits of using IT fully.

Another unique feature of the current study is incorporating time into the concept of technology diversity and investigating the hospital performance implication of changing the level of HIT diversity over time. Current technology adopting behavior should be understood in comparison with past actions of technology adoption. Considering the temporal dynamics of using technologies in the theories of technology adoption may significantly enhance our understanding of the nature and consequences of the organizational behavior involved in using IT in a hospital setting. Indeed, the findings from the longitudinal study suggest a negative relationship between velocity and hospital performance. In terms of velocity, the results suggest that when a hospital rapidly adopts diverse technologies in a short period, doing so may negatively affect performance. This is because diverse IT is sometimes used to mean complex IT (Xue et al. 2012). New technologies can drastically change both existing infrastructure and processes but do not automatically improve performance. Adopting many different HITs over a short period can increase uncertainties, particularly trust, use, and integration (Galbraith 1973). It is consonant with these findings that an attempt to rapidly change the level of HIT diversity is associated with a decline in performance. Thus, these findings imply that hospital IT managers need to consider how fast (or slowly) they should adopt different technologies.

Like all empirical research, this study has several limitations one must bear in mind while interpreting the results. First, it was unable to capture the extent to which care providers actually use diverse HIT. Second, despite our best attempts to control for sources of bias in the results, this study may still suffer from potential sources of uncontrolled endogeneity. Further, the study tested only two hospital performance measures; it did not consider other factors that affect organizational performance. For example, hospital size may affect the relationship between HIT diversity and hospital performance.

In conclusion, the current study was an effort to advance the literature on the effects of HITs on hospital performance by incorporating the two features of technology adoption, *diversity* and *velocity*. The study provided initial evidence that HIT diversity is positively related to hospital performance, but the velocity of HIT diversity change is negatively associated with it. From a practical point of view, hospitals are advised to adopt HITs while considering those already used in the past. Considering HIT adoption with its relation to past behavior enhances knowledge of the effects of HIT on hospital performance and benefits hospitals by unpacking their knowledge of status and the wisdom of the past to help them make better decisions about HIT adoption in the future.

REFERENCES

Adler-Milstein, J., and Huckman, R. S. 2013. "The Impact of Electronic Health Record Use on Physician Productivity," *The American Journal of Managed Care* (19:10).

Agha, L. 2014. "The Effects of Health Information Technology on the Costs and Quality of Medical Care," *Journal of Health Economics* (34), pp. 19-30.

Agarwal, R., Gao, G., DesRoches, C., and Jha, A. K. 2010. "Research Commentary—The Digital Transformation of Healthcare: Current Status and the Road Ahead," *Information Systems Research* (21:4), pp. 796-809.

Ancarani, A., Di Mauro, C., and Giammanco, M. D. 2011. "Patient Satisfaction, Managers' Climate Orientation and Organizational Climate," *International Journal of Operations & Production Management* (31:3), pp. 224-250.

Ancona, D. G., Goodman, P. S., Lawrence, B. S., and Tushman, M. L. 2001. "Time: A New Research Lens," *Academy of Management Review* (26:4), pp. 645-663.

Angst, C. M., Devaraj, S., and D'Arcy, J. 2012. "Dual Role of IT-Assisted Communication in Patient Care: A Validated Structure-Process-Outcome Framework," *Journal of Management Information Systems* (29:2), pp. 257-292.

Angst, C. M., Devaraj, S., Queenan, C. C., and Greenwood, B. 2011. "Performance Effects Related to the Sequence of Integration of Healthcare Technologies," *Production and Operations Management* (20:3), pp. 319-333.

Appari, A., Carian, E. K., Johnson, M. E., and Anthony, D. L. 2012. "Medication Administration Quality and Health Information Technology: A National Study of U.S. Hospitals," *Journal of the American Medical Informatics Association* (19:3), pp. 360-367.

Arabie, P. and Hubert, L. 1994. "Cluster Analysis in Marketing Research," In *Advanced Methods of Marketing Research*, Richard P. Bagozzi, ed. Cambridge, MA: Blackwell Business, pp. 160-79.

Aral, S., and Weill, P. 2007. "IT Assets, Organizational Capabilities, and Firm Performance: How Resource Allocations and Organizational Differences Explain Performance Variation," *Organization Science* (18:5), pp. 763-780.

Archibald, M. M., and Barnard, A. 2018. "Futurism in Nursing: Technology, Robotics and the Fundamentals of Care," *Journal of Clinical Nursing* (27:11-12), pp. 2473-2480.

Arellano, M., and Bond, S. 1991. "Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations," *The Review of Economic Studies* (58:2), pp. 277–297.

Aron, R., Dutta, S., Janakiraman, R., and Pathak, P. A. 2011. "The Impact of Automation of Systems on Medical Errors: Evidence from Field Research," *Information Systems Research* (22:3), pp. 429-446.

Ash, J. S., Sittig, D. F., Poon, E. G., Guappone, K., Campbell, E., and Dykstra, R. H. 2007. "The Extent and Importance of Unintended Consequences Related to Computerized Provider Order Entry," *Journal of the American Medical Informatics Association* (14:4), pp. 415-423.

Atasoy, H., Chen, P. Y., and Ganju, K. 2018. "The Spillover Effects of Health IT Investments on Regional Healthcare Costs," *Management Science* (64:6), pp. 2515-2534.

Baltagi, B. 2008. *Econometric Analysis of Panel Data*, Hoboken NJ: John Wiley & Sons.

Bardhan, I. R., and Thouin, M. F. 2013. "Health Information Technology and Its Impact on the Quality and Cost of Healthcare Delivery," *Decision Support Systems* (55:2), pp. 438-449.

Barney, J. 1991. “Firm Resources and Sustained Competitive Advantage,” *Journal of Management* (17:1), pp. 99-120.

Bates, D. W., Teich, J. M., Lee, J., Seger, D., Kuperman, G. J., Ma’Luf, N., Boyle, D., and Leape, L. 1999. “The Impact of Computerized Physician Order Entry on Medication Error Prevention,” *Journal of the American Medical Informatics Association* (6:4), pp. 313–321.

