8-7-2018

Three Empirical Essays on Health Informatics and Analytics

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THREE EMPIRICAL ESSAYS ON HEALTH INFORMATICS AND ANALYTICS

BY

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A Dissertation Submitted in Partial Fulfillment of the Requirements for the Degree

Of

Doctor of Philosophy

In the Robinson College of Business

Of

Georgia State University

GEORGIA STATE UNIVERSITY

ROBINSON COLLEGE OF BUSINESS

2018

ACCEPTANCE

This dissertation was prepared under the direction of the *Youyou Tao's* Dissertation Committee. It has been approved and accepted by all members of that committee, and it has been accepted in partial fulfillment of the requirements for the degree of Doctor of Philosophy in Business Administration in the J. Mack Robinson College of Business of Georgia State University.

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ABSTRACT

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BY

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07/16/2018

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Major Academic Unit: *Computer Information Systems*

Health Information Technology (HIT) has an important and widely acknowledged role in enhancing healthcare performance in the healthcare industry today. A great amount of literature has focused on the impact of HIT implementation, yet the studies provide mixed and inconclusive results on whether HIT implementation actually helps healthcare providers enhance healthcare performance. Here, we identify three possible research gaps that lead to these mixed and inclusive results. First, prior IS research has exclusively examined HIT complementarity simultaneously, but ignored the temporal perspective. Second, extant HIT research has primarily examined the relationship between HIT implementation and healthcare performance in a static framework, which may neglect the dynamic relationship between HIT and healthcare performance. Third, prior HIT value studies have typically examined HIT's impact on hospital-level outcomes, but no extant studies consider HIT impact on transition-level outcomes as disease progresses over time.

This dissertation addresses these gaps in three essays that draw upon three different lenses to study HIT implementation's impact on healthcare performance using three analytics methods. The first essay applies econometrics to study how various types of HIT complementarities simultaneously and sequentially impact diverse healthcare outcomes. In so doing, we find evidence of simultaneous and sequential complementarity wherein HIT applications are synergistic—not only within the same time period, but also across periods. The second essay uses advanced latent growth modeling to explore the dynamic, longitudinal relationship between HIT and healthcare outcomes after incorporating the nonlinear trajectory change of different HIT functions and the various dimensions of hospital performance. The third essay applies multi-state and hidden Markov models to examine how HIT functions' implementation levels impact a finer, more-granular-level healthcare outcome. This approach includes the dynamics of the transitions, including observable transitions (chronic to acute, acute to chronic, chronic to death, and acute to death) and underlying and unobservable transitions (minor to major disease and major disease to death). This essay examines how different types of HIT can improve different transitions types as diseases progress over time.

ACKNOWLEDGEMENTS

I am delighted to have the opportunity to express my appreciation and thanks to many faculty, family, and friends who made this dissertation possible.

First and foremost, I am extremely thankful to my advisor Dr. Abhay N. Mishra for his years of help, guidance, and support. I learned a lot from him—from methodologies to research writing and from a focused attitude toward research to a hardworking style in approaching it. I will never forget the stacks of papers in his office, and the times we worked together on a single paper again and again. From him, I learned that good research takes time, effort, and a persistent attitude and requires that we face and overcome many challenges. I am also particularly thankful to my other advisor, Dr. Mark Keil, for his guidance and encouragement. He is like a lighthouse—always guiding me from the dark places whenever I need help. I appreciate his kindness and patience with me.

I would like to express my thanks to my great committee members, Dr. Jeong-ha (Cath) Oh and Dr. Katherine Masyn. Dr. Cath Oh was the first professor to lead me into the big data analysis and healthcare IT research area. She is extremely patient and kind to me. Dr. Katherine Masyn guided me through the process of conducting latent growth modeling. I really admire her teaching style and am honored to have had the chance to work with her. Working with her is like working with a friend, exploring the unknown world using interesting data models and big datasets.

Next, I want to express my sincere gratitude toward Dr. Michael Gallivan, Dr. Daniel Robey, and Dr. Dezhi Wu. These three professors have given me a lot of support in both my academic and my personal life. I have enjoyed the time I spent with them as a student and as a friend.

I am thankful to the entire faculty and staff at the Department of Computer Information Systems, the Center for Health Information Technology, and other departments in the Robinson Business School for making my Ph.D. study there an unforgettable journey. I thank Drs. Arun Rai, Detmar Straub, Bala Ramesh, Lars Mathiassen, Veda Storey, William N. Robinson, Vijay K. Vaishnavi, Lisa Lambert, and Yichen Cheng for teaching me how to do research. I thank Dr. Andrea Aria for teaching me Java programming and giving considerable help in teaching. I thank Drs. Shuguang Hong, Aaron Baird, J.J. Po-An Hsieh, Yu-Kai Lin, Likoebe M Maruping, Ephraim R. McLean, Kurt Schmitz, J.P. Shim, and Ling Xue for giving me so much support during my Ph.D. program. I also want to thank my fellow doctoral students, especially Liwei Chen, Neetu Singh, Tianjie Deng, Hyung Koo Lee, Langtao Chen, Alan Yang, Sayed Almohri, Arun Aryal, Shane Givens, Zhitao Yin, Jessica Pye, Chaitanya Sambhara, Yanran Liu, Vitali Mindel, Shelly Wu, Xinling Liu, Xiaocong Cui, Yukun Yang, Pengcheng Wang, Tawfiq Alashoor, Amrita George, Zirun Qi, Mahesh Boodraj, Jong Seok Lee, Sumantra Sarkar, Ruilin Zhu, and Wenbo Guo for their friendship and support. Thank you also to Denise Wilson, Ade Afonja, and Adenike Brewington for your help along the way.

Thanks to all my friends for their friendship, company, and support, especially Siman Li, Di Yang, Hao Liu, Shengjie Li, Shiya Liang, and Jiewen Wu. They have all made my Ph.D. life more delightful.

I would like to express my special thanks to my parents, Li Tao and Yongguang Tao, for their unconditional love and support, and to my beloved husband, Orin Jaworski, for his encouragement, company, and spiritual enlightenment, and for making my life full of sunshine. I also thank my baby, Clement Jaworski, who is a gift to my life and always reminds me to be kind and gentle for the rest of my life.

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CHAPTER 1 INTRODUCTION

1.1 Motivation

Over the past decade, the adoption and use of health information technology (HIT) has increased significantly among U.S. healthcare providers. In 2015, 84 percent of non-federal acute care hospitals[1] had adopted a basic Electronic Health Record (EHR) to support the display of various data, including patient demographics, problems, and medications; clinician notes and medication orders; and laboratory and radiology results (Henry et al. 2016). Widespread HIT adoption and use significantly impacts clinical workflow, process performance, and interactions among patients and providers (Angst et al. 2017). Both practitioners and scholars are interested in assessing whether HIT impacts lead to enhanced healthcare performance. HIT's value can emanate from two sources: HIT implementation and healthcare analytics. First, implementing and using HIT facilitates real-time access to clinical information, reduces unnecessary duplicate tests, and decreases preventable medical errors (Adler-Milstein and Bates 2010). Second, the clinical data that HIT captures can be used to predict patients' risks of readmission, adverse health events, and death; these predictions enable effective clinical decision making and personalized interventions. Practitioners and scholars are also interested in assessing whether HIT's benefits are accompanied by the risk and unintended consequences that come from misconfigurations among workflow, users, and technologies.

From a research perspective, despite a significant amount of literature studying the impact of HIT implementation in the information systems (IS), health policy, health economics, and health informatics fields, debate continues about whether HIT implementation leads to

[1] Non-federal acute care hospitals include acute care general medical and surgical, general children's, and cancer hospitals owned by private/not-for-profit, investor-owned/for-profit, and state/local government.

improved healthcare performance. Indeed, empirical results suggest that HIT may have a positive impact (Amarasingham et al. 2009; Buntin et al. 2011; Lee et al. 2013; Menachemi et al. 2008), a negative impact (Ash et al. 2004; Nebeker et al. 2005), or little to no impact on healthcare quality (Agha 2014). Furthermore, results suggest that HIT may decrease (Bardhan and Thouin 2013; Borzekowski 2009; Menachemi et al. 2006), increase (Agha 2014), or have little to no impact on healthcare cost (Furukawa et al. 2010). These mixed and inconclusive results regarding HIT's impact require further investigation.

Based on my research, I posit that these mixed results can be attributed to three major sources. First, prior research in the IS field has predominantly examined the impact of each HIT function in isolation but rarely studied the joint impact of various HIT functions, which can impact healthcare performance both in isolation and in combination. When different HIT functions are applied in combination, their joint effects can exceed the sum of the values they generate individually. Ignoring the complementarity effect of mutually reinforcing HIT functions may lead to an inaccurate assessment of HIT impact on healthcare performance. Further, synergistic gains can occur when a HIT function implemented in one time period interacts with functions implemented in the same or different time periods. Thus, it is vital to examine both simultaneous and sequential complementarity effects of HIT.

Second, extant HIT research has focused primarily on the relationship between HIT implementation and healthcare performance in a static, linear framework. However, HIT implementation levels and healthcare performance measures can change in nonlinear ways over time. Overlooking this potential nonlinear change may lead to inaccurate estimations by the research model.

Finally, because prior HIT studies have typically examined HIT's impact on hospital-level outcomes, our understanding of HIT's effect is mostly limited to hospital-level performance. However, it is important to study HIT impact on lower-level outcomes because the clinical workflow enhancement those technologies facilitate (Amarasingham et al. 2009; Bardhan and Thouin 2013) and the new types of errors they introduce (Coiera et al. 2016; Kannampallil et al. 2017; Weiner et al. 2007) likely impact those lower-level outcomes. Indeed, researchers are increasingly studying HIT's value for patient-level outcomes such as readmission risk (Amarasingham et al. 2010; Bardhan et al. 2015), mortality risk (Amarasingham et al. 2010), and the risk of adverse health events (Lin et al. 2017). However, to the best of our knowledge, no existing research considers HIT's impact on outcomes at the patient-transition level. Specifically, we know little about the transitions between chronic and acute conditions in patients, how these transitions influence underlying health status, and whether HIT can impact these transitions.

This dissertation addresses these three gaps in the literature and draws upon three different lenses to study the impact of HIT implementation on healthcare performance. In the first essay (Chapter 2), we examine pairwise and three-way complementarity effects of HIT on hospital-level cost and quality performance. We also conceptualize simultaneous and sequential complementarities in which HIT applications are synergistic—both within the same time period and across time periods—and find evidence of both types of complementarities and their differential effects on healthcare quality and costs. This essay moves HIT literature forward by considering both simultaneous and temporal perspectives to explain the performance differences generated by the combined technologies.

The second essay (Chapter 3) explores how to use an advanced latent growth modeling technique—the Bivariate Dynamic Latent Difference Score Model (BDLDSM)—to explore the

dynamic and longitudinal relationship between HIT and healthcare outcomes after incorporating the nonlinear trajectory change of different HIT functions and various hospital performance dimensions. We first verified that both HIT implementation levels and healthcare performance change in a polynomial manner over time. Having incorporated these nonlinear trajectory changes in healthcare performance and HIT implementation-level variables, we examined how we could use the change in HIT implementation level to predict the subsequent change in healthcare performance over time. We used a BDLDSM to analyze this dynamic relationship. This essay extends current HIT studies to a dynamic, nonlinear perspective and suggests that researchers need to examine the relationship between HIT's impact on healthcare performance using a model that incorporates nonlinear functional forms of change.

While our first two essays studied the relationships between HIT implementation and hospital-level performance outcomes, our third essay (Chapter 4) focuses on how HIT application data might be used in predictive modeling. More specifically, this essay has two research objectives. First, it aims to examine how different HIT functions impact various types of observable transitions (chronic to acute, acute to chronic, chronic to death, and acute to death) and underlying and unobservable transitions (minor to major disease and major disease to death) as diseases progress over time. This essay is the first study in the information systems literature that empirically examines HIT value at the patient-transition level, where the unit of analysis is at both the transition and patient levels, and the unit of observation is at the transition level. The essay's findings provide both scholars and practitioners with a more complete picture of HIT's impact at a granular level. Our model also advances the IS field's current predictive health analytics research for examining multiple events as a disease progresses over time. To the best of

our knowledge, this is the first predictive health analytics study in the IS field that examines event history and predicts the transition between different events over time.

Our research uses a longitudinal dataset from 715 hospitals that had 67 million discharges in seven U.S. states during the study period (2008–2013). Table 1.1 below summarizes outcomes of interest, analysis levels, and analysis techniques; this is followed by a more detailed discussion of each of the essays.

Table 1.1 Summary of the Three Essays

	Essay 1	**Essay 2**	**Essay 3**
Title	Functional IT Complementarity and Technology Value in Health Care: A Longitudinal, Hospital-Level Investigation	A Bivariate Dynamic Latent Difference Score Model for Longitudinal Data Analysis	A Multi-State Markov Model for Patient Health Status Prediction
Outcome of Interest	Healthcare quality (clinical and experiential) and cost	Healthcare quality (clinical and experiential) and cost	Risk of transition between health statuses
Level of Analysis	Hospital level	Hospital level	Patient-transition level
Analysis Techniques	Econometrics Analysis: 1) Fixed-Effect Model 2) SUR Model 3) Fixed/Random-Effect Model	Latent Growth Modeling: 1) Bivariate Dynamic Latent Difference Score Model 2) Bivariate Latent Growth Modeling	Multi-State Markov Modeling: 1) Multi-State Markov Model 2) Multi-State Hidden Markov Model

1.2 Essay 1

In Essay 1, we examine functional IT complementarity between different HIT functions and their performance effects on multiple cost and quality measures. We conceptualize functional IT complementarity based on whether HIT innovations perform primary or supplementary tasks in the care-provision process, and whether they are applied in the same or different functional domains. Furthermore, emphasizing the usage context, we study how the impacts of functional IT interactions vary for chronic and acute health conditions. Finally, we examine both simultaneous and sequential complementarity, which is a departure from existing research that examines applications used during the same time period. Using five secondary data sources, we collected longitudinal data on HIT implementation levels, care quality and cost, and

demographic and environmental variables for the 715 hospitals. We examined pairwise and three-way complementarity effects of HITs on hospital-level cost and quality performance.

Our central findings are that, HIT applications interact and demonstrate pairwise and three-way complementarity. We further find that HIT application impact quality and cost differently for acute and chronic conditions. Finally, we find evidence of simultaneous and sequential complementarity, wherein HIT applications are synergistic both within a single time period and across time periods.

Essay 1 makes two major contributions. First, prior IS research has examined simultaneous complementarity exclusively and ignored the temporal perspective. Essay 1 contributes to the IS literature by considering both simultaneous and temporal perspectives to explain performance differences generated by technologies. Second, essay 1 demonstrates the importance of context in assessing complementarity between HIT applications. We find that HIT has different impacts for patients with chronic and acute conditions in terms of healthcare quality and costs. This result clearly illustrates the need for researchers to separately consider HIT's impact on chronic and acute conditions. We further suggest that researchers jointly examine HIT application and the clinical workflows specific to chronic and acute conditions to further illuminate the value creation possibilities in hospitals.

1.3 Essay 2

Essay 2 introduces the use of a BDLDSM to analyze the dynamic lead-lag association between predictor and outcome variables in a longitudinal framework. The BDLDSM is a powerful tool for IS researchers aiming to explore longitudinal theories related to change using a panel data set. In contrast to traditional longitudinal analysis methods, BDLDSM allows IS researchers to (1) examine dynamic lead-lag associations between two variables across time, (2) simultaneously

model change trajectories in two variables over time, (3) test for a reciprocal relationship between two variables over time, and (4) identify different types of dynamic effects.

We first review the most commonly applied longitudinal analysis methods in the IS field from 2008–2017 and then compare BDLDSM with these widely applied methods. We then discuss why the IS field needs BDLDSM, and introduce it with both linear and nonlinear functional forms of change. Next, we apply BDLDSM in a HIT impact context and unveil the dynamic interplay between different HIT functions and various dimensions of hospital performance. Finally, we compare BDLDSM using linear and nonlinear functional forms and compare BDLDSM with latent growth modeling. The essay concludes with a discussion of the implications of BDLDSM for longitudinal data analysis in the IS field.

Essay 2 contributes to the IS literature both by extending the current understanding of latent growth modeling (LGM) and introducing a sophisticated data analysis model, BDLDSM, to examine trajectory changes and analyze the dynamic lead-lag association between the predictor and outcome variables in a longitudinal data setting. The essay provides the first demonstration in the IS literature of separating the dependent variables' dynamic change effect into three parts: the overall mean trajectory change components, the within-variable proportional changes, and the cross-variable coupling effects. We also provide guidelines to test the dynamic lead-lag relationship between dependent and independent variables while considering the functional forms of change. Essay 2 contributes to the HIT literature by extending current HIT studies to a dynamic, nonlinear perspective. We find that all HIT implementation levels increase in a quadratic way over time, and healthcare performance measures grow with cubic trajectories over time. This suggests that researchers need to examine HIT's impact on healthcare performance using a model that incorporates nonlinear functional forms of change for both the

HIT and healthcare performance variables. Such an analysis method can also be extended to explore other longitudinal dynamic relationship in the IS field.

1.4 Essay 3

Our third essay identifies an important gap in predictive health analytics research in the IS field. The majority of predictive health analytics research predicts the transition from an initial state, such as the start of treatment, to a single endpoint, such as readmission or death (Amarasingham et al. 2010; Bardhan et al. 2015). This transition from one state to another state is defined as an *event* (Andersen and Keiding 2002). However, it is rare that only one event would happen in the course of hospitalization (Lin et al. 2017). It is more likely that, as a disease progresses over time, it will result in multiple events. If we analyze each event separately, we can neither capture the relations among different types of events nor uncover the dynamics of how patients transition among different events (Jackson 2011; Putter et al. 2006). In this essay, we propose a predictive model that examines multiple events to advance predictive health analytics research in the IS field.