Bates, D. W., Leape, L. L., Cullen, D. J., Laird, N., Petersen, L. A., Teich, J. M., Burdick, E., Hickey, M., Kleefield, S., Shea, B., Vander Vliet, M., and Seger, D. L. 1998. “Effect of Computerized Physician Order Entry and a Team Intervention on Prevention of Serious Medication Errors,” *The Journal of the American Medical Association* (280:15), pp. 1311–1316.

Berk, R. A. 2004. “Causal Inference for the Simple Linear Model,” *In Regression analysis: A Constructive Critique*, Berk, R. A., Thousand Oaks, CA: SAGE Publications Inc., pp. 81-102.

Bhargava, H. K., and Mishra, A. N. 2014. “Electronic Medical Records and Physician Productivity: Evidence from Panel Data Analysis,” *Management Science* (60:10), pp. 2543-2562.

Bond, S. R., and Windmeijer, F. 2005. “Reliable Inference for GMM Estimators? Finite Sample Properties of Alternative Test Procedures in Linear Panel Data Models,” *Econometric Reviews* (24), pp. 1–37.

Bradley, R. V., Esper, T. L., In, J., Lee, K. B., Bichescu, B. C., and Byrd, T. A. 2018. “The Joint Use of RFID and EDI: Implications for Hospital Performance,” *Production and Operations Management* (27:11), pp. 2071-2090.

Brynjolfsson, E., and Hitt, L. 1996. “Paradox Lost? Firm-Level Evidence on the Returns to Information Systems Spending,” *Management Science* (42:4), pp. 541-558.

Burke, D., Wang, B., Wan, T., and Diana, M. 2002. “Exploring Hospitals' Adoption of Information Technology,” *Journal of Medical System* (26:4), pp. 349-355.

Bunn, M. D. 1993. “Taxonomy of Buying Decision Approaches,” *Journal of Marketing* (57:1), pp. 38-56.

Buntin, M. B., Burke, M. F., Hoaglin, M. C., and Blumenthal, D. 2011. “The Benefits of Health Information Technology: A Review of the Recent Literature Shows Predominantly Positive Results,” *Health Affairs* (30:3), pp. 464-471.

Calinski, T., and Harabasz, J. 1974. “A Dendrite Method for Cluster Analysis," *Communications in Statistics-Theory and Methods* (3:1), pp. 1-27.

Cannon, J. P., and Perreault Jr, W. D. 1999. “Buyer–Seller Relationships in Business Markets,” *Journal of Marketing Research* (36:4), pp. 439-460.

Campbell, E. M., Li, H., Mori, T., Osterweil, P., and Guise, J. M. 2008. “The Impact of Health Information Technology on Work Process and Patient Care in Labor and Delivery,” In *Advances in Patient Safety: New Directions and Alternative Approaches (Vol. 4: Technology and Medication Safety)*, Rockville, MD: Agency for Healthcare Research and Quality (U.S.).

Chandrasekaran, A., Senot, C., and Boyer, K. K. 2012. “Process Management Impact on Clinical and Experiential Quality: Managing Tensions Between Safe and Patient Centered Healthcare,” *Manufacturing and Service Operations Management* (14:4), pp. 548-566.

Chen, D. Q., Preston, D. S., and Xia, W. 2013. "Enhancing Hospital Supply Chain Performance: A Relational View and Empirical Test," *Journal of Operations Management* (31:6), pp. 391-408.

Chirico, F., Sirmon, D. G., Sciascia, S., and Mazzola, P. 2011. "Resource Orchestration in Family Firms: Investigating How Entrepreneurial Orientation, Generational Involvement, and Participative Strategy Affect Performance," *Strategic Entrepreneurship Journal* (5:4), pp. 307-326.

Choi, I., Pinsonneault, A., Han, K., and Animesh, A. 2018. "The Effect of IT Resource Diversity on Firm Performance. *ICIS 2018 proceedings*.

Connelly, D. P., Park, Y. T., Du, J., Theera-Ampornpunt, N., Gordon, B. D., Bershow, B. A., Gensinger, R. A., Shrift, M., Routhe, D. T., and Speedie, S. M. 2012. "The Impact of Electronic Health Records on Care of Heart Failure Patients in the Emergency Room," *Journal of the American Medical Informatics Association* (19:3), pp. 334-340.

Coviello, N. E., Brodie, R. J., Danaher, P. J., and Johnston, W. J. 2002. "How Firms Relate to Their Markets: An Empirical Examination of Contemporary Marketing Practices," *Journal of Marketing* (66:3), pp. 33-46.

Davis, K., Doty, M. M., Shea, K., and Stremikis, K. 2009. "Health Information Technology and Physician Perceptions of Quality of Care and Satisfaction," *Health Policy* (90:2-3), pp. 239-246.

Deily, M. E., Hu, T., Terrizzi, S., Chou, S. Y., and Meyerhoefer, C. D. 2013. "The Impact of Health Information Technology Adoption by Outpatient Facilities on Pregnancy Outcomes," *Health Services Research* (48:1), pp. 70-94.

DesHarnais, S. I., McMahon Jr, L. F., Wroblewski, R. T., and Hogan, A. J. 1990. “Measuring Hospital Performance: The Development and Validation of Risk-Adjusted Indexes of Mortality, Readmissions, and Complications,” *Medical Care* (28:12), pp. 1127-1141.

DesRoches, C. M., Campbell, E. G., Vogeli, C., Zheng, J., Rao, S. R., Shields, A. E., Donelan, K., Rosenbaum, S., Bristol, S. J., Jha, A. K. 2010. “Electronic Health Records' Limited Successes Suggest More Targeted Uses,” *Health Affair* (20:4), pp. 639-646.

Devaraj, S., and Kohli, R. 2000. “Information Technology Payoff in the Healthcare Industry: A Longitudinal Study,” *Journal of Management Information Systems* (16:4), pp. 41-67.

Devaraj, S., Ow, T. T., and Kohli, R. 2013. “Examining the Impact of Information Technology and Patient Flow on Healthcare Performance: A Theory of Swift and Even Flow (TSEF) Perspective,” *Journal of Operations Management* (31:4), pp. 181-192.

Devaraj, S., and Kohli, R. 2003. “Performance Impacts of Information Technology: Is Actual Usage the Missing Link?” *Management Science* (49:3), pp. 273-289.

Di Liberto, A., Pigliaru, F., Mura, R. 2008. “How to Measure the Unobservable: A Panel Technique for the Analysis of TFP Convergence,” *Oxford Economic Papers* (60:2), pp. 343-368.

Dobrzykowski, D. D., Callaway, S. K., and Vonderembse, M. A. 2015. “Examining Pathways from Innovation Orientation to Patient Satisfaction: A Relational View of Healthcare Delivery,” *Decision Sciences* (46:5), pp. 863-899.

Duda, R. O. and Hart, P. E. 1973. *Pattern Classification and Scene Analysis,* New York, NY: John Wiley & Sons.

Duncan, N. B. 1995. “Capturing Flexibility of Information Technology Infrastructure: A Study of Resource Characteristics and Their Measure,” *Journal of Management Information Systems* (12:2), pp. 37–57.

Earl, M. 2001. “Knowledge Management Strategies: Toward a Taxonomy,” *Journal of Management Information Systems* (18:1), pp. 215-233.

Encinosa, W. E., and Bae, J. 2011. “Health Information Technology and Its Effects on Hospital Costs, Outcomes, and Patient Safety,” *INQUIRY: The Journal of Health Care Organization, Provision, and Financing* (48:4), pp. 288-303.

Fichman, R. G., Kohli, R., and Krishnan, R. 2011. “Editorial Overview—The Role of Information Systems in Healthcare: Current Research and Future Trends,” *Information Systems Research* (22:3), pp. 419-428.

Fiedler, K. D., Grover, V., and Teng, J. T. C. 1996. “An Empirically Derived Taxonomy of Information Technology Structure and its Relationship to Organizational Structure,” *Journal of Management Information Systems* (13:1), pp. 9-34.

Fornell, C., Johnson, M. D., Anderson, E. W., Cha, J., and Bryant, B. E. 1996. “The American Customer Satisfaction Index: Nature, Purpose, and Findings,” *Journal of Marketing* (60:4), pp. 7-18.

Freedman, D. A., Collier, D., Sekhon, J. S., and Stark, P. B. 2010. *Statistical Models and Causal Inference*, New York, NY: Cambridge University Press.

Furukawa, M. F., Raghu, T. S., Spaulding, T. J., and Vinze, A. 2008. “Adoption of Health Information Technology for Medication Safety in U.S. Hospitals, 2006,” *Health Affairs* (27:3), pp. 865-875.

Gabriel, M. H., Jones, E. B., Samy, L., and King, J. 2014. “Progress and Challenges: Implementation and Use of Health Information Technology Among Critical-Access Hospitals,” *Health Affairs* (33:7), pp. 1262-1271.

Galbraith, J., 1973. *Designing Complex Organizations,* Reading, MA: Addison-Wesley Publishing Company Inc.

Gardner, J. W., Boyer, K. K., and Gray, J. V. 2015. “Operational and Strategic Information Processing: Complementing Healthcare IT Infrastructure,” *Journal of Operations Management* (33-34), pp. 123-139.

Gardner, R. L., Cooper, E., Haskell, J., Harris, D. A., Poplau, S., Kroth, P. J., and Linzer, M. 2019. “Physician Stress and Burnout: The Impact of Health Information Technology,” *Journal of the American Medical Informatics Association* (26:2), pp. 106-114.

Gregor, S. 2006. “The Nature of Theory in Information Systems,” *MIS Quarterly* (30:3), pp. 611-642.

Hansen, L. P. 1982. “Large Sample Properties of Generalized Method of Moments Estimators,” *Econometrica* (51:4), pp. 1029–1054.

Hawes, J. M., and Crittenden, W. F. 1984. “A Taxonomy of Competitive Retailing Strategies,” *Strategic Management Journal* (5:3), pp. 275-287.

Helsen, K., and Green, P. E. 1991. “A Computational Study of Replicated Clustering with an Application to Market Segmentation,” *Decision Sciences* (22:5), pp. 1124-1141.

Hitt, L. M., and Tambe, P. 2016. “Health Care Information Technology, Work Organization, and Nursing Home Performance,” *ILR Review* (69:4), pp. 834-859.

Homburg, C., Jensen, O., and Krohmer, H. 2008. “Configurations of Marketing and Sales: A Taxonomy,” *Journal of Marketing* (72:2), pp. 133-154.

Homburg, C., Workman Jr, J. P., and Jensen, O. 2002. “A Configurational Perspective on Key Account Management,” *Journal of Marketing* (66:2), pp. 38-60.

Hsu, J., Huang, J., Fung, V., Robertson, N., Jimison, H., and Frankel, R. 2005. “Health Information Technology and Physician-Patient Interactions: Impact of Computers on Communication During Outpatient Primary Care Visits,” *Journal of the American Medical Informatics Association* (12:4), pp. 474-480.

Hubert, L., and Arabie, P. 1985. “Comparing Partitions,” *Journal of Classification* (2:1), pp. 193-218.

Hydari, M. Z., Telang, R., and Marella, W. M. 2019. “Saving Patient Ryan—Can Advanced Electronic Medical Records Make Patient Care Safer?” *Management Science* (65:5), pp. 2041-2059.

Iacus, S. M., King, G., and Porro, G. 2011. “Multivariate Matching Methods That Are Monotonic Imbalance Bounding,” *Journal of the American Statistical Association* (106:493), pp. 345-361.

Jaana, M., Ward, M. M., Pare, G., and Sicotte, C. 2006. “Antecedents of Clinical Information Technology Sophistication in Hospitals,” *Health Care Management Review* (31:4), pp. 289-299.

James, G., Witten, D., Hastie, T., and Tibshirani, R. 2013. *An introduction to statistical learning*, New York, NY: Springer.