Our first research objective is to detect the likelihood of a future transition from a minor to a more severe state and finally to death based on HIT implementation levels, hospital characteristics, and patient profile. Additionally, in the predictive model, we account for the transition between chronic and acute states as a disease progresses over time. Indeed, both literature and statistical evidence suggest that the transition between chronic and acute states would be a good indicator of the patient's underlying health status (Bernstein et al. 2017; Greenberg 2012; Zile et al. 2008) yet, surprisingly, to our knowledge, no existing research explores how to use this transition in predictive modeling.

Our second research objective is to study the impact of various HIT functions on the patient-transition level. Specifically, we want to explore HIT's impact on the transition between chronic and acute conditions, and the transition between a minor and a more severe health status. Prior HIT value studies have typically examined HIT's impact on hospital-level outcomes. These outcomes are usually end performance outcomes, which cannot capture HIT impact on lower-level, intermediate performance outcomes, which measure the intermediate stages in a clinical process. HIT can benefit clinical processes by improving core process workflows, such as reducing patients' transition between chronic and acute status while hospitalization. Here, we refer to these impacts as *intermediate measures* to differentiate them from traditional end performance measures, such as mortality rate and healthcare cost (Brandyberry et al. 1999). HIT can provide value to clinical processes by improving the workflow of the core processes, such as by reducing patients' transition between health states during hospitalization. Thus, it is vital to empirically study HIT impact on lower-level outcomes and more clearly and deeply understand how they impact intermediate healthcare performance.

Our contributions are twofold. First, our study contributes to predictive health analytics by proposing a predictive model that detects when a disease progresses from a minor to a more severe state; healthcare providers can use this information to intervene early with appropriate treatments and slow the worsening cycle of a disease. Our model advances current predictive health analytics research in the IS field by incorporating the dynamic transitions between chronic and acute diseases in predicting patient health status and by introducing a multi-state Markov model to examine multiple events in the disease progression process.

Second, our study contributes to the HIT business value literature by examining HIT value at the patient-transition level. We find empirical evidence on how different HIT functions

impact various patient-transition level outcomes. Assessing how different HIT functions impact different types of transitions will help healthcare providers more effectively allocate investment across various IT resources to achieve enhanced health outcomes.

1.5 Discussion

This dissertation contributes to the general empirical question of how HIT impacts healthcare performance; it also contributes theoretically and practically to the body of knowledge on HIT value. From a research perspective, we synthesize HIT value literature and identify three major reasons for the mixed and inconclusive results on HIT's impact. These reasons are a) ignoring the complementarity effect of different types of HIT; b) examining HIT impact primarily from a static, linear perspective, but not dynamic and nonlinear perspective; and c) studying HIT impact predominantly on hospital-level outcomes, with only limited studies on patient-level outcomes and no studies on patient-transition-level outcomes. This dissertation addresses these research gaps and examines HIT's value from three different perspectives.

First, extant complementarity literature ignores the fact that technologies can interact with one another temporally, assuming only that interactions occur simultaneously (Battisti et al. 2015; Kim and Mukhopadhyay 2011; Tiwana and Konsynski 2010). However, synergistic gains are possible when innovations implemented in one time period interact with those implemented in the same or a different time period. Previous literature does not differentiate between these alternatives. However, we find empirical evidence of simultaneous and sequential complementarity wherein HIT applications are synergistic, not only within the same time period but also across periods. Further, our results address mixed and inconclusive HIT impact findings by examining pairwise or three-way complementarity simultaneously and sequentially among different HIT applications, instead of examining HIT applications individually. Future research

should examine HIT impact not only in combination, but also by studying the complementarity of HIT value from both simultaneous and sequential perspectives.

Second, we extend the current literature on HIT impacts on healthcare performance to include a dynamic, nonlinear perspective. Empirical evidence shows that in terms of change of mean trajectories, both healthcare performance variables and HIT implementation level variables grow nonlinearity over time, and all healthcare performance variables change faster than HIT implementation level variables over time. This suggests the need for future research to incorporates nonlinear functional forms of change for both the HIT and healthcare performance variables in the research model when examining the relationship between HIT impact on healthcare performance.

Third, we assess the impacts of HIT value on both end performance outcomes, including mortality rate (Chapter 2 and 3) and healthcare cost (Chapter 2 and 3); intermediate performance outcomes, including experiential quality outcomes (Chapter 2 and 3); and patient-transition outcomes (Chapter 4). We also examine the impacts of HIT value from two analysis levels: hospital level (Chapter 2 and 3) and patient-transition level (Chapter 4). We find that HIT consistently enhances end performance measures. However, HIT impact on intermediate performance measures has mixed result. One plausible explanation may be that HIT is a sociotechnical system that relies on the context in which it is embedded, and the healthcare context largely involves people and processes (Coiera et al. 2016). If HIT is not designed to meet the needs of clinical practices and communication processes, it may lead to errors in communication and coordination; these errors, in turn, may lead to mixed result related to the intermediate performance outcomes. A plausible reason that HIT's negative impact from misconfiguration among workflow, users, and technologies presented only on intermediate

performance outcomes and not end performance outcomes may be because factors other than HIT impact end performance measures. Controlling such factors may be difficult. Studying HIT value for end and intermediate performance outcomes from both the hospital level and patient-transition level gives us a more complete, comprehensive picture of how health technologies impact healthcare performance.

This dissertation also has important methodology implications. First, we review the longitudinal techniques commonly applied in IS studies from 2008–2017 and demonstrate three different analysis techniques in those longitudinal studies: econometrics methods (Chapter 2), BDLDSM (Chapter 3), and multi-state Markov model (Chapter 4). This illuminates how IS researchers can use longitudinal methods to solve different research problems in the same research context. Second, we extend the IS field's current understanding of LGM by introducing BDLDSM to examine trajectory changes, analyze the dynamic lead-lag association between the predictor and outcome variables, and test for a reciprocal relationship between two variables in a longitudinal data setting. Third, we provide the first demonstration in the IS literature of how to apply the multi-state Markov model to both examine multiple events in the same model and study HIT value at the patient-transition level.

Finally, our research has key practical implications. First, we find that different combinations of technologies impact hospital performance in different ways. Given this, healthcare providers should identify optimal combinations of technological investments over time according to their priorities for performance improvement. Second, we find that different health technologies impact chronic and acute diseases in different ways. For example, the HIT interaction effects that impact quality or cost for patients with chronic conditions do not significantly impact quality and cost for patients with acute conditions. Therefore, when

allocating HIT resources, healthcare providers should consider how systems of technologies integrate into different disease workflows and prioritize different technology combinations depending on which performance variables are most important. Third, our findings emphasize the importance of estimating patients' health status based on the transition between a chronic and an acute status, which is a useful predictive analytics method for healthcare providers.

CHAPTER 2 FUNCTIONAL IT COMPLEMENTARITY AND TECHNOLOGY VALUE IN HEALTH CARE: A LONGITUDINAL, HOSPITAL-LEVEL INVESTIGATION

Abstract

This paper examines functional IT complementarity between different HIT innovations and their performance effects on multiple measures of cost and quality. We conceptualize functional IT complementarity based on whether HIT innovations perform primary or supplementary tasks in the care provision process, and whether they are applied in the same or different functional domains. Furthermore, emphasizing the context of use, we study how the impacts of functional IT interactions vary for chronic and acute health conditions. Finally, we examine both simultaneous and sequential complementarity, which is a departure from existing research that has examined applications employed in the same time period. Using five secondary data sources, we collected longitudinal data on HIT implementation levels, care quality and cost, and hospital demographic and environmental variables on 715 hospitals located in seven states in the U.S. We examined pairwise and three-way complementarity effects of HITs on hospital level cost and quality performance. Our central findings are that, HIT applications interact and demonstrate pairwise and three-way complementarity. We further find that HIT application impact quality and cost differently for acute and chronic conditions. Finally, we find evidence of simultaneous and sequential complementarity, wherein HIT applications are synergistic both within a single time period and across time periods. We discuss theoretical and pragmatic implications of our findings.

Keywords: IT Complementarity, Three-way Complementarity, Quality of Care, Cost of Care, Core Clinical Activities, Supplementary Clinical Activities, Health Information Technology (HIT), Business Value of IT, Sequential Complementarity, Inpatient Quality Indicator (IQI)

2.1 Introduction

"Innovations hardly ever function in isolation." (Rosenberg 1979)

"In the next 10 years, data science and software will do more for medicine than all of the biological sciences together." (Khosla 2013)

The health care industry is no stranger to technological and scientific innovations, however, in recent years, there has been considerable deliberation among researchers, practitioners and policy makers regarding the role of HIT innovations on the delivery of care (Agarwal et al. 2010; Banger and Graber 2015; Dranove et al. 2014; Lee et al. 2013). On the one hand, there is distinct excitement about the potential of HIT to transform health care access and delivery in the United States. On the other hand, some have sounded cautionary notes because evidence on the impacts of HIT on cost and quality has been mixed (Agarwal et al. 2010; Furukawa et al. 2010). In this study, we examine the interactive effects of various HIT applications on a variety of hospital-level cost and quality outcomes, in order to understand and unpack the issue of technology value in the health care industry.

Over the last two decades, researchers in information systems (IS), economics, organization theory and operations have sought to understand the joint impacts of various innovations, such as information technology (IT) applications, process transformations and organizational changes (Barua and Mukhopadhyay 2000; Bharadwaj et al. 2007; Brynjolfsson and Hitt 2000; Cassiman and Veugelers 2006; Ennen and Richter 2010; Forman 2005; Milgrom and Roberts 1990). A key insight emerging from this literature is that innovations may be less impactful in isolation, but when applied as mutually reinforcing elements, their joint effects can exceed the sum of values generated through them individually (Aral et al. 2012; Dewan et al. 2010; Tambe et al. 2012). Building on this notion, the concept of complementarity suggests that

if the levels of any subset of such innovations are increased, the marginal return to increase in any or all the remaining innovations rises. Complementary innovations have played a crucial role in many industries by streamlining operational processes, shaping firm strategies, enabling information sharing and coordination among key entities, facilitating effective decision making, and expediting the execution of critical tasks (e.g., Parmigiani and Mitchell (2009); Tiwana and Konsynski (2010)).

Although extant literature on complementarity has contributed significantly to our understanding of the relationships between innovations and their joint impacts on performance, we argue that it can be extended in several important ways. First, prior research has largely employed *post hoc* accounts of complementarity, i.e., explanations have depended on elements that are observed to be combined in a supermodular way (Grandori and Furnari 2009). However, complementary elements can be similar or different, and applied to the same or different activities and transactions in a system (Grandori and Furnari 2009). This aspect has been ignored in the literature, resulting in limited understanding of the sources of complementarity. Second, the context in which innovations are complementary has received insufficient attention in the literature. Tanriverdi and Ruefli (2004) argue that complementary inputs are activity-specific, i.e., their value is relevant in the context of specific activities. Thus, a deeper examination of the context may allow us to understand when innovations are complementary (Brynjolfsson and Milgrom 2012; Cassiman and Veugelers 2006; Ennen and Richter 2010). Third, a majority of studies examining complementarity has taken a cross-sectional perspective on performance changes over relatively short time spans (Brynjolfsson and Milgrom 2012; Ennen and Richter 2010). However, probing the evolution of complementarity over time, which requires longitudinal data, is a critical issue that researchers need to address (Brynjolfsson and Milgrom

2012). Fourth, complementarity literature ignores that innovations can interact with one another temporally, and rather treats them to have taken place simultaneously (Battisti et al. 2015; Kim and Mukhopadhyay 2011; Tiwana and Konsynski 2010). However, synergistic gains can occur when innovations implemented in one time period interact with those implemented in the same or a different time period. Extant literature does not differentiate between these alternatives (Battisti et al. 2015). Finally, focusing specifically on the IS literature, current work on complementarity has largely examined general purpose IT and measured it in the aggregate (Aral et al. 2012; Aral and Weill 2007). As a result, researchers lack insight into complementarities between specific technologies, the functions they support, and their contributions to different performance metrics.

Concurrently, considerable extant work has examined HIT and process digitization in health care, contributing much to our understanding of how digital innovations impact patient care, but this work is limited in three notable ways. First, although prior research distinguishes IT applications based on supported tasks, such as clinical, administrative, operational and strategic, it omits functional differences within clinical IT innovations (Beaumont 2011). For instance, although clinical documentation and results viewing are related to patient care, these are supplementary activities to the primary clinical tasks of deciding upon the treatment regimen for a patient and prescribing medicines, tests and procedures. It is likely that due to different functional foci, digitization of these two parts of clinical processes will impact hospital performance differently. Second, acute and chronic conditions have different characteristics, which has been largely ignored in HIT value studies, resulting in inadequate attention paid to the context of application that is critical in examining value (Agarwal et al. 2010; Susan and Stern 2002). Third, the literature in HIT has suffered from empirical limitations, such as, limited use of

panel data to attempt causal explanation of HIT impacts, and no consideration of complementarity *between* HIT applications.

In this study, we attempt to address limitations in extant research by examining complementarity among several HIT innovations used in hospitals. We conceptualize *functional IT complementarity*, discuss its underpinnings, and open the black box of monolithic IT. A majority of IT applications used in organizations are functional, i.e., they are used to accomplish specific organizational tasks. Accordingly, we do not examine HIT as a monolithic artifact, but rather focus on functions it enables hospitals to accomplish. Drawing upon prior literature (Earl 1996), we divide IT applications into two categories: those enabling core or primary functions and those enabling secondary, supplementary or support functions. Second, following Grandori and Furnari (2009), we pay close attention to how different functional HIT innovations interact with one another to provide complementarity. Third, we specifically account for the context by examining functional IT complementarity for both chronic and acute conditions.[2] Fourth, we explicitly examine temporal interactions between different functional HIT applications to assess if they are complementary. Finally, we examine a large number of performance outcomes to provide a comprehensive assessment of the impact of HIT on hospitals.

Specifically, we address three research questions: 1) How do functional IT innovations that facilitate core/primary functions and secondary/support functions within the broad umbrella of clinical processes impact hospital level outcomes? In particular, how do the effects of pairwise and three-way HIT complementarities manifest themselves? 2) How do the impacts of functional IT interactions vary for chronic and acute conditions? 3) How do temporal and simultaneous

[2] A chronic condition is defined as a condition that lasts 12 months or longer and meets one or both of the following tests: (a) it places limitations on self-care, independent living, and social interactions; (b) it results in the need for ongoing intervention with medical products, services, and special equipment (https://www.hcup-us.ahrq.gov/db/vars/chronn/kidnote.jsp).

interactions among functional IT innovations impact performance? We focus our inquiry on hospitals because they are pivotal to the U.S. health care system, providing a variety of services to patients with acute and/or chronic conditions, and accounting for the largest single item of expense in the health care industry.

We constructed a panel dataset over the 2008-2013 period, comprising 715 hospitals from seven states: California, Florida, Maryland, New Jersey, New York, North Carolina and Washington. We merged data from five sources: Healthcare Cost and Utilization Project's state inpatient datasets (HCUP-SID), American Hospital Association (AHA)'s annual survey and IT supplement datasets, the hospital consumer assessment of health care providers and systems (HCAHPS) surveys, and cost reports from Centers for Medicare & Medicaid Services (CMS). We used two cost measures calculated from the HCUP database and the CMS cost report. Both *clinical outcomes*, focusing on inpatient mortality, and *experiential outcomes*, focusing on patient perceptions, were used as quality measures. We analyzed our panel data using the Hausman Taylor model and conducted several robustness tests to verify our results. We also conducted several tests to assess complementarities between functional IT applications. Our central findings are that although there are direct effects of functional IT applications on various hospital-level performance metrics, these applications do interact with one another and demonstrate pairwise and three-way complementarity effects. We further find that the impacts of HIT applications on quality and cost differ for acute and chronic conditions. Finally, we find evidence of simultaneous and sequential complementarity wherein different HIT applications are synergistic not only within the same time period but also across periods.

2.2 Background Literature and Theoretical Development

We draw upon two broad streams of literature. The first stream examines the impact of HIT applications on various health care outcomes. Researchers in health services research, health informatics and IS have examined these issues in detail. This stream of research allows us to conceptualize the different types of HIT applications used in this study, to introduce the various hospital level quality and cost performance metrics, and to synthesize prior results. The second stream of literature on complementarity of innovations allows us to conceptualize the nature of complementarity between various HIT applications.

2.2.1 HIT and Its Implications

Examining the business value of IT has a rich tradition of research in the IS literature (Barua and Mukhopadhyay 2000; Brynjolfsson and Hitt 2000; Melville et al. 2004). In recent years, researchers have actively examined the impact of IT investments and use in the U.S. health care industry. Specifically, researchers have been interested in two major outcomes, namely the quality and cost of care (Agha 2014; Angst et al. 2011; Dranove et al. 2014; Menon and Kohli 2013). Considerable prior work has examined care quality and cost in isolation, but recent research has begun to study these outcomes simultaneously. Providing a rationale for this, Lee et al. (2013) suggest that quality gains may not be captured unless clinical progress translates into economic ones, such as increased prices or lower costs, and thus, it is important to examine both quality and cost of care concurrently to fully assess the impact of HIT.

Prior literature has found mixed impact of IT on quality. A stream of research has suggested that hospitals with more advanced IT have fewer complications and lower mortality rates (Amarasingham et al. 2009; Buntin et al. 2011; Lee et al. 2013; Miller and Tucker 2011), while another stream has revealed mixed impacts, with lower mortality rates, but higher

complications (Furukawa et al. 2010), little or no significant impact (Agha 2014; Parente and McCullough 2009) and adverse impact (Ash et al. 2004; Nebeker et al. 2005). These results may be a manifestation of a wide variety of quality measures used in extant literature, resulting in inconsistent comparisons. For example, the quality indicators developed by the Agency for Healthcare Research and Quality (AHRQ) are mostly disease-specific measures (Farquhar 2008; Greenberg et al. 2009; Mutter et al. 2008). On the other hand, patient mortality rates are general quality measures (Agha 2014).

The impact of IT on cost arises largely from decreased utilization of care. IT is expected to enable better diagnosis and task execution, eliminating the need for unnecessary tests and treatments (Chaudhry et al. 2006; Hillestad et al. 2005). Extant research examining the relationship between HIT and cost has again found mixed results. For instance, Bardhan and Thouin (2013) found HIT to lower costs, but Agha (2014) found that HIT is associated with a 1.3 percent increase in billed charges, and has no evidence of cost savings after five years of adoption (Agha 2014). Dranove et al. (2014) found no significant decrease in costs, measured as hospital operating expense per admission, after the implementation of electronic medical records (EMRs) in hospitals. Other researchers have also found HIT impacts to be insignificant on cost and efficiency (Furukawa et al. 2010; Parente and McCullough 2009; Sharma et al. 2016). Offering an interesting perspective on this issue, Atasoy et al. (2017) have suggested that HIT may increase costs for adopting hospitals, but due to spillover effects, reduce costs at neighboring hospitals.

Prior literature hints that the impact of IT on quality and cost of care may be context-dependent (McCullough et al. 2010). For instance, patients with chronic diseases are more likely to have health data in their file that is relevant to their disease, which may favorably impact their

treatment (Chaudhry et al. 2006). This information can be used to check for allergies, drug interactions, doses, and communication between providers (Unertl et al. 2009). It can also be used to create patient-specific treatment plans. Finally, IT can be used to chart a chronic patients' health conditions, compliance and outcomes longitudinally, potentially reducing adverse drug events and poor health outcomes at the hospital. Patients with acute conditions may not benefit to the same extent from the mechanics discussed above.

In the last decade, four systematic reviews of HIT literature have been performed by health informatics researchers (Buntin et al. 2011; Chaudhry et al. 2006; Goldzweig et al. 2009; Jones et al. 2014). These reviews suggest that overall, HIT impacts care provision processes, and the quality and safety of health care. However, others seem to be less convinced about these results. The prestigious Institute of Medicine suggested in a report in 2011 that the evidence for the impact of HIT is still mixed (see:www.nationalacademies.org/hmd/~/media/Files/Report%20Files/2011/Health-IT/HealthITandPatientSafetyreportbrieffinal_new.pdf). Further, Hydari et al. (2014) have suggested that the impact of HIT on performance outcomes is an empirical issue, worthy of further research.

A synthesis of prior literature reveals three prominent themes. First, researchers have examined effects of HIT individually, such as computerized provider order entry (CPOE) and clinical decision support systems (CDSS) (Bates et al. 2001; Garg et al. 2005; O'Connor et al. 2011) without considering their complementary effects. A small number of studies have examined the impact of multiple HITs, but ignored their interaction effects (see Sharma et al. 2016 for an exception). For example, Menachemi and colleagues have examined the effects of clinical, administrative, and strategic HIT on financial and quality measures. They found all three types of HIT improve financial performance (Menachemi et al. 2006), but their impacts differ for

patient safety and inpatient quality performance (Menachemi et al. 2008; Menachemi et al. 2007). Similarly, Bardhan and Thouin (2013) studied the impact of clinical systems, financial systems, scheduling systems, and human resource systems on the quality and cost of health care delivery, without considering their interaction effects. They found clinical systems and scheduling systems are associated with best practices for treatment of heart attacks, heart failures, and pneumonia, and financial systems are correlated with lower operating expenses in hospitals. In another study, Bardhan et al. (2015) examined the effects of administrative, clinical and cardiology IT on readmission. Although influential, this study does not consider the interaction effects of various types of HIT. In summary, extant research has largely examined individual technologies rather than their joint impacts, which may disguise how different HIT components can impact performance synergistically.

Second, prior studies contain data and/or methodology limitations. These include studying HIT impacts on performance using either small sample sizes (Aron et al. 2011; Kaushal et al. 2006) or cross-sectional data (Amarasingham et al. 2009; DesRoches et al. 2010; Linder et al. 2007). For instance, Aron et al. (2011) conducted a field study of *two hospitals* and found that automating medical error prevention systems results in fewer medical errors. DesRoches et al. (2010) applied a cross-sectional dataset to examine the relationship between electronic health records adoption and health care quality and efficiency measures. However, the relationship between HIT use and health care performance is subject to temporal effects with different time lags and learning effects (Angst et el. 2011), and thus, benefits may not be realized for an extended time (Devaraj and Kohli 2000; Sharma et al. 2016). Accordingly, in recent years, researchers have applied longitudinal datasets and advanced models (Atasoy et al. 2017; Bardhan and Thouin 2013; Furukawa et al. 2010; Menon and Kohli 2013; Sharma et al. 2016), yet most

studies remain cross-sectional and/or informed by small samples acquired from selected hospital systems.

Third, most HIT studies have examined one performance outcome, such as quality or cost (Sharma et al. 2016). This singular focus on one metric may fail to account for the trade-offs that exist between various performance dimensions, such as clinical outcomes, cost and timeliness (Chandrasekaran et al. 2012; Senot et al. 2016). In order to address these issues, recent research has begun examining HIT using multiple dimensions of performance. For example, Agha (2014) and Bardhan and Thouin (2013) studied the impact of HIT adoption on both quality and cost. Sharma et al. (2016) examined the effects of two HIT bundles – Clinical HIT and Augmented Clinical HIT – on cost and process quality outcomes. These recent studies, however, are exceptions, with a majority examining one outcome.

In summary, although there is a rich body of research from both health care and IS scholars examining the relationship between HIT and health care performance, it has been challenging to obtain a consistent view of HIT impacts due to conflicting evidence. Further, data and methodology limitations as well as the use of a variety of metrics have made cross-study comparisons difficult. Finally, a majority of studies have explored technologies individually, with few explicitly focusing on complementarity, and none examining pairwise or three-way complementarity *among* different HIT applications.

2.2.2 Complementarity of Innovations

The complementarity perspective originated in the economics literature in the late 19th century. It posits that economic factors of production are complementary if the total value created by combining two or more factors exceeds the value that would be generated through these factors in isolation, i.e., the impact of one factor on an outcome is amplified by increasing the other

factor. Milgrom and Roberts (1990;1995) conducted pioneering work on complementarity. They laid out the foundation of complementarity between technological innovations, organizational changes directed toward greater functional flexibility, and higher skill levels in organizations. Researchers in a wide variety of disciplines, including IS, have used the complementarity framework to examine synergistic relationships between technological innovations, organizational strategies, structures and processes, and the external environment.

The complementarity perspective has been credited with addressing one of the limitations of the resource-based view (RBV) of the firm (Wade and Hulland 2004; Xiao 2007). While RBV does not adequately account for the fact that resources often act in combination to create value, the raison d'être of the complementarity perspective is to analyze these interactions. It is important to note that although the complementarity perspective addresses limitations in the RBV literature, it has its own limitations. Most prominently, the complementarity perspective *does not* constitute a theory, but is rather a *meso* level approach, which enables researchers to detect relationships between different factors of production and performance (Brynjolfsson and Milgrom 2012; Ennen and Richter 2010). It lacks a well-defined set of theoretical constructs and causal logic to establish relationships (Ennen and Richter 2010). It further offers little guidance on when complementarities occur or which elements complement one another. Thus, it may be difficult to offer precise predictions about relationships between specific elements in a study or to assign clear boundary conditions (Ennen and Richter 2010). As a result, extant research in this domain has inductively inferred complementarity from empirical analyses.

Grandori and Furnari (2009) have attempted to conceptualize the nature of complementarity among different elements. They posit that the extent and type of complementarity are dependent on the interacting elements and the domains in which they are

employed. Interacting elements can be similar or different, and can be applied together to the same or a different function/application domain. Based on this conceptualization, Grandori and Furnari (2009) propose two possible combination of elements that generate complementarity and two others that do not. *Symbiotic complementarity* is generated when different elements are applied to the same application domain or function. *Pooled complementarity* is generated when similar elements are applied to different application domains. Other combinations do not usually generate complementarity. When similar elements are applied to the same application domain, they may become substitutes or their combinations may become redundant. Dissimilar elements applied to different application domains are independent, i.e., neither complementary nor substitutes. We use this rarely adopted approach to build the complementarity perspective.

Prior empirical research has used two approaches to establish complementarity (Aral et al. 2012; Brynjolfsson and Milgrom 2012). The first approach is used when a performance outcome variable is either not of interest or not available. Complementarity is established if different practices or elements are found to cluster in organizations more significantly than a random chance would predict (Brynjolfsson and Milgrom 2012). The second approach is used when a reliable performance variable is available and of interest. Complementarity is established if joint implementations of these practices or elements are demonstrated to lead to better performance than the summation of impacts of individual applications of practices or elements. The first approach is more common in the literature.

A recent advance in the literature has been to examine three-way complementarity (Aral et al. 2012; Brynjolfsson and Milgrom 2012; Tambe et al. 2012). The key idea here is that interacting elements form a system of components such that correlations between any two components of the system are positive when the third component is also positive, but not

necessarily otherwise (Aral et al. 2012). Empirical work examining three-way complementarity is limited in the IS literature, with only two published papers to our knowledge. Aral et al. (2012) studied three-way complementarity between IT, human resource analytics and performance pay implementation in organizations, and found that the joint application of these practices has a higher productivity premium than when they are employed separately. Tambe et el. (2012) found that external focus, decentralization and IT provide three-way complementarity, as demonstrated by improved product innovation capabilities.

The use of the complementarity perspective is limited in health care literature (exceptions include Dranove et al. 2014; Sharma et al. 2016). In this study, we apply the complementarity perspective to analyze how different HIT applications implemented to accomplish core and support functions in hospitals interrelate with one another and whether such relationships produce supermodular value. In the health care literature, researchers have identified two core clinical functions, task execution (TE) and decision support (DS) (Riaño et al. 2012; Unertl et al. 2009; Walker and Carayon 2009), which HIT can facilitate and streamline. The latter enables physicians to diagnose patient conditions and provide evidence-based and customized clinical care guidance. The former enables care providers to execute treatment plans by entering medications, clinical procedures, radiology and other lab orders. These key clinical functions are supported by other functions that are also IT-enabled. For instance, it is important to have access to patients' medical information, as well as the results of prior tests and procedures performed on and medications taken by patients. This information helps assess the efficacy of the treatment regimen. We wish to emphasize that these activities are conceptualized as support activities because the major purpose of documentation and results viewing is to provide a comprehensive assessment of the patient's health so physicians responsible for medical care can better diagnose

and plan the treatment regimen by using DS IT and implement their treatment plans by using TE IT.

We employ the conceptualization proposed by Grandori and Furnari (2009) to examine the nature of complementarity. We conceptualize DS as the level of CDSS implementation in a hospital. A CDSS aids decision support by enabling care providers to accurately diagnose patient conditions, consult latest evidence and provide patient-specific care. We conceptualize TE IT as the level of CPOE implementation in a hospital. A CPOE system facilitates task execution by enabling care providers to offer instructions to nurses and technicians, and to order medications, tests and procedures. Finally, we conceptualize support IT as the level of electronic documentation and results viewing implementation in a hospital. These applications enable care providers to access and record patient information, and to view the results of prior tests, medications and procedures to make assessments and adjustments. It is evident that information obtained from the supporting applications is essential for the diagnosis of medical conditions, determination of the treatment regimen and the further ordering of medications, tests and procedures.

TE and DS ITs are both similar, as they are used to perform core activities in the care provision process, but their application domains are different. Accordingly, we posit that the nature of complementarity, if any exists between them, is *pooled*. TE and support IT, as well as DS and support IT, are examples of interacting elements that are different, but applied to the same application domain together. TE and DS facilitate the core activities of ordering and decision making respectively, and support IT enables the execution of these tasks. Thus, we posit that the nature of complementarity, if any exists between TE and support IT, as well as between DS and support IT, is *symbiotic*. Ennen and Richter (2010) suggest that resources and

applications of different types may produce higher complementarity than those of the same type. We investigate the nature of complementarities between the posited pooled and symbiotic complementarities in our context.

2.3 Data and Measurement

2.3.1 Data Sources

We constructed a longitudinal dataset from multiple sources of archival data spanning 2008-2013. Our first source of data is the HCUP-SID database. This dataset provides five files: 1) *Core file* that contains data elements, such as patient demographics, length of stay, discharge status, and number of procedures; 2) *Diagnosis and Procedure Groups file*, containing diagnostic and procedure information for each hospital discharge; 3) *Disease Severity Measures file* that contains severity information related to each discharge in the core file; 4) *Charges file*, containing detailed and summarized charge information; and 5) *AHA Linkage file* to connect HCUP-SID files with AHA's survey and IT supplement files.[3] The unit of data collection in these files is at the hospital discharge level. We calculate hospital level clinical quality and cost by aggregating the information at the discharge level.

We use the HCAHPS survey to obtain experiential quality data, which provides a perceptual assessment of patients' experiences during their stay at a hospital (Boulding et al. 2011; Senot et al. 2016; Sharma et al. 2016). The survey measures patients' perceptions of the following components after their discharge from a hospital: communication with doctors and nurses, communication about medicines, and communication about post-discharge recovery. It also measures patients' willingness to recommend the hospital, and their overall rating of a

[3] More information about these files can be obtained at: https://hcup-us.ahrq.gov/db/state/siddist/Introduction_to_SID.pdf

hospital. This survey is administered to get a random sample of adult inpatients after their discharge. Survey results are averaged to get experiential quality at the hospital level.

We use three sources of data to estimate the impacts of HIT on cost. Our first source is the HCUP charges files that contains information about the total charge for each inpatient discharge. Our second source is the Medicare cost report, which provides total inpatient charge data at the hospital level. Our third source is the HCUP cost-to-charge ratio file that contains hospital-specific cost-to-charge ratios.

We employ AHA annual survey and its IT supplement datasets to obtain hospital characteristics and HIT implementation data. The annual survey dataset provides hospitals demographics, organization structure, and operational and financial information on more than 6,300 hospitals in the U.S. The IT supplement dataset contains HIT implementation level information on more than 3,300 hospitals.

To combine AHA, AHA IT and HCUP datasets, we first aggregated the discharge-level data in HCUP to the hospital-level and then matched the data sets using the unique hospital ID from the *AHA Linkage file*. We then combined this dataset with HCAHPS survey, CMS outcomes files, and Medicare cost report using the unique Medicare ID. Our final sample comprised 715 hospitals with 2,054 observations from 2009 to 2013. Table 2.1 provides descriptive statistics and correlations between variables and online Appendix 2A provides the definitions, references, and data sources for variables.

Table 2.1 Descriptive Statistics and Pairwise Correlation Matrix

	Mean	Stdev	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1 IQI 91 Chronic Composite	0.340	0.175	1															
2 IQI 91 Acute Composite	0.294	0.080	0.78*	1														
3 Communication Score	0.869	0.032	0.16*	0.14*	1													
4 Rating Score	0.900	0.041	-0.03	-0.05*	0.82*	1												
5 Recommend Score	0.939	0.031	0.01	-0.05*	0.79*	0.91*	1											
6 IQI 91 Chronic Cost	13,032	6,403	-0.20*	-0.26*	-0.05*	0.07*	0.10*	1										
7 IQI 91 Acute Cost	11,188	3,560	-0.20*	-0.14*	-0.01*	0.08*	0.08*	0.73*	1									
8 Cost Per Discharge	10,086	4,143	-0.06*	-0.03	0.17*	0.19*	0.20*	0.67*	0.61*	1								
9 DS_{t-1}	2.770	2.352	-0.02	-0.08*	0.07*	0.10*	0.09*	0.09*	0.02	0.01	1							
10 TE_{t-1}	1.444	2.129	0.00	-0.03	0.02	0.06*	0.07*	0.15*	0.09*	0.10*	0.51*	1						
11 Support IT_{t-1}	8.283	3.431	-0.08*	-0.16*	0.12*	0.18*	0.18*	0.13*	0.02	0.06*	0.60*	0.43*	1					
12 Bed Size	306	268	0.00	-0.21*	-0.14*	-0.02	0.03	0.47*	0.17*	0.25*	0.19*	0.24*	0.19*	1				
13 Not-For-Profit	0.723	0.447	0.06*	-0.01	0.12*	0.13*	0.20*	0.02	-0.01	0.06*	-0.04	0.02	-0.01	0.08*	1			
14 Teaching	0.131	0.337	0.04	-0.03	-0.06*	0.01	0.07*	0.48*	0.23*	0.33*	0.13*	0.28*	0.12*	0.57*	0.03	1		
15 HHI	0.173	0.161	0.10*	0.13*	0.25*	0.16*	0.17*	-0.18*	-0.16*	-0.12*	-0.04	-0.05*	-0.02	-0.14*	-0.01	-0.15*	1	
16 IT Network $Effect_{t-1}$	122	101	-0.11*	-0.13*	-0.22*	-0.12*	-0.16*	0.11*	0.12*	0.05*	0.09*	0.15*	0.08*	0.16*	0.00	0.12*	-0.57*	1

* $p<0.05$

2.3.2 Operationalization of Outcome Variables: Quality of Care

Our clinical quality measures include the inpatient quality indicator IQI 91 composite quality. The IQI 91 quality measure is available as a composite measure that takes into account mortalities for both acute and chronic conditions. The Inpatient Quality Indicators (IQIs) were developed by experts at University of California, San Francisco, Stanford University Evidence-based Practice Center, and University of California, Davis. Compared to other indicators such as simple mortality rate and medical error rate, IQIs are risk-adjusted and face-validated quality measurements (Menachemi et al. 2008). As a result, IQIs are considered to be more reliable, and are frequently used by researchers.