Jost, L. 2007. “Partitioning Diversity into Independent Alpha and Beta Components,” *Ecology* (88:10), pp. 2427-2439.

Karahanna, E., Chen, A., Liu, Q. B., and Serrano, C. 2019. "Capitalizing on Health Information Technology to Enable Digital Advantage in U.S. Hospitals," *MIS Quarterly* (43:1), pp. 113-140.

Ketchen, D. J., and Shook, C. L. 1996. "The Application of Cluster Analysis in Strategic Management Research: An Analysis and Critique," *Strategic management journal* (17:6), pp. 441-458.

Kohli, R., and Tan, S. S. L. 2016. "Electronic Health Records: How Can IS Researchers Contribute to Transforming Healthcare?" *MIS Quarterly* (40:3), pp. 553-573.

Kohli, R., and Devaraj, S. 2003. "Measuring Information Technology Payoff: A Meta-Analysis of Structural Variables in Firm-Level Empirical Research," *Information Systems Research* (14:2), pp. 127-145.

Koppel, R., Metlay, J. P., Cohen, A., Abaluck, B., Localio, A. R., Kimmel, S. E., and Strom, B. L. 2005. "Role of Computerized Physician Order Entry Systems in Facilitating Medication Errors," *Journal of American Medical Association* (293:10), pp. 1197-1203.

Kucher, N., Koo, S., Quiroz, R., Cooper, J., Paterno, M., Soukonnikov, B., and Goldhaber, S. 2005. "Electronic Alerts to Prevent Venous Thromboembolism Among Hospitalized Patients," *New England Journal of Medicine*, (352:10), pp. 969-977.

Kuperman, G. J., and Gibson, R. F. 2003. "Computer Physician Order Entry: Benefits, Costs, and Issues," *Annals of Internal Medicine* (139:1), pp. 31-39.

Larsen, K. R. T. 2003. "A Taxonomy of Antecedents of Information Systems Success: Variable Analysis Studies," *Journal of Management Information Systems* (20:2), pp. 169-246.

Lawrence, T. B., Winn, M. I., and Jennings, P. D. 2001. "The Temporal Dynamics of Institutionalization," *Academy of Management Review* (26:4), pp. 624-644.

Lebart L, Morineau A, Piron M (2000). *Statistique Exploratoire Multidimensionnelle*, Paris: Dunod.

Lee, J., McCullough, J. S., and Town, R. J. 2013. “The Impact of Health Information Technology on Hospital Productivity,” *The RAND Journal of Economics* (44:3), pp. 545-568.

Linder, J. A., Ma, J., Bates, D. W., Middleton, B., and Stafford, R. S. 2007. “Electronic Health Record Use and the Quality of Ambulatory Care in the United States,” Archives of Internal Medicine (167:13), pp. 1400-1405.

Lucas Jr, H., Agarwal, R., Clemons, E. K., El Sawy, O. A., and Weber, B. 2013. “Impactful Research on Transformational Information Technology: An Opportunity to Inform New Audiences,” *MIS Quarterly* (37:2), pp. 371-382.

Marley, K. A., Collier, D. A., and Meyer Goldstein, S. 2004. “The Role of Clinical and Process Quality in Achieving Patient Satisfaction in Hospitals,” *Decision Sciences* (35:3), pp. 349-369.

Martínez, O., and Reyes-Valdés, M. H. 2008. “Defining Diversity, Specialization, and Gene Specificity in Transcriptomes Through Information Theory,” *Proceedings of the National Academy of Sciences* (105:28), pp. 9709-9714.

Mason, R. O., and Mitroff, I. I. 1973. “A Program for Research on Management Information Systems,” *Management Science* (19:5), pp. 475-487.

Mayr, E. 1969. *Principles of Systematic Zoology*. New York, NY: McGraw-Hill.

McCullough, J. S., Casey, M., Moscovice, I., and Prasad, S. 2010. “The Effect of Health Information Technology on Quality in U.S. hospitals,” *Health Affairs* (29:4), pp. 647-654.

McCullough, J. S. 2008. “The Adoption of Hospital Information Systems,” *Health Economics* (17:5), pp. 649-664.

McCullough, J. S., Parente, S. T., and Town, R. 2016. “Health Information Technology and Patient Outcomes: The Role of Information and Labor Coordination,” *The RAND Journal of Economics* (47:1), pp. 207-236.

McIntyre, R. M., and Blashfield, R. K. 1980. “A Nearest-Centroid Technique for Evaluating the Minimum-Variance Clustering Procedure,” *Multivariate Behavioral Research* (15:2), pp. 225–38.

McKelvey, B. 1978. “Organizational Systematics: Taxonomic Lessons from Biology,” *Management Science* (24:13), pp. 1428-1440.

McKelvey, B. 1982. *Organizational Systematics: Taxonomy, Evolution, Classification*, Berkeley, CA: University of California Press.

McKenna, R. M., Dwyer, D., and Rizzo, J. A. 2018. “Is HIT a Hit? The Impact of Health Information Technology on Inpatient Hospital Outcomes,” *Applied Economics* (50:27), pp. 3016-3028.

Melville, N., Kraemer, K., and Gurbaxani, V. 2004. “Information Technology and Organizational Performance: An Integrative Model of IT Business Value,” *MIS Quarterly* (28:2), pp. 283-322.

Menachemi, N., Burkhardt, J., Shewchuk, R., Burke, D., and Brooks, R. 2006. “Hospital Information Technology and Positive Financial Performance: A Different Approach to ROI,” *Journal of Healthcare Management* (15:1), pp. 40-58.

Menon, N. M., Yaylacicegi, U., and Cezar, A. 2009. “Differential Effects of the Two Types of Information Systems: A Hospital-Based Study,” *Journal of Management Information Systems* (26:1), pp. 297-316.

Miller, A. R., and Tucker, C. E. 2011. “Can Health Care Information Technology Save Babies?” *Journal of Political Economy* (119:2), pp. 289-324.

Milligan, G. W., and Cooper, M. C. 1985. “An Examination of Procedures for Determining the Number of Clusters in a Data Set,” *Psychometrika* (50:2), pp. 129-79.

Milligan, G. W., and Cooper, M. C. 1987. “Methodology Review: Clustering Methods,” *Applied Psychological Measurement* (11:4), pp. 329-54.

Milligan, G. W., and Hirtle, S. C. 2003. “Clustering and Classification Methods,” In *Handbook of Psychology: Research Methods in Psychology*, Vol. 2, J. A. Schinka, W. F. Velicer, and I. B. Weiner, eds. New York, NY: John Wiley & Sons, pp. 165-86.

Mithas, S., Krishnan, M. S., and Fornell, C. 2016. “Research Note—Information Technology, Customer Satisfaction, and Profit: Theory and Evidence,” *Information Systems Research* (27:1), pp. 166-181.

Mithas, S., and Rust, R. T. 2016. “How Information Technology Strategy and Investments Influence Firm Performance: Conjecture and Empirical Evidence,” *MIS Quarterly* (40:1), pp. 223-245.

National Health Expenditure Accounts. 2019. *National Health Expenditures Projections 2019-2018* from https://www.cms.gov/Research-Statistics-Data-and-Systems/Statistics-Trends-and-Reports/NationalHealthExpendData/NationalHealthAccountsProjected.

Newton, I. 1802. *Mathematical Principles of Natural Philosophy*, London: A. Strahan

Nevo, S., and Wade, M. R. 2010. “The Formation and Value of IT-Enabled Resources: Antecedents and Consequences of Synergistic Relationships,” *MIS Quarterly* (34:1), pp. 163-183.

Oh, J. H., Zheng, Z., and Bardhan, I. R. 2018. “Sooner or Later? Health Information Technology, Length of Stay, and Readmission Risk,” *Production and Operations Management* (27:11), pp. 2038-2053.

Ozdas, A., Speroff, T., Waitman, L. R., Ozbolt, J., Butler, J., Miller, R. A. 2006. “Integrating Best of Care Protocols into Clinicians’ Workflow via Care Provider Order Entry: Impact on Quality-of-Care Indicators for Acute Myocardial Infarction,” *Journal of the American Medical Informatics Association* (13:2), pp. 188-196.

Parente, S. T., and McCullough, J. S. 2009. “Health Information Technology and Patient Safety: Evidence from Panel Data,” *Health Affairs* (28:2), pp. 357-360.

Pentland, B.T., and Feldman, M. S. 2008. “Designing Routines: On the Folly of Designing Artifacts, While Hoping for Patterns of Action,” *Information and Organization* (18:4), pp. 235–250.

Pinsonneault, A., Addas, S., Qian, C., Dakshinamoorthy, V., and Tamblyn, R. 2017. “Integrated Health Information Technology and the Quality of Patient Care: A Natural Experiment,” *Journal of Management Information Systems* (34:2), pp. 457-486.

Prahalad, P., Tanenbaum, M., Hood, K., and Maahs, D. M. 2018. “Diabetes Technology: Improving Care, Improving Patient-Reported Outcomes and Preventing Complications in Young People with Type1 Diabetes,” *Diabetic Medicine* (35:4), pp. 419-429.

Premkumar, G., and Roberts, M. 1999. “Adoption of New Information Technologies in Rural Small Businesses,” *Omega* (27:4), pp. 467-484.

Posey, C., Roberts, T. L., Lowry, P. B., Bennett, R. J., and Courtney, J. F. 2013. "Insiders' Protection of Organizational Information Assets: Development of a Systematics-Based Taxonomy and Theory of Diversity for Protection-Motivated Behaviors," *MIS Quarterly* (37:4), pp. 1189-1210.

Punj, G., and Stewart, D. W. 1983. "Cluster Analysis in Marketing Research: Review and Suggestions for Application," *Journal of Marketing Research* (20:2), pp. 134-48.

Queenan, C. C., Angst, C. M., and Devaraj, S. 2011. "Doctors' Orders—If They're Electronic, Do They Improve Patient Satisfaction? A Complements/Substitutes Perspective," *Journal of Operations Management* (29:7-8), pp. 639-649.

Rand, W. M. 1971. "Objective Criteria for the Evaluation of Clustering Methods," *Journal of the American Statistical Association* (66:336), pp. 846–50.

Rich, P. 1992. "The Organizational Taxonomy: Definition and Design," *Academy of Management Review* (17:4), pp. 758–81.

Roberts, L. L., Ward, M. M., Brokel, J. M., Wakefield, D. S., Crandall, D. K., and Conlon, P. 2010. "Impact of Health Information Technology on Detection of Potential Adverse Drug Events at the Ordering Stage," *American Journal of Health-System Pharmacy* (67:21), pp. 1838-1846.

Rodrigues, J. J., Segundo, D. B. D. R., Junqueira, H. A., Sabino, M. H., Prince, R. M., Al-Muhtadi, J., and De Albuquerque, V. H. C. 2018. "Enabling Technologies for the Internet of Health Things," *IEEE Access* (6), pp. 13129-13141.

Roman-Belmonte, J. M., De la Corte-Rodriguez, H., and Rodriguez-Merchan, E. C. 2018. "How Blockchain Technology Can Change Medicine," *Postgraduate Medicine* (130:4), pp. 420-427.

Romanow, D., Rai, A., and Keil, M. 2018. "CPOE-Enabled Coordination: Appropriation for Deep Structure Use and Impacts on Patient Outcomes," *MIS Quarterly* (42:1), pp. 189-212.

Ross, H. H. 1974. *Biological Systematics*, Reading, MA: Addison-Wesley.

Sabherwal, R., and Jeyaraj, A. 2015. "Information Technology Impacts on Firm Performance: An Extension of Kohli and Devaraj (2003)," *MIS Quarterly* (39:4), pp. 809-836.

Senot, C., Chandrasekaran, A., Ward, P. T., Tucker, A. L., and Moffatt-Bruce, S. D. 2016. "The Impact of Combining Conformance and Experiential Quality on Hospitals' Readmissions and Cost Performance," *Management Science* (62:3), pp. 829–848.