The IQI 91 composite quality measures consider mortality related to six conditions: acute myocardial infarction (IQI 15), heart failure (IQI 16), acute stroke (IQI 17), gastrointestinal hemorrhage (IQI 18), hip fracture (IQI 19), and pneumonia (IQI 20). Mortality rates for these conditions vary substantially across institutions. Furthermore, evidence suggests that high mortality may be associated with a deficiency in the quality of care. Thus, IQI 91 mortality measures provide us with a good set of validated, extensively-used and well-understood metrics to assess clinical quality. To evaluate chronic and acute quality separately, we mapped the six IQI 91 conditions against the chronic indicator variable from the HCUP dataset. We found that Acute Myocardial Infarction (AMI), Heart Failure (HF), and Acute Stroke are all chronic diseases, hence, we conceptualize mortality rates for IQI 15, IQI 16 and IQI 17 as our clinical quality measure for chronic conditions. We also found that 96.8% of Gastrointestinal Hemorrhage, Hip Fracture, and Pneumonia (PN) conditions are classified as acute. We use only those discharges for which these three conditions are classified as acute, excluding others from further consideration, and conceptualize mortality rates for IQI 18, IQI 19 and IQI 20 as our

clinical quality measure for acute conditions. The calculation of these measures is involved; please see Appendix 2B for methodological and procedural details. Consistent with statistical theory (Collett 2003), we applied logit transformation on the IQI 91 chronic and acute measures to ensure the predictions of the percentage dependent variable would be within the unit interval.

We used three measures to study experiential quality: communication score, rating score, and recommendation score. The communication score is calculated by four items in the HCAHPS survey (see online Appendix 2C, Part I for all HCAHPS survey items). The response categories for question 1 to 3 are "Never/Sometimes," "Usually," or "Always.", and the response categories for question 4 are "Yes" or "No." For question 1 to 3, we used the sum of the percentage of respondents who answered "Always" and "Usually", and for question 4, the percentage of patients who answered "Yes" to measure communication score. We calculated the average score for these four items. Following recent research (Chandrasekaran et al. 2012; Senot et al. 2016; Sharma et al. 2016) and consistent with statistical theory (Collett 2003), we applied logit transformation on the average score computed earlier. The communication score is given by the following equation with *i* as the individual hospitals and *Q* as the average score of the four items:

$$Communication\ Score_i = Ln\ [\frac{Q_i}{1 - Q_i}]$$

To calculate the rating score, we used the patients' overall rating for a hospital, which is expressed on a 10-point scale. Ratings of 9 or 10 are considered high; ratings of 7 or 8 are considered medium; and ratings of 6 or lower are considered low. We calculated sum of the percentage of high and medium ratings that each hospital received, and then applied logit transformation on it (Collett 2003). The final rating score is given by the following equation with *i* as the individual hospitals and *PR* as the high rating percentage:

$$Rating\ Score_i = Ln\ [\frac{PR_i}{1 - PR_i}]$$

To calculate the recommendation score, we examined if patients would recommend the hospital to friends and family. The survey has 3 answers for recommendation score: "Yes, definitely recommend the hospital," "Probably recommend the hospital," and "Not recommend the hospital." For each hospital, we calculated the sum of the percentage of patients who would definitely recommend the hospital and patients who would probably recommend the hospital (Angst et al. 2012), and then applied logit transformation on it (Collett 2003). The recommendation score is given by the following equation with *i* as the individual hospitals and *R* as the recommendation percentage:

$$Recommendation\ Score_i = Ln\ [\frac{R_i}{1 - R_i}]$$

2.3.3 Operationalization of Outcome Variables: Cost

We employed two broad measures of hospital cost: IQI 91 costs and cost per discharge. To calculate IQI 91 costs at the hospital level, we first multiply the charge amount for each discharge by cost-to-charge ratio. These costs are then averaged over three chronic IQI 91 conditions and three IQI 91 acute conditions to obtain for IQI 91 chronic and IQI 91 acute costs, respectively, at the hospital level. Our second measure, cost per discharge, examines overall costs, not just those relevant to IQI conditions. It is measured by a hospital's total inpatient charge reported by the CMS cost report, multiplied by the cost-to-charge ratio obtained from the cost-to-charge ratio file and divided by the number of discharges calculated from HCUP database. Following recent research, the cost measures are log transformed for further analysis (Senot et al. 2016; Sharma et al. 2016).

2.3.4 Explanatory Variables

The main explanatory variables in our model corresponding to HIT implementation include DS IT (CDSS), TE IT (CPOE), result viewing IT, and electronic clinical documentation (ECD). Result viewing and ECD are jointly conceptualized as support IT because these application, while invaluable in patient care, play supporting roles to the primary clinical tasks of diagnosis and ordering. HIT implementation is measured by a six-point scale, where 1 indicates "fully implemented across all units," and 6 indicates "not in place and not considering implementing." The AHA IT survey, which serves as the source of these measures, is reported in Appendix 2C, part II.

In order to calculate HIT implementation levels, we first recoded the original data. Responses between 2 and 6 were recoded as 0, and the original coding of 1 was retained as one. This coding scheme separates full implementation from no- or partial implementation. We group hospitals that have partial and no implementation of HITs together because synergistic impacts at the hospital level are possible only when HITs are fully implemented hospital-wide. Hospitals with no HIT implementation are not likely to have these impacts. Hospitals with HIT implementations in few but not all units may enjoy some benefits within those units, but suffer from coordination and duplication issues arising from having to maintain both electronic and paper-based systems. Second, we constructed three HIT variables – DS IT, TE IT, and support IT - by counting the number of technologies completely implemented at a hospital in each HIT category. This approach has been widely used in the IS and health care literature (Angst et al. 2012; Borzekowski 2009; Burke and Menachemi 2004; Menachemi et al. 2008). We then standardize IT variables to remove potential multicollinearity in the pairwise and three-way interaction terms. Individual items measuring the implementation of each HIT application and

the temporal trend in the implementation levels are presented in online Appendix 2D. We can infer that: 1) the implementation levels for most HIT applications continuously increase from 2008 to 2012, and 2) overall, the implementation levels of support IT are higher than those of DS IT or TE IT.

2.3.5 Control Variables

To account for other factors that may influence HIT impact on hospital performance, we also included several control variables in our analysis. These include hospital-level variables (e.g., size, profit status, and teaching status) obtained from AHA survey datasets. Further, prior literature indicates that due to network effects, HIT implementation behavior in a hospital can be influenced by other hospitals in the same market (Miller and Tucker 2009). In addition, market competition can also influence HIT implementation efforts (Miller and Tucker 2009). Thus, we include these two variables in our study. For a focal hospital, we operationalize IT network effects and market competition at the level of hospital referral region (HRR). To calculate the IT network and competition effects, hospitals are aggregated into HRRs. IT network effect is measured by averaging IT implementation levels across all the hospitals in the HRR, excluding the focal hospital. Competition is measured by Herfindahl-Hirschman Index (HHI).

2.4 Data Analysis and Results

We performed a series of analyses whose results we report in stages. First, we report results from correlation and performance tests. Next, we present the cube view, which provides us with a graphical framework to test and explain the system effect of complementarity by unveiling if joint implementations of different HITs can achieve a higher impact on performance than the sum of individual effects (Aral et al. 2012; Brynjolfsson and Milgrom 2012; Tambe et al. 2012). Following that, we conduct post-hoc analyses to uncover complementarity relationship among

different types of HIT implementation levels and the healthcare performance. Finally, we present findings from a series of robustness tests performed to verify our results.

2.4.1 Correlation Tests

We conduct a partial correlation test to examine the association among three HIT applications. We further assess how these correlations change over time (Tambe et al. 2012). The correlation test cannot provide direct evidence of performance, but it can provide an indication of whether certain HIT applications may be complementary, which is indicated by a statistically positive correlation between their implementation levels and a rising trend of this correlation over time. We find that after controlling for hospital characteristics, IT network effect, market competition, state effect, and year effect, correlations between DS and TE, DS and support IT, and TE and support IT are 0.45, 0.53 and 0.36, respectively. These correlations are significant at $p < 0.001$, providing suggestive evidence of complementarity. We also examine how the implementation levels of one HIT change over time when other HIT applications are both high (one standard deviation above the mean), or both low (one standard deviation below the mean), or mismatched. Our findings suggest that the implementation level for one type of HIT in hospitals with two other HITs matched high grow at a faster rate as compared to hospitals with HITs mismatched or matched at a low level. These results are presented in Figure 2.1.

a. Decision Support IT | b. Task Execution IT | c. Support IT

Figure 2.1 IT Implementation Levels over Time

2.4.2 Performance Test

We use the fixed effect (FE) model as our main empirical method to analyze the panel data. FE model takes into account the unobserved, time-invariant heterogeneity at the hospital level that may correlate with the IT variables[4]. In this case, we can use the within-hospital variation for identification. The use of FE model with panel data allows us to control the potential impact of unobserved individual heterogeneity, which has been a significant concern in the complementarity literature (Aral et al. 2012; Brynjolfsson and Milgrom 2012; Dranove et al. 2014; Cassiman and Veugelers 2006). We estimated the following econometric model:

$$\textbf{Performance (i, t)} = \textbf{HIT}'_{it}\boldsymbol{\beta} + \textbf{Control}'_{it}\boldsymbol{\eta} + \alpha_i + \varepsilon_{it},$$

where the dependent variables include different quality and cost measures for a hospital at time t; HIT_{it} are HIT variables, including lagged individual IT variables (e.g. $DS_{i,\,t-1}$, $TE_{i,\,t-1}$, $Support_{i,\,t-1}$), pairwise and three-way interactions between lagged IT variables (e.g. $DS_{i,\,t-1}\times Support_{i,\,t-1}$, $TE_{i,\,t-1}\times Support_{i,\,t-1}$, $DS_{i,\,t-1}\times TE_{i,\,t-1}$, $DS_{i,\,t-1}\times TE_{i,\,t-1}\times Support_{i,\,t-1}$); $Control_{it}$ are the time-varying control variables, including hospital characteristic variables (*Hospital Size (log)* $_{i,\,t}$, *Teaching* $_{i,\,t}$), lagged IT network effect variables (e.g. *IT Network Effect* $_{i,\,t-1}$), and market competition effect (*HHI* $_{i,\,t}$), non-profit hospital (*Not-For-Profit* $_{i,\,t}$), and year effect; α_i is the time-invariant unobserved hospital effect; and ε_{it} the time-varying unobserved hospital effect.

Identification in our analysis comes from time series variation in the levels of HIT implemented by hospitals. Given that we are interested in examining the causal effect of HIT applications on hospital performance, it is important that we address some potential validity threats, such as selection effect, reverse causality, simultaneity, and unobserved hospital heterogeneity (Angrist and Pischke 2009). Not every hospital responds to AHA's request to

[4] We performed Durbin–Wu–Hausman tests, which results also suggest that fixed effect model provides consistent results than random effect model.

complete the IT supplement survey. Thus, it is likely that there is a selection bias. To examine the potential selection bias, we performed the Heckman selection test. Our results indicate that selection effect is not a significant concern (see Appendix 2E1). In order to assess reverse causality, we estimated a number of models with one year lagged performance indicators as explanatory variables and HIT implementation levels as outcome variables. We do not find evidence of reverse causality for HIT application in any of the models (see Appendix 2E2-E4). We can rule out simultaneity based on extensive evidence in the IS and HIT literature that suggests that there is a considerable time gap between IT implementation and organizational level impacts. Finally, unobserved hospital heterogeneity could be related to performance impacts. To the extent that such heterogeneity is not systematically related to HIT implementation levels or does not change systematically after HIT, we expect the impact of such heterogeneity to be small.

We estimate HT models to examine both simultaneous and temporal HIT complementarities. HITs are lagged one year and two years in these analyses. We begin by analyzing simultaneous HIT interaction models with three HITs either lagged one year or two years together. We then estimate temporal complementarity models with support IT implemented before or after DS and TE, TE implemented before or after DS and support IT, and DS implemented before or after TE and support IT. We discuss these results in the following two sections.

2.4.3 Simultaneous HIT Complementarity

Table 2.2 shows hospital performance effects of HIT when each of the three applications is lagged either one-year (see Part I) or two-years (see Part II). Focusing on Part I, we examine the impact of these lagged HITs in combination, including both, pairwise and three-way interactions.

We find that the interaction effect between DS_{t-1} and $Support_{t-1}$ decreases cost-per-discharge ($p<.05$). The interaction between TE_{t-1} and $Support_{t-1}$ and the interaction between DS_{t-1} and TE_{t-1} have no significant effect on any outcome variable. Further, three-way interaction effect among DS_{t-1}, TE_{t-1}, and $Support_{t-1}$ leads to decreased IQI 91 chronic mortality rate ($p<.1$), implying the three-way interaction effect of DS, TE and support IT leads to an increase in IQI 91 chronic quality. We explore this effect further using the cube view of complementarity in a later section.

Looking at the results from Part II, we notice that DS_{t-2}, TE_{t-2}, and $Support_{t-2}$ impact various performance measures differently. Our results show the interaction effect between DS_{t-2} and $Support_{t-2}$ increases rating score ($p<.1$). The interaction effect between TE_{t-2} and $Support_{t-2}$ increases clinical chronic quality by decreasing mortality rate for IQI 91 chronic composite ($p<0.01$). Besides increasing clinical quality, the interaction between TE_{t-2} and $Support_{t-2}$ decreases IQI 91 chronic disease cost ($p<.05$) and IQI 91 acute disease cost ($p<.1$). This result suggests that hospitals that implemented both TE and support IT have lower average IQI 91 disease cost for both chronic and acute discharges two years later. The interaction between TE_{t-2} and DS_{t-2} has a weakly significant effect on IQI 91 chronic composite ($p<.1$) and cost per discharge ($p<.1$). Three-way interaction between DS_{t-2}, TE_{t-2} and $Support_{t-2}$ leads to an increase in communication score ($p<.05$) and recommendation score ($p<.1$). Again, we will discuss this effect further in a later section.

Table 2.2 Simultaneous Complementarity Models

	(1) IQI 91 Chronic Composite	(2) IQI 91 Acute Composite	(3) Communication Score	(4) Rating Score	(5) Recommendation score	(6) IQI 91 Chronic Cost	(7) IQI 91 Acute Cost	(8) Cost per Discharge
Part I. Models for DS_{t-1}, TE_{t-1}, and $Support_{t-1}$								
$DS_{t-1} \times Support_{t-1}$	-0.0045	0.0059	0.0022	0.0086	-0.0111	-0.0001	-0.0057	**-0.0092***
	(0.012)	(0.006)	(0.005)	(0.010)	(0.011)	(0.005)	(0.004)	**(0.004)**
$TE_{t-1} \times Support_{t-1}$	-0.0045	0.0012	0.0064	0.0095	0.0133	-0.0066	-0.0003	-0.0087
	(0.016)	(0.008)	(0.006)	(0.010)	(0.014)	(0.006)	(0.006)	(0.006)
$DS_{t-1} \times TE_{t-1}$	0.0031	-0.0075	0.0006	0.0006	0.0022	-0.0074	0.0009	0.0011
	(0.013)	(0.008)	(0.005)	(0.009)	(0.012)	(0.006)	(0.006)	(0.004)
$DS_{t-1} \times TE_{t-1} \times Support_{t-1}$	**-0.0226+**	-0.0078	0.0063	0.0141	0.0000	0.0052	-0.0011	-0.0026
	(0.013)	(0.007)	(0.005)	(0.010)	(0.011)	(0.005)	(0.004)	(0.004)
# Observations	2,054	2,054	2,049	2,049	2,049	2,054	2,054	2,054
# hospital	715	715	713	713	713	715	715	715
R^2	0.044	0.045	0.373	0.119	0.037	0.131	0.125	0.231
Part II. Models for DS_{t-2}, TE_{t-2}, and $Support_{t-2}$								
$DS_{t-2} \times Support_{t-2}$	0.0142	0.0015	0.0050	**0.0177+**	-0.0032	0.0021	0.0000	-0.0067
	(0.015)	(0.008)	(0.005)	**(0.010)**	(0.015)	(0.005)	(0.005)	(0.005)
$TE_{t-2} \times Support_{t-2}$	**-0.0477****	-0.0055	0.0029	-0.0010	-0.0086	**-0.0187***	**-0.0187+**	0.0051
	(0.018)	(0.011)	(0.005)	(0.011)	(0.015)	**(0.009)**	**(0.010)**	(0.007)
$DS_{t-2} \times TE_{t-2}$	**0.0259+**	0.0052	-0.0047	-0.0120	0.0004	-0.0004	0.0004	**-0.0091+**
	(0.015)	(0.008)	(0.004)	(0.009)	(0.012)	(0.009)	(0.010)	**(0.005)**
$DS_{t-2} \times TE_{t-2} \times Support_{t-2}$	-0.0115	0.0051	**0.0099***	0.0113	**0.0242+**	-0.0026	-0.0060	0.0018
	(0.016)	(0.009)	**(0.004)**	(0.010)	**(0.013)**	(0.008)	(0.009)	(0.006)
# Observations	1,548	1,548	1,541	1,541	1,541	1,548	1,548	1,548
# hospital	646	646	644	644	644	646	646	646
R^2	0.043	0.042	0.328	0.093	0.024	0.124	0.119	0.176

(1) Robust standard errors in parentheses (2) *** p<0.001, ** p<0.01, * p<0.05, + p<0.1 (3) Direct IT effect is included (4) All control variables including hospital-level variables (e.g., size, profit status, and teaching status), IT network effect, market competition effect, and year effect are included (5) Constant is included

2.4.4 Temporal HIT Complementarity

We present three sets of analyses to assess if HIT applications implemented in different years interact with one another and impact performance outcomes. Part I in Table 2.3 provides details on performance impacts of interactions when support IT is lagged two time periods while DS and TE are lagged one time period. We notice that the effects of two-way interaction between DS_{t-1} and $Support_{t-2}$ are negative on recommendation score ($p<.1$) and cost per discharge ($p<.05$). The interaction between TE_{t-1} and $Support_{t-2}$ influences communication score ($p<.1$). DS_{t-1} and TE_{t-1} together enhance acute clinical quality by decreasing IQI 91 acute morality rate ($p<.1$). The three-way interaction between DS_{t-1}, TE_{t-1}, and $Support_{t-2}$ facilitates improvement in clinical quality by reducing IQI 91 chronic composite mortality rate and in cost reduction by decreasing IQI 91 acute cost ($p<.1$ for both effects).