Shannon, C. 1948. "A Mathematical Theory of Communication," *The Bell System Technical Journal* (27:3), pp. 379-423.

Sharma, L., Chandrasekaran, A., Boyer, K. K., and McDermott, C. M. 2016. "The Impact of Health Information Technology Bundles on Hospital Performance: An Econometric Study," *Journal of Operations Management* (41), pp. 25-41.

Shmueli, G., and Koppius, O. R. 2011. "Predictive Analytics in Information Systems Research," *MIS Quarterly* (35:3), pp. 553-572.

Sirmon, D. G., Hitt, M. A., and Ireland, R. D. 2007. "Managing Firm Resources in Dynamic Environments to Create Value: Looking Inside the Black Box," *Academy of management review* (32:1), pp. 273-292.

Sirmon, D. G., Gove, S., and Hitt, M. A. 2008. "Resource Management in Dyadic Competitive Rivalry: The Effects of Resource Bundling and Deployment," *Academy of Management journal* (51:5), pp. 919-935.

Sirmon, D. G., Hitt, M. A., Ireland, R. D., and Gilbert, B. A. 2011. "Resource Orchestration to Create Competitive Advantage: Breadth, Depth, and Life Cycle Effects," *Journal of Management*, (37:5), pp. 1390-1412.

Slater, S. F., and Olson, E. M. 2001. "Marketing's Contribution to the Implementation of Business Strategy: An Empirical Analysis," *Strategic Management Journal* (22:11), pp. 1055–1067.

Stock, G. N., and Tatikonda, M. V. 2008. "The Joint Influence of Technology Uncertainty and Interorganizational Interaction on External Technology Integration Success," *Journal of Operation Management* (26), pp. 65-80.

Stratman, J. K. 2007. "Realizing Benefits from Enterprise Resource Planning: Does Strategic Focus Matter?" Production and Operations Management (16:2), pp. 203–216.

Tallon, P. P. 2007. "A Process-Oriented Perspective on the Alignment of Information Technology and Business Strategy," *Journal of Management Inform Systems* (24:3), pp. 227–268.

Tushman, M. L., Nadler, D. A. 1978. "Information Processing as an Integrating Concept in Organization Design," *Academy of Management Review* (3:3), pp. 613–624.

Wade, M., and Hulland, J. 2004. "The Resource-Based View and Information Systems Research: Review, Extension, and Suggestions for Future Research," *MIS Quarterly* (28:1), pp. 107-142.

Wang, B. B., Wan, T. T., Burke, D. E., Bazzoli, G. J., and Lin, B. Y. 2005. "Factors Influencing Health Information System Adoption in American Hospitals," *Health Care Management Review* (30:1), pp. 44-51.

Wang, T., Wang, Y., and McLeod, A. 2018. “Do Health Information Technology Investments Impact Hospital Financial Performance and Productivity?” *International Journal of Accounting Information Systems* (28), pp. 1-13.

Waller, R. A., and Duncan, D. B. 1969. “A Bayes Rule for the Symmetric Multiple Comparisons Problem,” *Journal of the American Statistical Association* (64:328), pp. 1484-1503.

Ward, J. H., Jr. 1963. “Hierarchical Grouping to Optimize an Objective Function,” *Journal of the American Statistical Association* (58:301), pp. 236–44.

Wooldridge, J. M. 2016. *Introductory Econometrics: A Modern Approach*, Boston MA: Cengage Learning.

Xue, L., Ray, G., and Sambamurthy, V. 2012. “Efficiency or Innovation: How do Industry Environments Moderate the Effects of Firms' IT Asset Portfolios?” *MIS Quarterly* (36:2), pp. 509-528.

Zhang, N. J., Seblega, B., Wan, T., Unruh, L., Agiro, A., and Miao, L. 2013. “Health Information Technology Adoption in U.S. Acute Care Hospitals,” *Journal of Medical Systems* (37:2).

Zhao, M., Hamadi, H., Rob Haley, D., White-Williams, C., Liu, X., and Spaulding, A. 2019. “The Relationship Between Health Information Technology Laboratory Tracking Systems and Hospital Financial Performance and Quality,” *Hospital Topics* (97:3), pp. **99-106.**

APPENDIX A Healthcare Information Technology List

Table A1. Healthcare Information Technology List

Category	IT application
Laboratory	Laboratory Information System
Pharmacy	Pharmacy Management System
Electronic Medical Record	Clinical Data Repository (CDR)
Electronic Medical Record	Clinical Decision Support (CDS)
Electronic Medical Record	Computerized Practitioner Order Entry (CPOE)
Electronic Medical Record	Physician Documentation
Nursing	Nursing Documentation
Nursing	Electronic Medication Administration Record (EMAR)
Nursing	RFID – Patient Tracking
Supply Chain Management	RFID – Supply Tracking
Utilization Review/Risk Management	Data Warehousing/Mining – Clinical
Financial Decision Support	Data Warehousing/Mining – Financial
Radiology & PACS	Radiology Information System
Radiology & PACS	Radiology – Angiography
Radiology & PACS	Radiology - CR (Computed Radiography)
Radiology & PACS	Radiology - CT (Computerized Tomography)
Radiology & PACS	Radiology - DF (Digital Fluoroscopy)
Radiology & PACS	Radiology – Mammography
Radiology & PACS	Radiology - DR (Digital Radiography)
Radiology & PACS	Radiology - MRI (Magnetic Resonance Imaging)
Radiology & PACS	Radiology - Nuclear Medicine
Radiology & PACS	Radiology - US (Ultrasound)
Radiology & PACS	Radiology – Orthopedic
Cardiology & PACS	Cardiology - Cath Lab
Cardiology & PACS	Cardiology - CT (Computerized Tomography)
Cardiology & PACS	Cardiology – Echocardiology
Cardiology & PACS	Cardiology - Intravascular Ultrasound
Cardiology & PACS	Cardiology - Nuclear Cardiology
Cardiology & PACS	Cardiology Information System
Health Information Exchange (HIE)	Health Information Exchange (HIE)