Part II in Table 2.3 shows performance impacts of interactions when support IT is lagged one time period while DS and TE are lagged two time periods. Examining two-way interactions, we observe that the interaction between DS_{t-2} and $Support_{t-1}$ has no significant effect on any outcome variable. We also find that the interaction between TE_{t-2} and $Support_{t-1}$ decreases communication score ($p<.05$), while the interaction between DS_{t-2} and TE_{t-2} has a negative effect on cost per discharge ($p<.1$). The three-way interaction between DS_{t-2}, TE_{t-2}, and $Support_{t-1}$ enhances communication score significantly ($p<.01$). It is interesting to note that three-way interaction effect increases clinical quality and decreases cost when support IT is implemented one year before DS and TE and increases experiential quality when support IT is implemented one year after DS and TE.

Table 2.3 Temporal Complementarity Models of Support IT

	(1) IQI 91 Chronic Composite	(2) IQI 91 Acute Composite	(3) Communication Score	(4) Rating Score	(5) Recommendation score	(6) IQI 91 Chronic Cost	(7) IQI 91 Acute Cost	(8) Cost per Discharge
Part I. Models for DS_{t-1}, TE_{t-1}, and $Support_{t-2}$								
$DS_{t-1} \times Support_{t-2}$	0.0082	0.0005	-0.0039	0.0090	**-0.0266**$^{+}$	-0.0104	-0.0034	**-0.0121***
	(0.016)	(0.010)	(0.006)	(0.015)	**(0.015)**	(0.006)	(0.006)	**(0.006)**
$TE_{t-1} \times Support_{t-2}$	-0.0024	-0.0017	**0.0125**$^{+}$	-0.0195	0.0251	0.0017	-0.0009	0.0039
	(0.021)	(0.013)	**(0.007)**	(0.018)	(0.017)	(0.008)	(0.008)	(0.008)
$DS_{t-1} \times TE_{t-1}$	0.0087	**-0.0176**$^{+}$	0.0043	0.0117	-0.0065	-0.0024	0.0043	-0.0002
	(0.014)	**(0.009)**	(0.006)	(0.013)	(0.014)	(0.006)	(0.006)	(0.005)
$DS_{t-1} \times TE_{t-1} \times Support_{t-2}$	**-0.0300**$^{+}$	-0.0025	-0.0006	0.0255	-0.0118	-0.0074	**-0.0126**$^{+}$	-0.0093
	(0.016)	(0.011)	(0.006)	(0.018)	(0.016)	(0.008)	**(0.007)**	(0.007)
# Observations	1,191	1,191	1,188	1,188	1,188	1,191	1,191	1,191
# hospital	499	499	499	499	499	499	499	499
R^2	0.041	0.040	0.320	0.105	0.037	0.109	0.109	0.175
Part II. Models for DS_{t-2}, TE_{t-2}, and $Support_{t-1}$								
$DS_{t-2} \times Support_{t-1}$	0.0005	-0.0000	0.0061	0.0068	0.0009	0.0063	0.0039	-0.0025
	(0.016)	(0.008)	(0.005)	(0.011)	(0.015)	(0.007)	(0.007)	(0.008)
$TE_{t-2} \times Support_{t-1}$	-0.0051	0.0145	**-0.0124***	-0.0077	-0.0242	-0.0021	0.0022	0.0027
	(0.018)	(0.009)	**(0.006)**	(0.012)	(0.016)	(0.007)	(0.008)	(0.007)
$DS_{t-2} \times TE_{t-2}$	0.0031	0.0086	0.0015	-0.0008	0.0059	-0.0103	-0.0100	**-0.0086**$^{+}$
	(0.014)	(0.007)	(0.004)	(0.010)	(0.013)	(0.008)	(0.008)	**(0.005)**
$DS_{t-2} \times TE_{t-2} \times Support_{t-1}$	0.0225	-0.0115	**0.0130****	0.0073	0.0225	-0.0034	-0.0066	0.0005
	(0.016)	(0.008)	**(0.004)**	(0.014)	(0.015)	(0.007)	(0.007)	(0.006)
# Observations	1,191	1,191	1,188	1,188	1,188	1,191	1,191	1,191
# hospital	499	499	499	499	499	499	499	499
R^2	0.046	0.040	0.325	0.093	0.036	0.110	0.109	0.173

(1) Robust standard errors in parentheses (2) *** p<0.001, ** p<0.01, * p<0.05, + p<0.1 (3) Direct IT effect is included (4) All control variables including hospital-level variables (e.g., size, profit status, and teaching status), IT network effect, market competition effect, and year effect are included (5) Constant is included

Part I in Table 2.4 depicts performance impacts of interactions when TE is lagged two time periods while DS and support IT are lagged one time period. Two-way interaction effect between DS_{t-1} and $Support_{t-1}$ reduces cost-per-discharge (p<.1). The interaction between TE_{t-2} and $Support_{t-1}$ does not have any significant effect. The interaction between DS_{t-1} and TE_{t-2} deceases cost per discharge (p<.05). The three-way interaction between DS_{t-1}, TE_{t-2}, and $Support_{t-1}$ enhances the communication score (p<0.001) and increases cost per discharge (p<.1).

Part II presents performance impacts of interactions when TE is lagged one time period while DS and support IT are lagged two time periods. We discover that interactions between $Support_{t-2}$ and DS_{t-2}, between $Support_{t-2}$, and TE_{t-1}, and between DS_{t-2} and TE_{t-1} have no significant impact on any performance outcome. The three-way interaction between DS_{t-2}, TE_{t-1}, and $Support_{t-2}$ enhances the communication score (p<0.001) and rating score (p<.1).

Table 2.4 Temporal Complementarity Models of TE

	(1) IQI 91 Chronic Composite	(2) IQI 91 Acute Composite	(3) Communication Score	(4) Rating Score	(5) Recommendation score	(6) IQI 91 Chronic Cost	(7) IQI 91 Acute Cost	(8) Cost per Discharge
Part I. Models for DS_{t-1}, TE_{t-2}, and $Support_{t-1}$								
$DS_{t-1} \times Support_{t-1}$	-0.0048	-0.0005	0.0009	0.0089	-0.0140	0.0024	0.0032	**-0.0084**$^{+}$
	(0.015)	(0.008)	(0.005)	(0.011)	(0.014)	(0.006)	(0.006)	**(0.005)**
$TE_{t-2} \times Support_{t-1}$	0.0152	0.0172	-0.0062	-0.0056	-0.0068	-0.0044	-0.0019	0.0051
	(0.017)	(0.011)	(0.006)	(0.012)	(0.016)	(0.008)	(0.009)	(0.006)
$DS_{t-1} \times TE_{t-2}$	-0.0169	-0.0072	-0.0007	-0.0033	-0.0040	0.0010	0.0011	**-0.0092***
	(0.013)	(0.010)	(0.006)	(0.012)	(0.014)	(0.008)	(0.008)	**(0.004)**
$DS_{t-1} \times TE_{t-2} \times Support_{t-1}$	0.0137	-0.0026	**0.0161*****	0.0225	0.0036	-0.0041	-0.0076	**0.0069+**
	(0.013)	(0.008)	**(0.004)**	(0.014)	(0.013)	(0.008)	(0.008)	**(0.004)**
# Observations	1,191	1,191	1,188	1,188	1,188	1,191	1,191	1,191
# hospital	499	499	499	499	499	499	499	499
R^2	0.044	0.036	0.324	0.096	0.030	0.103	0.104	0.178
Part II. Models for DS_{t-2}, TE_{t-1}, and $Support_{t-2}$								
$DS_{t-2} \times Support_{t-2}$	0.0071	0.0011	0.0066	0.0178	-0.0021	-0.0040	-0.0073	-0.0089
	(0.017)	(0.008)	(0.005)	(0.011)	(0.014)	(0.007)	(0.006)	(0.005)
$TE_{t-1} \times Support_{t-2}$	-0.0192	-0.0051	0.0073	-0.0013	0.0071	-0.0026	-0.0043	-0.0038
	(0.018)	(0.010)	(0.005)	(0.009)	(0.012)	(0.008)	(0.008)	(0.007)
$DS_{t-2} \times TE_{t-1}$	0.0101	0.0008	-0.0039	-0.0140	-0.0122	-0.0048	-0.0017	-0.0006
	(0.015)	(0.008)	(0.004)	(0.009)	(0.012)	(0.007)	(0.008)	(0.005)
$DS_{t-2} \times TE_{t-1} \times Support_{t-2}$	-0.0218	-0.0024	**0.0155*****	**0.0195**$^{+}$	0.0156	-0.0047	-0.0049	-0.0007
	(0.016)	(0.009)	**(0.004)**	**(0.011)**	(0.013)	(0.007)	(0.007)	(0.005)
# Observations	1,191	1,191	1,188	1,188	1,188	1,191	1,191	1,191
# hospital	499	499	499	499	499	499	499	499
R^2	0.042	0.036	0.336	0.109	0.037	0.109	0.108	0.172

(1) Robust standard errors in parentheses (2) *** p<0.001, ** p<0.01, * p<0.05, + p<0.1 (3) Direct IT effect is included (4) All control variables including hospital-level variables (e.g., size, profit status, and teaching status), IT network effect, market competition effect, and year effect are included (5) Constant is included

Part I in Table 2.5 illustrates performance impacts of interaction when DS is lagged two time periods while support IT and TE are lagged one time period. We notice that there is no interaction effect between DS_{t-2} and $Support_{t-1}$ and between TE_{t-1} and $Support_{t-1}$. Two-way interaction effect between DS_{t-2} and TE_{t-1} decreases rating score ($p<.05$) and decreases chronic cost ($p<.05$). The three-way interaction between DS_{t-2}, TE_{t-1}, and $Support_{t-1}$ enhances the communication score ($p<.05$) and rating score ($p<.1$).

Part II presents performance impacts of interactions when DS is lagged one time period while TE and support IT are lagged two time periods. We find that the two-way interaction effect between DS_{t-1} and $Support_{t-2}$ decreases cost-per-discharge ($p<.05$), suggesting DS complements with support IT in reducing cost if DS is implemented one year after support IT. We also find that the two-way interaction effect between TE_{t-2} and $Support_{t-2}$ decreases both IQI 91 chronic cost and IQI 91 acute cost ($p<.05$ in both effects). There is no interaction effect between DS_{t-1} and TE_{t-2}. Furthermore, three-way interaction between DS_{t-1}, TE_{t-2} and $Support_{t-2}$ enhances the communication score ($p<.1$).

Table 2.5 Temporal Complementarity Models of DS

	(1) IQI 91 Chronic Composite	(2) IQI 91 Acute Composite	(3) Communication Score	(4) Rating Score	(5) Recommendation score	(6) IQI 91 Chronic Cost	(7) IQI 91 Acute Cost	(8) Cost per Discharge
Part I. Models for DS_{t-2}, TE_{t-1}, and $Support_{t-1}$								
$DS_{t-2} \times Support_{t-1}$	0.0059	0.0072	0.0014	0.0083	-0.0021	0.0081	0.0053	-0.0006
	(0.015)	(0.007)	(0.005)	(0.011)	(0.013)	(0.006)	(0.006)	(0.007)
$TE_{t-1} \times Support_{t-1}$	-0.0104	0.0062	0.0036	0.0124	-0.0093	0.0041	0.0053	-0.0083
	(0.020)	(0.009)	(0.006)	(0.012)	(0.016)	(0.006)	(0.006)	(0.008)
$DS_{t-2} \times TE_{t-1}$	-0.0019	-0.0001	-0.0022	**-0.0217***	-0.0099	**-0.0110***	-0.0068	-0.0014
	(0.016)	(0.008)	(0.005)	**(0.011)**	(0.013)	**(0.005)**	(0.005)	(0.005)
$DS_{t-2} \times TE_{t-1} \times Support_{t-1}$	-0.0030	-0.0074	**0.0105***	**0.0232+**	0.0118	0.0009	-0.0016	-0.0015
	(0.016)	(0.008)	**(0.005)**	**(0.012)**	(0.013)	(0.005)	(0.005)	(0.005)
# Observations	1,191	1,191	1,188	1,188	1,188	1,191	1,191	1,191
# hospital	499	499	499	499	499	499	499	499
R^2	0.045	0.039	0.323	0.096	0.035	0.112	0.106	0.173
Part II. Models for DS_{t-1}, TE_{t-2}, and $Support_{t-2}$								
$DS_{t-1} \times Support_{t-2}$	0.0079	-0.0041	-0.0001	-0.0004	-0.0217	-0.0065	-0.0013	**-0.0101***
	(0.017)	(0.010)	(0.006)	(0.013)	(0.014)	(0.006)	(0.006)	**(0.005)**
$TE_{t-2} \times Support_{t-2}$	-0.0288	-0.0022	0.0122	0.0138	0.0134	**-0.0262***	**-0.0251***	-0.0017
	(0.024)	(0.015)	(0.008)	(0.018)	(0.018)	**(0.011)**	**(0.012)**	(0.006)
$DS_{t-1} \times TE_{t-2}$	0.0059	0.0048	-0.0058	-0.0035	-0.0043	0.0058	0.0069	-0.0032
	(0.014)	(0.009)	(0.005)	(0.010)	(0.013)	(0.008)	(0.009)	(0.004)
$DS_{t-1} \times TE_{t-2} \times Support_{t-2}$	-0.0142	-0.0098	**0.0109+**	0.0053	-0.0031	0.0022	-0.0046	0.0019
	(0.017)	(0.011)	**(0.006)**	(0.018)	(0.015)	(0.009)	(0.009)	(0.005)
# Observations	1,191	1,191	1,188	1,188	1,188	1,191	1,191	1,191
# hospital	499	499	499	499	499	499	499	499
R^2	0.039	0.033	0.325	0.102	0.034	0.123	0.123	0.173

(1) Robust standard errors in parentheses (2) *** p<0.001, ** p<0.01, * p<0.05, + p<0.1 (3) Direct IT effect is included (4) All control variables including hospital-level variables (e.g., size, profit status, and teaching status), IT network effect, market competition effect, and year effect are included (5) Constant is included

2.4.5 The Cube View of Three-Way Complementarities

To understand the nature of complementarities among the three HIT applications, we present the system effect by employing performance difference tests and a cube view of complementarities. We examine each *significant* three-way interaction from Tables 2.2-2.5 to assess if three-way complementarities exist. Figure 2.2 is a generic representation of the cube view of complementarity. In the figure, the x-axis represents DS, the y-axis represents TE, and the z-axis represents support IT. Depending on the three-way complementarity we intend to examine, the three axes can represent DS, TE and support IT, time lagged one period or two periods. To assign coordinates in the cube, we use 0 and 1 to represent low and high levels of implementation, respectively. For example, the coordinate (1, 0, 1) indicates that a hospital implemented a high level of DS, a low level of TE, and a high level of support IT.

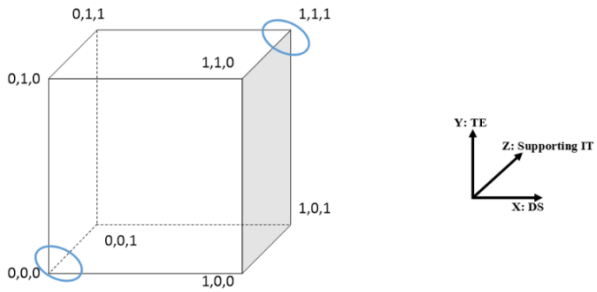


Figure 2.2 Cube View of Complementarities

In order to assess three way complementarity, we verify if each of the three pairs of variables is complementary and if all three variables are complementary together (Aral et al. 2012; Brynjolfsson and Milgrom 2012; Tambe et al. 2012). For each pair of variables, we calculate two differences: 1) when two variables are at high level, then what is the performance difference when the third variable is high vs. when it is low, and 2) when two variables are at low level, then what is the performance difference when the third variable is high vs. when it is low. If the former performance differential is larger than the latter for outcomes, such as revenues, profitability, productivity, or lower for outcomes, such as costs, and mortality, then there is partial evidence for three-way complementarity. For example, to assess whether a high level of *DS* reduces IQI 91 mortality rate more in the presence of high levels of *TE* and *Support*, we test if F(1,1,1) - F(0,1,1) < F(1,0,0) - F(0,0,0). Similarly, to test whether a high level of *DS* increases experiential quality more in the presence of *TE* and *Support*, we test if F(1,1,1) - F(0,1,1) > F(1,0,0) - F(0,0,0). For a comprehensive analysis of three-way complementarity, these tests are performed two more times, once to assess if high level of *TE* enhances performance more in the presence of high levels of *DS* and *Support*, and if high level of *Support* enhances performance more in the presence of high levels of *DS* and *TE*. The final and fourth test is a system test considering all three pairs of the edges simultaneously.

In Tables 2.6-2.13, we present the system test of complementarity for all three-way interactions found significant in Tables 2.2-2.5. Out of thirteen three-way interactions found significant in Tables 2.2-2.5, three-way complementarity is supported for nine interaction and not supported for the other four. Simultaneous complementarity is supported for two three-way interactions and not supported for one such interactions, and sequential complementarity is supported for seven three-way interactions and not supported for three such interactions. We find evidence of three-way complementarity for experiential quality, clinical quality, and the cost measures.

Table 2.6 System Tests of Complementarities: DS $_{t-1}$×TE $_{t-1}$×Support $_{t-1}$

Complementarity Between:	Test	IQI 91 Chronic Composite	
TE and Support IT	F(1,1,1) - F(0,1,1) > F(1,0,0) - F(0,0,0)	Fail	p=0.087
DS and Support IT	F(1,1,1) - F(1,0,1) > F(0,1,0) - F(0,0,0)	Fail	p=0.064
TE and DS	F(1,1,1) - F(1,1,0) > F(0,0,1) - F(0,0,0)	Fail	p=0.085
The System	[F(1,1,1) - F(0,1,1) + F(1,1,1) - F(1,0,1) + F(1,1,1) - F(1,1,0)] - [F(1,0,0) - F(0,0,0) + F(0,1,0) - F(0,0,0) + F(0,0,1) - F(0,0,0)] < 0	✓	p=0.032*

Table 2.7 System Tests of Complementarities: DS $_{t-2}$×TE $_{t-2}$×Support $_{t-2}$

Complementarity Between:	Test	Communication Score		Recommendation Score	
TE and Support IT	F(1,1,1) - F(0,1,1) > F(1,0,0) - F(0,0,0)	Fail	p=0.066	Fail	p=0.126
DS and Support IT	F(1,1,1) - F(1,0,1) > F(0,1,0) - F(0,0,0)	Fail	p=0.083	Fail	p=0.182
TE and DS	F(1,1,1) - F(1,1,0) > F(0,0,1) - F(0,0,0)	✓	p=0.001***	Fail	p=0.215
The System	[F(1,1,1) - F(0,1,1) + F(1,1,1) - F(1,0,1) + F(1,1,1) - F(1,1,0)] - [F(1,0,0) - F(0,0,0) + F(0,1,0) - F(0,0,0) + F(0,0,1) - F(0,0,0)] > 0	✓	p=0.003**	Fail	p=0.082

Table 2.8 System Tests of Complementarities: DS $_{t-1}$×TE $_{t-1}$×Support $_{t-2}$

Complementarity Between:	Test	IQI 91 Chronic Composite		IQI 91 Acute Cost	
TE and Support IT	F(1,1,1) - F(0,1,1) < F(1,0,0) - F(0,0,0)	Fail	p=0.300	Fail	p=0.097
DS and Support IT	F(1,1,1) - F(1,0,1) < F(0,1,0) - F(0,0,0)	Fail	p=0.102	Fail	p=0.124
TE and DS	F(1,1,1) - F(1,1,0) < F(0,0,1) - F(0,0,0)	Fail	p=0.101	✓	p=0.022*
The System	[F(1,1,1) - F(0,1,1) + F(1,1,1) - F(1,0,1) + F(1,1,1) - F(1,1,0)] - [F(1,0,0) - F(0,0,0) + F(0,1,0) - F(0,0,0) + F(0,0,1) - F(0,0,0)] < 0	Fail	p=0.081	✓	p=0.019*

Table 2.9 System Tests of Complementarities: DS $_{t-2}$×TE $_{t-2}$×Support $_{t-1}$

Complementarity Between:	Test	Communication Score	
TE and Support IT	F(1,1,1) - F(0,1,1) > F(1,0,0) - F(0,0,0)	✓	p=0.002**
DS and Support IT	F(1,1,1) - F(1,0,1) > F(0,1,0) - F(0,0,0)	Fail	p=0.370
TE and DS	F(1,1,1) - F(1,1,0) > F(0,0,1) - F(0,0,0)	Fail	p=0.168
The System	[F(1,1,1) - F(0,1,1) + F(1,1,1) - F(1,0,1) + F(1,1,1) - F(1,1,0)] - [F(1,0,0) - F(0,0,0) + F(0,1,0) - F(0,0,0) + F(0,0,1) - F(0,0,0)] > 0	✓	p=0.030*

Table 2.10 System Tests of Complementarities: DS $_{t-1}$×TE $_{t-2}$×Support $_{t-1}$

Complementarity Between:	Test	Communication Score		Cost per Discharge	
TE and Support IT	F(1,1,1) - F(0,1,1) > F(1,0,0) - F(0,0,0)	✓	p=0.024*	Fail	0.057
DS and Support IT	F(1,1,1) - F(1,0,1) > F(0,1,0) - F(0,0,0)	Fail	p=0.071	Fail	0.674
TE and DS	F(1,1,1) - F(1,1,0) > F(0,0,1) - F(0,0,0)	Fail	p=0.063	Fail	0.672
The System	[F(1,1,1) - F(0,1,1) + F(1,1,1) - F(1,0,1) + F(1,1,1) - F(1,1,0)] - [F(1,0,0) - F(0,0,0) + F(0,1,0) - F(0,0,0) + F(0,0,1) - F(0,0,0)] > 0	✓	p=0.011*	Fail	0.392

Table 2.11 System Tests of Complementarities: DS $_{t-2}$×TE $_{t-1}$×Support $_{t-2}$

Complementarity Between:	Test	Communication Score		Rating Score	
TE and Support IT	F(1,1,1) - F(0,1,1) > F(1,0,0) - F(0,0,0)	✓	p=0.007**	✓	p=0.050*
DS and Support IT	F(1,1,1) - F(1,0,1) > F(0,1,0) - F(0,0,0)	✓	p=0.001***	Fail	p=0.368
TE and DS	F(1,1,1) - F(1,1,0) > F(0,0,1) - F(0,0,0)	✓	p=0.000***	✓	p=0.009**
The System	[F(1,1,1) - F(0,1,1) + F(1,1,1) - F(1,0,1) + F(1,1,1) - F(1,1,0)] - [F(1,0,0) - F(0,0,0) + F(0,1,0) - F(0,0,0) + F(0,0,1) - F(0,0,0)] > 0	✓	p=0.000***	✓	p=0.025*

Table 2.12 System Tests of Complementarities: DS $_{t-2}$×TE $_{t-1}$×Support $_{t-1}$

Complementarity Between:	Test	Communication Score		Rating Score	
TE and Support IT	F(1,1,1) - F(0,1,1) > F(1,0,0) - F(0,0,0)	✓	p=0.046*	Fail	p=0.225
DS and Support IT	F(1,1,1) - F(1,0,1) > F(0,1,0) - F(0,0,0)	Fail	p=0.051	Fail	p=0.188
TE and DS	F(1,1,1) - F(1,1,0) > F(0,0,1) - F(0,0,0)	✓	p=0.035*	✓	p=0.023*
The System	[F(1,1,1) - F(0,1,1) + F(1,1,1) - F(1,0,1) + F(1,1,1) - F(1,1,0)] - [F(1,0,0) - F(0,0,0) + F(0,1,0) - F(0,0,0) + F(0,0,1) - F(0,0,0)] > 0	✓	p=0.013*	Fail	p=0.057

Table 2.13 System Tests of Complementarities: DS $_{t-1}$×TE $_{t-2}$×Support $_{t-2}$

Complementarity Between:	Test	Communication Score	
TE and Support IT	F(1,1,1) - F(0,1,1) > F(1,0,0) - F(0,0,0)	Fail	p=0.324
DS and Support IT	F(1,1,1) - F(1,0,1) > F(0,1,0) - F(0,0,0)	✓	p=0.004**
TE and DS	F(1,1,1) - F(1,1,0) > F(0,0,1) - F(0,0,0)	✓	p=0.003**
The System	[F(1,1,1) - F(0,1,1) + F(1,1,1) - F(1,0,1) + F(1,1,1) - F(1,1,0)] - [F(1,0,0) - F(0,0,0) + F(0,1,0) - F(0,0,0) + F(0,0,1) - F(0,0,0)] > 0	✓	p=0.010*

2.4.6 Post-hoc Analyses

To better understand the three-way complementarity effects, we conducted predictive margin plots in Figure 2.3-2.11 as the post-hoc analyses, which analyses provide us further insights on the complementarity relationship among different types of HIT implementation levels and the healthcare performance. For instance, Figure 2.3 demonstrates the relationship between DS implementation and IQI 91 chronic quality at high and low levels of TE and Support IT when each of the three IT applications is lagged one-year. From this graph, we can infer that if a hospital has high TE and high Support IT, it will show about 0.66% decrease in chronic mortality rate as its DS increases from low to high. Similarly, if a hospital has low TE and low Support IT, it will show about 0.56% decrease in chronic mortality rate as its DS increases from low to high. On the other hand, if a hospital has high TE and low Support IT, it will show about 1.61% increase in chronic mortality rate as its DS increases from low to high. If a hospital has low TE and high Support IT, it will show about 0.94% increase in chronic mortality rate as its DS increases from low to high. The detailed description of each figure is presented from Figure 2.3 to 2.11. Overall, we find that if a hospital has matched TE and Support IT at either high or low level, it will show enhanced healthcare performance as DS increases from low to high. Yet, we also find that if a hospital has high TE but low Support IT, it will show decreased healthcare performance as DS increases from low to high. If a hospital has high Support IT and low TE, sometimes it will show slightly enhanced healthcare performance while the other times it will show decreased healthcare performance.

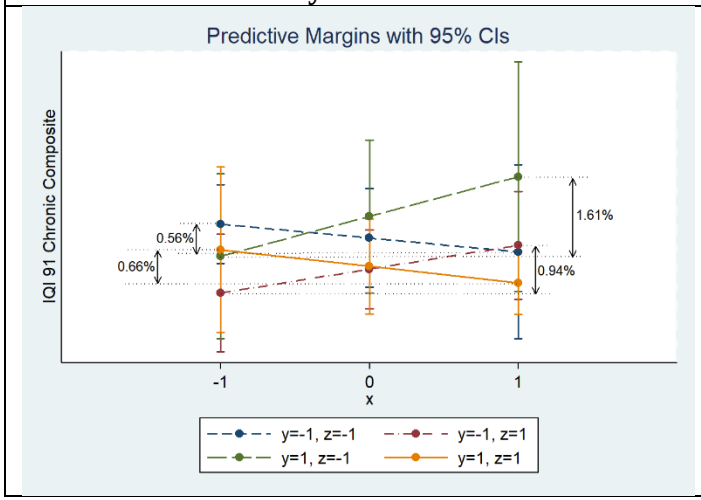
Three-Way Interaction Plot	Description
	The graph demonstrates the relationship between DS implementation and IQI 91 chronic quality at high and low levels of TE and Support IT when each of the three IT applications is lagged one-year. From this graph, we can infer that if a hospital has high TE and high Support IT, it will show about 0.66% decrease in chronic mortality rate as its DS increases from low to high. Similarly, if a hospital has low TE and low Support IT, it will show about 0.56% decrease in chronic mortality rate as its DS increases from low to high. On the other hand, if a hospital has high TE and low Support IT, it will show about 1.61% increase in chronic mortality rate as its DS increases from low to high. If a hospital has low TE and high Support IT, it will show about 0.94% increase in chronic mortality rate as its DS increases from low to high.

Figure 2.3 Three Way Interaction ($DS_{t-1} \times TE_{t-1} \times Support_{t-1}$) Plot for IQI 91 Chronic Composite

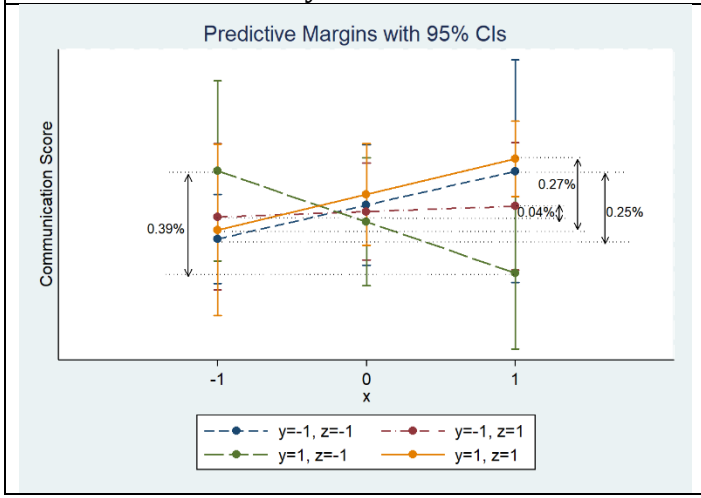
Three-Way Interaction Plot	Description
	The graph demonstrates the relationship between DS implementation and communication score at high and low levels of TE and Support IT when each of the three IT applications is lagged two-year. If a hospital has high TE and high Support IT, it will show about 0.27% increase in communication score as its DS increases from low to high. Similarly, if a hospital has low TE and low Support IT, it will show about 0.25% improvement in communication score as its DS increases from low to high. If a hospital has low TE and high Support IT, it will show about 0.04% increase in communication score as its DS increases from low to high. On the other hand, if a hospital has high TE and low Support IT, it will show about 0.39% decrease in communication score as its DS increases from low to high.

Figure 2.4 Three Way Interaction ($DS_{t-2} \times TE_{t-2} \times Support_{t-2}$) Plot for Communication Score

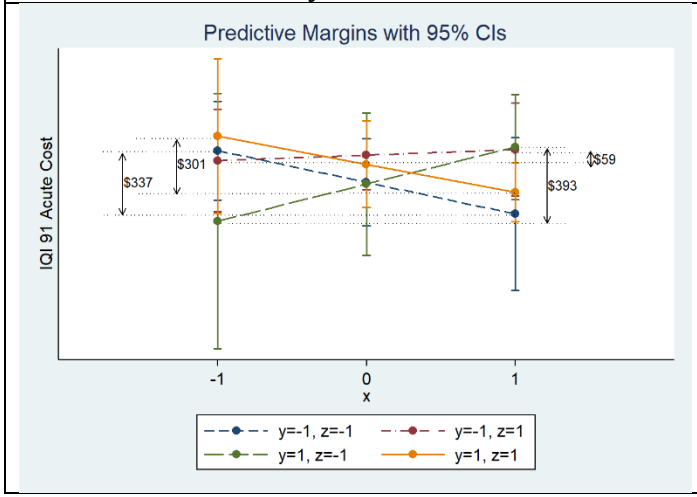
Three-Way Interaction Plot	Description
	The graph demonstrates the relationship between DS implementation and IQI 91 acute cost at high and low levels of TE and Support IT when DS and TE are lagged one-year and Support IT lagged two-year. If a hospital has high TE and high Support IT, it is associated with about $301 decrease in average acute patient cost as its DS increases from low to high. Similarly, if a hospital has low TE and low Support IT, it will show about $337 decrease in average acute patient cost as its DS increases from low to high. On the other hand, if a hospital has high TE and low Support IT, it will show about $393 increase in average acute patient cost as its DS increases from low to high. If a hospital has low TE and high Support IT, it will show about $59 increase in average acute patient cost as its DS increases from low to high.

Figure 2.5 Three Way Interaction (DS $_{t-1}$×TE $_{t-1}$×Support $_{t-2}$) Plot for IQI 91 Acute Cost

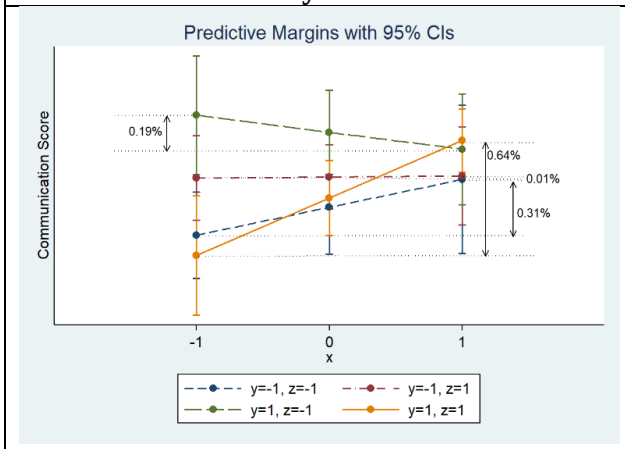
Three-Way Interaction Plot	Description
	The graph demonstrates the relationship between DS implementation and communication score at high and low levels of TE and Support IT when DS and TE are lagged two-year and Support IT lagged one-year. If a hospital has high TE and high Support IT, it will show about 0.64% increase in communication score as its DS increases from low to high. Similarly, if a hospital has low TE and low Support IT, it will show about 0.31% improvement in communication score as its DS increases from low to high. If a hospital has low TE and high Support IT, it will show about 0.01% increase in communication score as its DS increases from low to high. On the other hand, if a hospital has high TE and low Support IT, it will show about 0.19% decrease in communication score as its DS increases from low to high.