APPENDIX B Organizational IT Adoption Studies

Table 1 A Review of Studies on Organizational IT Adoption Studies

Study	Dataset	IT measures	Performance measures	Outcomes	Temporal dimension
Adler-Milstein et al. (2013)	EHR task logs	EHR	Clinician productivity	Greater EHR use is associated with higher levels of productivity.	N
Agha (2014)	HIMSS	EMR, CDS	Medical expenditures Readmission rate Mortality rate	HIT is associated with an increase in billed charges. HIT adoption have no impact on readmission rate and mortality rate.	Time lags
Angst et al. (2011)	HIMSS	6 information technologies for Cardiology	Cost per patient Length of stay (LOS)	Sequence of technology adoption impacts hospital cost and LOS. Foundational technologies first tend to perform better.	Sequence of technology adoption
Angst et al. (2012)	HIMSS, CMS, HCAHPS	Administrative HIT Cardiology IT	Technical protocols of care Interpersonal care	Administrative HIT affects Interpersonal Care. Cardiology HIT affects Technical Protocols of Patient Care	Time lags
Appari et al. (2012)	HIMSS, CMS	CPOE, EMAR	Medication quality	Implementation and duration of use of health information technologies are associated with improved adherence to medication guidelines at US hospitals	Length of technology usage
Ash et al. (2007)	Primary data from 179 hospitals	CPOE	Unintended adverse consequences of CPOE	There is no relation between kinds of unintended consequences and number of years CPOE has been used	N
Atasoy et al. (2018)	HIMSS, American Community Survey data of the U.S. Census	HER	Operational cost	Significant spillover effects by reducing the costs of neighboring hospitals	Time lags
Bardhan and Thouin (2013)	HIMSS, CMS	Clinical information systems, Financial systems Scheduling systems, HR systems	Operational cost Care quality	Usage of clinical information systems and scheduling applications is positively associated with care quality. Usage of financial management systems is associated with lower hospital operating expenses.	N
Bates et al. (1999)	Patient sample from a hospital	CPOE	Medication error	CPOE decreased the rate of non-intercepted serious medication errors	N

Table 2 A Review of Studies on Organizational IT Adoption Studies (Continued)

Study	Dataset	IT measures	Performance measures	Outcomes	Temporal dimension
Bhargava and Mishra (2014)	Primary data from 87 physicians in 12 primary care clinics	EMR	Productivity of physicians	Productivity drops immediately after technology implementation and recovers partly over the next few months.	Time lags
Bradley et al. (2018)	HIMSS, CMS	RFID, EDI	Supply chain cost efficiency Personnel expenses Readmission rate	Over time, better supply chain cost efficiency, lower personnel expenses, and a consistent reduction in readmission rates accrue from the long term	Length of technology usage
Campbell et al. (2008)	Primary data from 200 medical staff	EHR	Work activities of medical staff	After introduction of an EHR, direct patient care activities increased.	N
Connelly et al. (2012)	Primary data from 5166 adults in three metropolitan emergency departments	EHR	LOS Hospitalization rate Morality rate	Using HER is associated with decreased mortality rate and hospitalization rate, but not associated with hospital LOS.	N
Davis et al. (2009)	Primary data from 6088 physicians in 2006 in seven countries	Information system functional capacity	Coordination and safety of care Physician satisfaction	Information system infrastructure are better able to address coordination and safety issues, particularly for patients with multiple chronic conditions, as well as to maintain primary care physician workforce satisfaction	N
Deily et al. (2012)	Administrative claims data on 491,832 births, HIMSS	Clinical HIT Non-clinical HIT	LOS, Incidence of obstetric trauma and preventable complications	Greater use of clinical HIT applications is associated with reduced incidence of obstetric trauma and preventable complications, as well as longer LOS	N
DesRoches et al. (2010)	2952 hospitals for the year 2008	EMR	Mortality LOS Readmission rate Hospital cost	EMR use is not associated with improvements in hospital cost and quality.	N
Devaraj and Kohli (2000)	Primary data from 8 hospitals	DSS	Revenue Mortality rates Customer satisfaction	DSS lead to improved hospital performance after a time lag	Time lags

Table 3 A Review of Studies on Organizational IT Adoption Studies (Continued)

Study	Dataset	IT measures	Performance measures	Outcomes	Temporal dimension
Devaraj and Kohli (2003)	Primary data from 8 hospitals	DSS	Mortality rate Revenue	DSS use leads to improved hospital performance after a time lag	Time lags
Devaraj et al. (2013)	Solucient, Inc. data, Comparion Medical Analytics	IT investment	LOS Revenue Mortality Complications	IT investments in a hospital lead to performance improvement	N
Encinosa and Bae (2011)	MarketScan database AHA	EMR	Patient safety Morality rate Readmission rate Expenditure	EMRs do not reduce the rate of patient safety events. However, once an event occurs, EMRs reduce death and readmissions. A cost offset of $1.75 per $1 spent on IT capital	N
Gardner et al. (2015)	HIMSS, CMS, Primary data from 19 hospitals	HIT infrastructure level (the proportion of information technologies that a given hospital has adopted as live and used in daily operations)	Care quality Patient satisfaction	Positive and significant coefficients in most models	N
Gardner et al. (2019)	Primary data from 4197 practicing physicians	EHR	Physician burn-out	HIT-related stress is measurable, common (about 70% among respondents), specialty-related, and independently predictive of burnout symptoms.	N
Hitt and Tambe (2016)	Primary data from 304 nursing home Panel data from New York Satate Ridediencial Health Care Facilities Cost Reports	EMR	Productivity Efficiency Cost	A positive effect of EMR-system implementation, on the order of 1% higher productivity, 3% greater efficiency, but approximately 2.7% higher cost.	N
Hsu et al. (2005)	Primary data from 313 patients in a hospital	Physicians' computer use	Patient satisfaction	Overall patient satisfaction with visits increased seven months after the introduction of computers.	N

Table 4 A Review of Studies on Organizational IT Adoption Studies (Continued)

Study	Dataset	IT measures	Performance measures	Outcomes	Temporal dimension
Hydari et al. (2019)	HIMSS, CMS, AHA, PHC4, PSA	CPOE, PD	Patient safety	CPOE and PD lead to improved patient safety	Time lags
Koppel et al. (2005)	Data from a 2002-2004 survey of 261 hospitals	CPOE	Prescription error risks	Use of CPOE facilitated 22 types of medication error risks	N
Kucher et al. (2005)	2500 patients from a single hospital	Computer alert system	Rates of deep-vein thrombosis and pulmonary embolism	Use of the computer alert program reduced the rate of deep-vein thrombosis and pulmonary embolism	N
Lee et al. (2013)	OSHPD, HIMSS	IT capital	Productivity	Positive relationship between IT capital and hospital productivity	Time lags
Linder et al. (2007)	Data from a 2003-2004 survey	EMR	17 ambulatory quality indicators	Use of EMR is not associated with improvements in quality of ambulatory care	N
McCullough et al. (2010)	HIMSS, CMS data	CPOE	CMS Process of Care Measures	CPOE is associated with improvements in two pneumonia quality measures	N
McKenna et al. (2018)	HIMSS, SPARCS	CDR, CPOE, CDSS	Mortality rate	Hospitals that have adopted either a CDS and CPOE, or a CDS and CDSS realize a reduction of 0.3 percentage points in their severity-adjusted mortality rates	N
Menachemi et al. (2006)	HIMSS, Primary data	Clinical HIT Administrative HIT Strategic HIT	Financial Performance	Increased HIT use is associated with higher revenues, cash flows, etc although it also leads to increased cost	N
Menon et al. (2009)	WaDoH	Clinical IT Administrative IT	Labor productivity Patient days per employee	HIT improve hospital output after a time lag	Time lags
Miller and Tucker (2011)	HIMSS, Infant Mentality Data from CDC	EMR	Infant mortality rate	EMRs reduces neonatal mortality by 16 deaths per 100,000 live births.	N
Oh et al. (2018)	HIMSS	15 HIT applications (e.g. CPOE, BI, EMAR, RFID)	LOS deviation from standard guidelines Readmission risk	HIT implementation is associated with a reduction in the deviation	N

Table 5 A Review of Studies on Organizational IT Adoption Studies (Continued)

Study	Dataset	IT measures	Performance measures	Outcomes	Temporal dimension
Parente and McCullough (2009)	Medicare patient data	EMR	Patient safety	EMR have a small, positive effect on patient safety	N
Queenan et al. (2011)	HIMSS, HCAHPS	CPOE IT infrastructure	Patient satisfaction	CPOE use increases patient satisfaction	N
Robersts et al. (2010)	Primary data from 9 hospitals	CPOE, CDSS	Adverse drug events (ADE) alerts	CPOE and CDSS increased the number of potential ADE alerts for pharmacist review and the number of true-positive ADE alerts identified per 1000 admissions	N
Romanow et al. (2018)	Survey from 224 patient care teams	CPOE	Patient satisfaction	Using CPOE in a comprehensive manner, patient care team members are better able to coordinate patient care and are able to better inform the patient about their care, ultimately leading to improved patient satisfaction.	N
Sharma et al. (2016)	HIMSS, CMS	Clinical HIT Augmented clinical HIT Administrative HIT	Cost per bed Conformance quality Experiential quality (interaction)	Complementarities between Clinical and Augmented Clinical HIT with respect to conformance quality but not cost outcomes	N
Wang et al. (2018)	Definitive Healthcare database	IT expenditure	Financial Performance (ROA) Productivity	Health information technology expenses are positively associated with hospitals' return on assets and productivity	N
Zhao et al. (2019)	CMS, AHAAS	Laboratory tracking systems	Financial Performance	Hospitals with laboratory tracking systems reported better financial performance on five financial performance measures	N

APPENDIX C Data Sources

American Hospital Association (AHA)

American Hospital Association (AHA) Founded in 1898, the American Hospital Association (AHA) is the national organization that represents healthcare organizations including all types of hospitals, health care networks, and their patients and communities. AHA includes nearly 5,000 hospitals, health care systems, networks, other providers of care and 43,000 individual members. It focuses on getting members' perspectives and needs heard and addressed in national health policy development, legislative and regulatory debates, and judicial matters. AHA also provides education and information on health care issues and trends. AHA maintains a comprehensive census of United States hospitals based on the AHA Annual Survey of Hospitals conducted since 1946. The database is released annually and covers organizational structure, personnel, hospital facilities and services, and financial performance. It has been used by government agencies, research universities, health policy organizations, health care vendors, and professional services firms.

Source: http://www.aha.org/

American Hospital Directory (AHD)

The American Hospital Directory (AHD) provides information on more than 6,000 hospitals nationwide from authoritative sources. The data and statistics are derived from both public and private sources such as Medicare claims data, hospital cost reports, and commercial licensors. AHD is not affiliated with the American Hospital Association (AHA).

Source: https://www.ahd.com/

Center for Medicare & Medicaid Services (CMS)

The Centers for Medicare & Medicaid Services (CMS) is a federal agency within the Department of Health and Human Services (HHS). It works in partnership with state governments to administer programs such as Medicare, Medicaid, the State Children's Health Insurance Program (SCHIP), and health insurance portability standards.

Source: https://www.cms.gov/

Healthcare Information and Management Systems Society (HIMSS)

As a global, cause-based, non-profit organization founded in 1961, HIMSS (Healthcare Information and Management Systems Society) focuses on improving health engagements and the access, quality, cost-effectiveness, and value of healthcare through information technology (IT). Headquartered in Chicago and with offices in the United States, Europe, and Asia, HIMSS engages the global health IT community by providing thought leadership, community building, professional development, public policy, and events. HIMSS Analytics, a wholly owned subsidiary of HIMSS, leads efforts in healthcare research and advisory for healthcare delivery organizations, IT companies, governmental entities, and financial, pharmaceutical, consulting and emerging technology solution partners worldwide. It conducts an annual study on United States healthcare organizations to collect data on the inventory and use of healthcare information technology.

Source: http://www.himss.org/, http://www.himssanalytics.org/