Figure 2.6 Three Way Interaction (DS $_{t-2}$×TE $_{t-2}$×Support $_{t-1}$) Plot for Communication Score

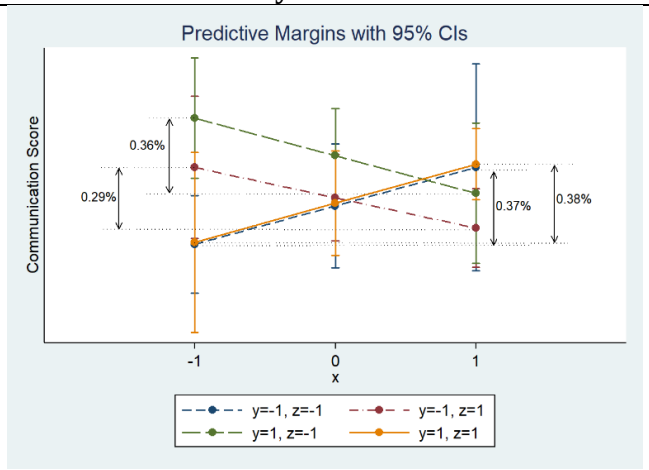
Three-Way Interaction Plot	Description
	The graph demonstrates the relationship between DS implementation and communication score at high and low levels of TE and Support IT when DS and Support IT are lagged one-year and TE lagged two-year. If a hospital has high TE and high Support IT, it will show about 0.38% increase in communication score as its DS increases from low to high. Similarly, if a hospital has low TE and low Support IT, it will show about 0.37% improvement in communication score as its DS increases from low to high. On the other hand, if a hospital has high TE and low Support IT, it will show about 0.36% decrease in communication score as its DS increases from low to high. If a hospital has low TE and high Support IT, it will show about 0.29% decrease in communication score as its DS increases from low to high.

Figure 2.6 Three Way Interaction ($DS_{t-1} \times TE_{t-2} \times Support_{t-1}$) Plot for Communication Score

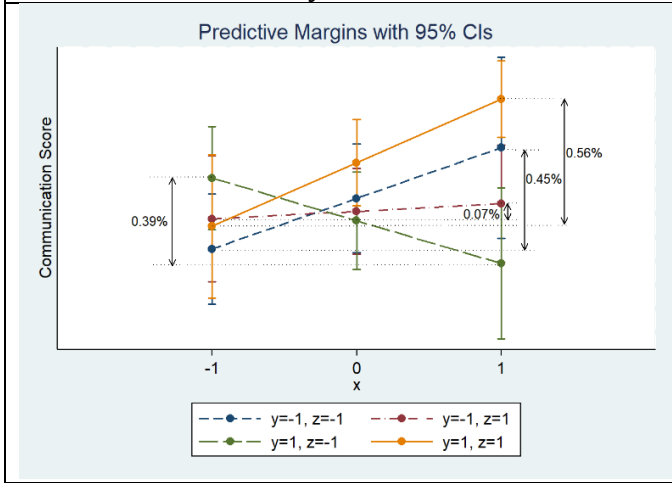
Three-Way Interaction Plot	Description
	The graph demonstrates the relationship between DS implementation and communication score at high and low levels of TE and Support IT when DS and Support IT are lagged two-year and TE lagged one-year. If a hospital has high TE and high Support IT, it will show about 0.56% increase in communication score as its DS increases from low to high. Similarly, if a hospital has low TE and low Support IT, it will show about 0.45% improvement in communication score as its DS increases from low to high. If a hospital has low TE and high Support IT, it will show about 0.07% increase in communication score as its DS increases from low to high. On the other hand, if a hospital has high TE and low Support IT, it will show about 0.39% decrease in communication score as its DS increases from low to high.

Figure 2.7 Three Way Interaction ($DS_{t-2} \times TE_{t-1} \times Support_{t-2}$) Plot for Communication Score

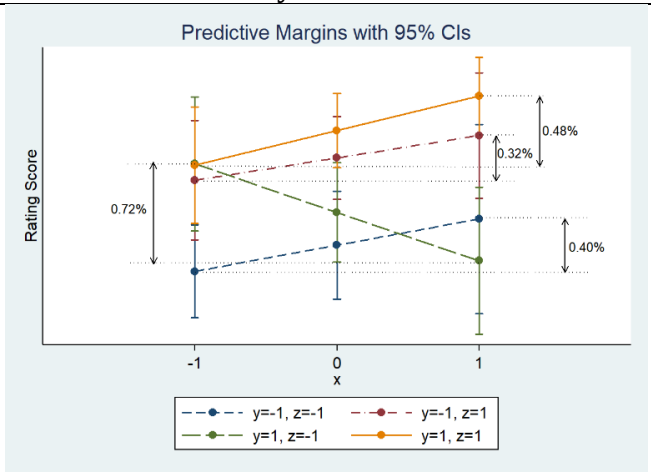
Three-Way Interaction Plot	Description
	The graph demonstrates the relationship between DS implementation and rating score at high and low levels of TE and Support IT when DS and Support IT are lagged two-year and TE lagged one-year. If a hospital has high TE and high Support IT, it will show about 0.48% increase in rating score as its DS increases from low to high. Similarly, if a hospital has low TE and low Support IT, it will show about 0.40% improvement in rating score as its DS increases from low to high. If a hospital has low TE and high Support IT, it will show about 0.32% increase in rating score as its DS increases from low to high. On the other hand, if a hospital has high TE and low Support IT, it will show about 0.72% decrease in rating score as its DS increases from low to high.

Figure 2.8 Three Way Interaction ($DS_{t-2} \times TE_{t-1} \times Support_{t-2}$) Plot for Rating Score

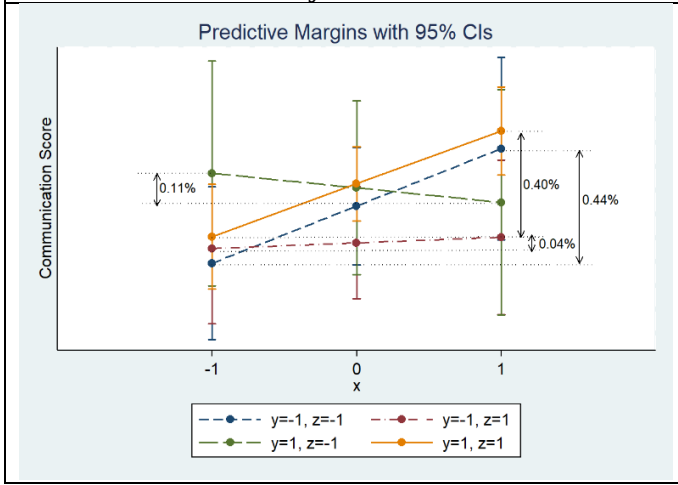
Three-Way Interaction Plot	Description
	The graph demonstrates the relationship between DS implementation and communication score at high and low levels of TE and Support IT when TE and Support IT are lagged one-year and DS lagged two-year. If a hospital has high TE and high Support IT, it will show about 0.40% increase in communication score as its DS increases from low to high. Similarly, if a hospital has low TE and low Support IT, it will show about 0.44% improvement in communication score as its DS increases from low to high. If a hospital has low TE and high Support IT, it will show about 0.04% increase in communication score as its DS increases from low to high. On the other hand, if a hospital has high TE and low Support IT, it will show about 0.11% decrease in communication score as its DS increases from low to high.

Figure 2.9 Three Way Interaction ($DS_{t-2} \times TE_{t-1} \times Support_{t-1}$) Plot for Communication Score

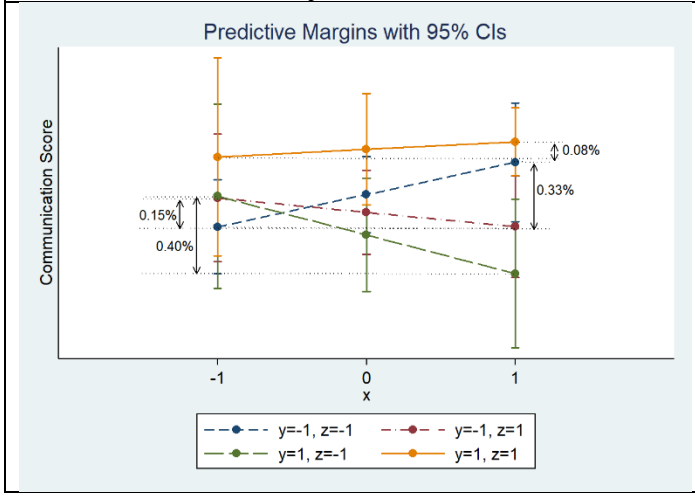
Three-Way Interaction Plot	Description
	The graph demonstrates the relationship between DS implementation and communication score at high and low levels of TE and Support IT when TE and Support IT are lagged two-year and DS lagged one-year. If a hospital has high TE and high Support IT, it will show about 0.08% increase in communication score as its DS increases from low to high. Similarly, if a hospital has low TE and low Support IT, it will show about 0.33% improvement in communication score as its DS increases from low to high. On the other hand, if a hospital has high TE and low Support IT, it will show about 0.40% decrease in communication score as its DS increases from low to high. If a hospital has low TE and high Support IT, it will show about 0.15% decrease in communication score as its DS increases from low to high.

Figure 2.10 Three Way Interaction ($DS_{t-1} \times TE_{t-2} \times Support_{t-2}$) Plot for Communication Score

2.5 Robustness Checks

We investigate the robustness of our main results by applying a variety of alternative models and specifications. We first show that our findings are robust to alternative model specifications to rule out the possibility of specification bias. We then apply a different approach to operationalizing the independent variables in the model to rule out the possible bias from variable operationalization. Finally, we show that our findings are robust to the inclusion of additional covariates to rule out the possibility of omitted variables bias. These results are reported in Appendix 2F.

Since the baseline FE models may have contemporaneous cross-equation error correlations with each other due to potential associations between health care quality and cost, we conducted seemingly unrelated regressions (SUR) to examine the relationship between health care quality and cost measures. We conducted the robustness test in a system of four SUR analyses to allow correlation among the error terms of different sets of quality and cost models (Appendix 2F, Table 2F1-2F4). The results of SUR models broadly agree with the baseline model, which indicates that our FE model results are robust.

We performed two additional sets of robustness analyses. First, we operationalized our explanatory HIT variables using a different approach. Besides using the count of technologies, the Saidin Index is also applied widely to operationalize HIT adoption by researchers (Sharma et al. 2016). The Saidin Index is a weighted sum that takes into account the rarity of HIT implementation by giving higher weights to rare technologies compared to those widely used by other hospitals. The results using Saidin Index are largely consistent with those using the count of technologies (Table 2F5-2F8). Finally, we include additional control variables in the models to assuage concerns that some important missing variables may drive our results (Table F9-F12).

These include hospital characteristic variables such as female patient percentage, percentages of Medicare and Medicaid patients, and health system affiliation. Results obtained from these analyses broadly agree with those from our baseline model.

2.6 Discussion and Conclusion

Hospitals in the United States are under increasing pressure from multiple stakeholders to enhance the quality of health care while decreasing costs, and to improve patients' experience during their stay at hospitals. Policy makers and researchers have deliberated if HITs may facilitate these outcomes. With the meaningful use (MU) program firmly in place, the focus of researchers has shifted from examining the adoption of HITs to assessing their impacts. Agarwal et al. (2010) posit that a coherent understanding of the relationship between HIT and health care performance has not yet been reached, especially as discussions pertain to conflicting impacts of HIT on quality and cost. Our study contributes to this stream of research by examining pairwise and three-way complementarities of HITs. Previous research has found evidence that simultaneous complementarities improve productivity and performance (Aral et al. 2012; Tambe et al. 2012). However, little research has examined complementarity from a temporal perspective and in a health care context. Additionally, there is limited research on three-way complementarity in the IS literature. We move the IT complementarity and HIT literature forward by examining both simultaneous and temporal complementarity in the health care industry. Rather than studying the effects of HITs individually, we examine how a system of technological innovations, such as DS, TE, and support IT work together to generate superior performance.

Overall, we discover that HIT applications simultaneously and temporally complement each other to generate higher health care performance than when they are implemented

separately. Moreover, our results indicate that different combinations of technologies impact hospital performance differently in terms of cost and clinical and experiential quality. As a result, health care providers need to identify optimal combinations of technological investments over time according to their priority of the performance improvement. We next discuss the impact of HIT on experiential quality, cost measures, and IQI 91 quality measures, subsequent to which we discuss the complementarity effects.

Our results suggest that significant pairwise interaction effects between DS and support IT, between TE and support IT, and between DS and TE may sometimes lead to decreased experiential quality; however, the significant three-way interaction effects always lead to the experiential quality enhancement. DS and support IT may jointly affect experiential quality because when DS is integrated with clinical documentation and results viewing systems, clinicians are enabled to provide customized *advice* to patients about medications, treatment procedures and post-discharge care, increasing the value of such communication for patients. Further, with the integration between DS and support IT, clinicians can send customized reminders, which may be especially useful for post-discharge care of patients (Bardhan and Thouin 2013). Similarly, the complementarity effect between TE and support IT facilitates clinicians to *prescribe* medications, lab tests and treatment procedures based on patients' clinical records and outcomes of prior treatments. The access to patients' clinical records and prior results enables clinicians to be more effective in prescribing and communicating with patients regarding their treatment, enhancing patient satisfaction. Three-way complementarity between DS, TE and support IT potentially combines these two effects during the advice and prescription processes and therefore enhances experiential quality.

Examining the impact of HIT on cost, we find that although the direct effects of DS, TE, and support IT both increase and decrease costs (direct effects are not presented in Table 2.2-2.5), pairwise HIT interaction effects lead to reductions in costs. This result may explain why some prior studies, which examine the effects of HIT in isolation, find it to be associated with increased medical expenditures (Agha 2014; Sidorov 2006). When implemented in combination, HITs appear to improve cost performance for hospitals. The joint application of HITs can allow clinicians to provide specific services to patients, to offer necessary screening tests, to check for drug-drug and drug allergy interactions, to enforce greater compliances of clinical guidelines, and to support both, the adoption of standard operating procedures and evidence-based practices (Bardhan and Thouin 2013). The complementary effects of HITs are engendered because their joint application reduces unnecessary and duplicative care, and provides necessary care proactively in order to reduce the occurrence of adverse events during patients' stays in the hospital, which can increase costs substantially. Three-way interactions of DS, TE, and support IT result in two significant impacts on cost. When support IT is implemented one time period before DS and TE, the three-way interactions lowers IQI 91 acute cost ($p<.1$; see Table 2.3, Part I), whereas when TE is implemented one time period before DS and support IT, the three-way interactions increases cost per discharge ($p<.1$; see Table 2.4, Part I).

Our results show that pairwise complementarity between TE and support IT improves clinical performance for chronic patients when both are lagged two year, along with DS ($p<.01$; see Table 2.2, Part II). The use of support IT and TE together for clinical care enables clinicians to provide medications and conduct tests and procedures that are patient-specific, resulting in lower occurrence of serious medication and procedures errors, which leads to enhanced clinical quality (Queenan et al. 2011). However, we find that pairwise complementarity between DS and

support IT have no impact on clinical performance for both acute and chronic patients. We also noticed that when patient information and prior results are available through $support_{t-2}$, the complementarity between DS_{t-1} and TE_{t-1} results in enhanced quality performance for IQI 91 acute composite. Similarly, support IT can possibly complement DS and generate patient-specific suggestions and treatment guidelines. Finally, we find that two three-way interactions between DS, TE and support IT, when all three HIT applications are lagged one year and when support IT is implemented one time period before TE and DS reduces IQI 91 chronic mortality, and thus enhances quality of care.

2.6.1 Summarized Pairwise and Three-Way Complementarity Effects

In order to facilitate a broad understanding of pairwise and three-way complementarity effects between DS, TE and support IT, both from simultaneous and sequential perspectives, we next discuss these effects. Our analysis uncovers four key results. First, from the correlation analysis, we find that DS, TE, and support IT implementations are mutually correlated, and this relationship grows over time. Further, we find that the three HITs simultaneously and temporally complement one another to produce higher experiential quality than when each is implemented separately. Second, our results indicate that different combination of technologies impacts hospital performance differently with regard to clinical quality, experiential quality and cost. For example, experiential quality is enhanced by the pairwise complementarity between DS and support IT and between TE and support IT; IQI 91 chronic quality is improved by the pairwise complementarity between TE and support IT; IQI 91 acute quality is improved by the pairwise complementarity between DS and TE; and health care cost is reduced by the pairwise complementarity between DS and support IT, TE and support IT, and between DS and TE. Third, different implementation stages of the technologies also affect health care performance

differently. For instance, we find the pairwise complementarity of TE and support IT performs best when they are both implemented for two years. Specifically, we find the pairwise complementarity of TE and support IT only enhances chronic quality and reduces cost when they are simultaneously implemented for two time periods and DS is implemented in the same year or one-year later. In contrast, misconfiguration of technologies may lead to lower performance. For example, Part II in Table 2.3 indicates the pairwise complementarity of TE and support IT may lead to decreased communication score if TE is implemented one year before support IT. Finally, we find that out of 20 significant pairwise effects found in Tables 2.2-2.5, 3 does not support complementarity, 11 support symbiotic complementarity and 6 support pooled complementarity. Note that we characterize interaction between DS and TE as pooled, and those between DS and support IT and TE and support IT as symbiotic. We are unable to firmly support the conjecture of Ennen and Richter (2010), but we do have some rough indication that dissimilar innovations may be more powerful when applied together. Based on these results, we posit that care providers need to identify optimal combinations of technologies over time according to their priority, and pay attention to the coordination mechanism of these technologies.

2.6.2 Limitations of the Research

Our study suffers from several limitations. First, we used data from only seven states in the U.S. Other researchers may wish to consider collecting data from a larger number of states in the country. We note that states chosen in this study account for approximately 35 percent of U.S. population, spread across different geographical areas, allowing us to study a broad cross-section of the U.S. population. Second, we aggregated individual discharge-level information up to the level of a hospital. Although consistent with our objective to examine performance outcomes of HIT applications in isolation and in combination at the organization level, aggregation doesn't

allow us to study quality and/or cost differentials at the level of individual patients or diseases. In fact, aggregation may dampen and hide some of the effects that may be found at the individual patient level. Third, due to the lack of data, we are unable to study the impact of HIT applications on operational and financial performance metrics. Finally, this study examined complementarity only *among* technology elements. Future research can examine complementarity *between* technology and *other* hospital characteristics and settings.

2.6.3 Research Contributions and Implications

There is a rich tradition of complementarity research in IS, strategy, operations and economics fields. In the IS field, the complementarity perspective has been used for exploring joint effects of IT and R&D (Bardhan et al. 2013), technology and knowledge (Aral and Weill 2007; Lee 2008), technology and strategy (Gilsing et al. 2008; Tanriverdi 2006), technology and organizational structure or process (Tiwana and Konsynski 2010), and technology and policies or practices (Hitt and Brynjolfsson 1997; Tambe et al. 2012). However, prior research in IS has examined simultaneous complementarity exclusively and ignored the temporal perspective. We move this stream of literature forward by considering both simultaneous and temporal perspectives to explain performance differences generated by technologies. These technologies may create synergies with others that are implemented in the same, or a different, time period. We propose, and our results strongly suggest, that researchers need to incorporate temporal complementarity in future research. Previous research indicates changing only one or a subset of organizational practices may lead to lower performance, and therefore, recommends changing entire practices in a system simultaneously to reap the maximum benefits (Brynjolfsson and Milgrom 2012; Milgrom and Roberts 1990). Yet, in practice, simultaneously implementing all the changes can be difficult because of coordination and synchronization problems (Brynjolfsson

and Milgrom 2012). Our study examines both simultaneous and temporal impacts of technology innovations on organizational performance. We demonstrate that the complementarity effect can lead to better performance under both simultaneous and temporal regimes. We further reveal how the complementarity effects on technologies impact healthcare performance. We find that when TE and Support IT implementation level matches, it would lead to enhanced healthcare performance when DS increases from low to high level. This view studied in the health care context can be extended to studies in both service industries and manufacturing industries when exploring the interaction effects among technologies that facilitate task execution, decision making, and supporting activities.

In order to understand the impacts of various IT applications in totality, it is critical that researchers not examine their effects in isolation. As discussed earlier, prior research in HIT has reached some contradictory conclusions because it examined HIT applications in isolation. When multiple technologies are brought to bear simultaneously or in sequence, their joint effects can easily surpass the sum of their individual effects. We find evidence of this in our study. We suggest that future research examine pairwise and three-way complementarities between various technologies, and also between technologies and organizational practices, to appreciate and appropriate the overall potential of HIT. We suggest that it may be worthwhile to consider the functional aspects of various IT applications, as in which functionalities do these enable organizations to accomplish. In contrast to much extant work on IT complementarity, which conceptualizes IT at the generic level, this study adopts such a functional approach in conceptualizing various technologies, and applies it in the context of health care.

This research demonstrates the importance of context in assessing complementarity between HIT applications. We note that HIT determinants of chronic and acute quality and costs

are largely different. In fact, among all the pairwise and three-way effects examined, we find only two interactions, between DS_{t-2} and TE_{t-2} when support IT is also implemented at t-2 (Table 2.2) and between TE_{t-2} and $support_{t-2}$ when DS is implemented at t-1 (Table 2.5), lowers costs for both chronic and acute conditions. In all other instances, we find that direct or interaction effects that impact chronic quality or cost do not significantly impact acute quality and cost, and *vice versa*. We believe that this is a strong result and an important contribution to the HIT and IT complementarity literature. This result clearly illustrates the need to for researchers to consider the impact of HIT on chronic and acute conditions separately. We further suggest that researchers jointly examine the application of HIT and the clinical workflows specific to chronic and acute conditions to throw additional light on value creation possibilities in hospitals.

Finally, we suggest that researchers examine a wide variety and dimensions of performance outcomes to examine complementarity. Firms typically have multiple objectives related to revenues, costs, profitability, product and service quality, and customer satisfaction. Our results suggest there are trade-offs among these outcomes. Thus, studying a comprehensive set of performance metrics can unveil the systematic effect of HIT on hospitals. Additionally, we suggest that researchers obtain a panel long-enough to discern temporal trends of how various combinations of HIT applications impact different organizational outcomes. We are able to analyze a panel comprising six years of data; we speculate that a longer panel may provide even more robust results. For instance, we are unable to detect any impact of HIT that is more than two time periods lagged. It may be possible in a longer panel to detect such effects.

2.6.4 Implications for Practice

This study has significant pragmatic implications for decisions makers in hospitals. In particular, managers need to be aware of how different HIT functions complement one another to

systematically impact health care performance. They also need to implement HIT applications strategically in different stages to realize various performance improvements. For example, pairwise complementarity effect of TE and support IT leads to superior health care performance when the two are implemented simultaneously.

Our research introduces the idea that different HITs impact chronic and acute diseases differently. Therefore, health care providers also need to consider how systems of technologies integrate into different disease workflows when they allocate HIT resources. Furthermore, it is important for managers to realize that there are trade-offs among various performance outcomes and that HIT applications, even in combination, are not a panacea for all that ails the health care industry. Managers may want to prioritize different combinations of technologies contingent on which performance variables are important, and also realize that technology may not impact all outcomes.

2.6.5 Conclusion

As the largest single item of expense in the health care industry, hospitals constitute a vital organizational setting in which to analyze the impact of health information technologies. This research has examined pairwise and three-way complementarity effects of three HIT applications from both simultaneous and sequential perspectives. We paid particular attention to the context of technology application by examining the impacts of various HIT applications separately and in combination on chronic and acute conditions. We attempted to address several limitations in extant literature in IS, HIT and health services research by examining a large number of performance outcomes variables, including clinical quality, cost and experiential quality. We leveraged data from five different data sources, collected over six years, and created a unique panel to analyze complementarity of health information technologies. We conducted a series of

robustness tests to confirm the validity of our results. The results reported in this paper have considerable implications for both researchers and practitioners. We believe that this study makes key contributions to the literature and represents an important step into an area of inquiry – simultaneous and sequential IT complementarity in health care, and more broadly, other contexts – that is under-represented in the literature, yet presents a significant potential for theoretical and practical advancement.

Appendix

Appendix 2A: Variables, Definitions, References and Data Sources

Variable	Description	Reference in the Literature	Data Source
IQI 91 Chronic Composite	Measured by chronic mortality rate from IQI 91 composite[5]; we apply logit transformation to this number.	Menachemi et al. (2008); Mutter et al. (2008)	HCUP
IQI 91 Acute Composite	Measured by acute mortality rate from IQI 91 composite; we apply logit transformation to this number.		HCUP
Communication score	Measured by average communication percentage score $= \frac{Q_i}{1-Q_i}$, where Q_i is the sum of the average percentage of patients who perceived the communication from the hospital to be always good or usually good; we apply logit transformation to this number.	Sharma et al. (2016); Senot et al. (2016); Angst et al. (2012); Boulding et al. (2011); Chandrasekaran et al. (2012)	HCAHPS survey
Rating Score	Measured by rating percentage score $RatingScore = \frac{PR_i}{1-PR_i}$, where PR_i is the percentage of patients who gave the hospital a rating of 7 to 10 (medium or high); we apply logit transformation to this number.		HCAHPS survey
Recommendation Score	Measured by percentage score $RecommendScore = \frac{R_i}{1-R_i}$, where R_i is the percentage of patients who would definitely or probably recommend the hospital; we apply logit transformation to this number.		HCAHPS survey
IQI 91 Chronic Cost	Measured by hospital's average cost (total charge × cost-to-charge ratio/the number of discharges) from 3 chronic diseases included in IQI 91 composite; we apply natural log to this number.	N/A	HCUP and cost-to-charge ratio file
IQI 91 Acute Cost	Measured by hospital's average cost (total charge × cost-to-charge ratio/the number of discharges) from 3 acute diseases included in IQI 91 composite; we apply natural log to this number.	N/A	HCUP and cost-to-charge ratio file
Cost Per Discharge (CMS)	Measured by a hospital's total inpatient charge reported by the CMS cost report, multiplied by the cost-to-charge ratio and divided by the number of discharges; we apply natural log to this number.	Sharma et al. (2016); Senot et al. (2016)	CMS cost report, HCUP, and cost-to-charge ratio file
Decision Support IT	Measured by the total number of fully implemented decision support IT features.	Burke and Menachemi (2004); Menachemi et al. (2006); Angst et al. (2012)	AHA IT survey
Task Execution	Measured by the total number of fully implemented CPOE features.		AHA IT survey
Support IT	Measured by the total number of result viewing and electronic clinical documentation features.		AHA IT survey
Hospital Size	Number of beds in a hospital; we apply natural log to this number.	Kwon and Johnson (2014)	AHA survey
Not-For-Profit	Dummy variable: 1 for not-for profit hospitals; 0 for for-profit hospitals.	Angst et al. (2012)	AHA survey
Teaching	Dummy variable: 1 for teaching hospitals; 0 for non-teaching hospitals.	Kwon and Johnson (2014)	AHA survey
Market Competition (HHI)	Measured by Herfindahl-Hirschman Index (HHI), which is the sum of squared market shares for all of the hospitals in a hospital referral region (HRR). Market share is calculated as the number of discharges from that hospital divided by the total number of discharges from all hospitals in the market.	Mutter et al. (2008)	AHA survey and HCUP
IT Network Effect	Measured by average IT implementation level in hospitals, excluding the focal hospital in the HRR in which the focal hospital belongs.	Miller and Tucker (2009); Tucker (2008)	AHA survey and AHA IT survey

[5] Acute Myocardial Infarction (AMI), Heart Failure, and Acute Stroke are chronic conditions, and Gastrointestinal Hemorrhage, Hip Fracture, and Pneumonia are acute conditions.

Appendix 2B: Calculation of IQI 91 Composite Quality Measures

The calculation of IQI 91 composite quality measures is involved. This appendix provides information on how the measures are calculated using the guidelines and SAS software code provided by AHRQ.[6] The code is easily available, and used widely by researchers to calculate IQI 91 quality. The steps are below:

Step 1. The first step is to calculate the mortality rate for each of the six IQI 91 composite conditions. Determine the total number of patients, aged 18 or older, who die from a particular IQI 91 condition, in relation to the total number of discharges of patients with the same age profile and disease condition in a hospital. The ratio of the two numbers provides the mortality rate, called observed mortality rate.

Step 2. Next, the expected mortality rate is calculated, which estimates the mortality rate a hospital would have if it had the same patient mix as the reference population (RP).[7]

Step 3. Risk-adjusted rate is computed for each IQI 91 condition by dividing observed rate by the expected rate. This calculated rate is then scaled by the RP to obtain the risk-adjusted ratio (RR).

Step 4. Reliability-adjusted ratio (RAR) is calculated using the weighted average of the RR and the RP, where the weight depends on reliability degree for the IQI 91 indicator and the healthcare provider: RAR = (RR × weight) + [RP × (1 – weight)].

Step 5. IQI 91 composite quality measure is obtained by using the weighted RARs following the listed expression: Composite = [indicator_1 RAR × weight_1] + [indicator_2 RAR × weight_2] + . . . + [indicator_N RAR × weight_N], where the weight used in the expression depends on the relative

[6] Quality indicator user guide for IQI composite measures can be obtained at: https://www.qualityindicators.ahrq.gov/Downloads/Modules/IQI/IQI_Composite_Development.pdf

[7] The reference population consists of the discharges from all the participating states in the HCUP-SID from 2001-2003.

frequency of the denominator for each IQI in the RP and reflects the amount of risk of mortality in the selected IQIs from a given population[8].

8 IQI 91 in these conditions are weighted 0.1468 (IQI15), 0.2704 (IQI16), 0.1356 (IQI17), 0.1312(IQI18), 0.0679 (IQI19), and 0.248 (IQI20) in order to calculate the overall IQI 91 composite quality measure. The weight of IQI 15-17 are used for IQI 91 chronic composite calculation and the weights of IQI 18-20 are used for IQI 91 acute composite calculation (www.qualityindicators.ahrq.gov/Downloads/Modules/IQI/V43/Composite_User_Technical_Specification_IQI_4.3.pdf).

Appendix 2C: Measures

Part I. Survey Items for Experiential Quality (Source: HCAHPS Survey)

The core of the HCAHPS survey comprises 21 items measuring patient's perception on hospital experience. These items encompass 11 key topics that related to communication with doctors, communication with nurses, responsiveness of hospital staff, pain management, communication about medicines, discharge information, cleanliness of the hospital environment, quietness of the hospital environment, transition of care, hospital rating, and willingness to recommend hospital. This survey was asked to a random sample of recently discharged patients (between 48 hours and 6 weeks after discharge). Only patients who admitted in the medical, surgical and maternity care service lines are eligible for the survey. There are four methods to collect the data: 1) mail only, 2) telephone only, 3) mixed (mail followed by telephone), and 4) active interactive voice response. This patient-level data later aggregated into the hospital-level data with patient-mix adjusted by CMS, and published in Hospital Compare website. For the purpose of this study, we select 4 topics related to communication, 1 topic related to overall rating, and 1 topic related to patients' willingness to recommend. The topics related to communication are composites that constructed from two or three survey items. We present the topics and items in the following list with items formatted in italics:

Communication

(1) How often did nurses communicate well with patients?

During this hospital stay...

How often did nurses treat you with courtesy and respect?

How often did nurses listen carefully to you?

How often did nurses explain things in a way you could understand?

(2) How often did doctors communicate well with patients?

During this hospital stay...

How often did doctors treat you with courtesy and respect?

How often did doctors listen carefully to you?

How often did doctors explain things in a way you could understand?

(3) How often did staff explain about medicines before giving them to patients?

Before giving you any new medicine…

How often did hospital staff tell you what the medicine was for?

How often did hospital staff describe possible side effects in a way you could understand?

(4) Were patients given information about what to do during their recovery at home? (Yes /No)

During this hospital stay...

Did hospital staff talk with you about whether you would have the help you needed when you left the hospital?

Did you get information in writing about what symptoms or health problems to look out for after you left the hospital?

The response categories for question (1) to (3) are “Never/Sometimes”, “Usually” or “Always”, and the response categories for question (4) are “Yes” or “No”.

Rating

How do patients rate the hospital overall?

What number would you use to rate this hospital during your stay?

The response categories are “0-6” (Low), “7-8” (Medium), or “9-10” (High).

Recommendation

Would patients recommend the hospital to friends and family?

Would you recommend this hospital to your friends and family?

The response categories are “Yes, definitely recommend the hospital”, “Probably recommend the hospital”, or “Not recommend the hospital”.

Part II. IT Items Scale (Source: AHA IT Supplement Files)

HIT implementation is measured by a six-point scheme as follows:

1 = Fully implemented across all units

2 = Fully implemented in at least one unit

3 = Beginning to implement in at least one unit

4 = Have resources to implement in the next year

5 = Do not have resources but considering implementing

6 = Not in place and not considering implementing

Appendix 2D: HIT Variable List

IT Indicators		Full Implementation Percentages				
		2008	2009	2010	2011	2012
Decision Support IT: CDSS	*Clinical guidelines*	17.36%	19.76%	23.23%	33.95%	47.31%
	Clinical reminders	23.83%	25.00%	27.36%	39.34%	51.84%
	Drug allergy alerts	55.18%	53.83%	56.10%	65.63%	80.17%
	Drug-drug interaction alerts	53.63%	52.62%	56.89%	64.60%	79.89%
	Drug-Lab interaction alerts	39.12%	39.52%	42.52%	51.55%	68.27%
	Drug dosing support	34.20%	36.29%	40.94%	49.28%	61.47%
Task-Execution IT: CPOE	*Laboratory tests*	19.17%	23.39%	24.41%	31.68%	52.69%
	Radiology tests	20.47%	23.19%	23.82%	32.09%	52.97%
	Medications	19.69%	19.56%	21.46%	30.23%	52.41%
	Consultation requests	17.88%	17.54%	18.90%	28.36%	48.16%
	Nursing orders	22.02%	24.40%	24.61%	34.16%	55.24%
Support IT: Results Viewing	*Lab reports*	91.97%	89.72%	89.57%	92.75%	97.17%
	Radiology reports	91.97%	90.32%	89.37%	92.34%	97.17%
	Radiology images	81.87%	83.27%	87.20%	89.23%	95.18%
	Diagnostic test results	62.18%	67.74%	66.54%	72.26%	83.29%
	Diagnostic test images	40.93%	51.41%	56.10%	63.35%	69.69%
	Consultant reports	57.77%	62.50%	62.80%	67.08%	76.77%
Support IT: Electronic Clinical Documentation	*Patient demographics*	87.82%	88.31%	88.39%	92.55%	96.32%
	Physician notes	11.66%	13.31%	12.99%	18.22%	31.16%
	Nursing Notes	40.16%	43.95%	45.47%	57.14%	75.92%
	Problem lists	27.20%	31.65%	26.97%	42.24%	62.32%
	Medication lists	51.55%	54.84%	54.92%	64.80%	83.00%
	Discharge summaries	48.70%	52.22%	56.50%	55.90%	71.95%
	Advanced directives	40.67%	41.94%	46.85%	58.18%	72.52%

Appendix 2E: Heckman Selection and Reverse Causality Tests

To estimate the Heckman selection models, we first calculated the average values of both dependent and independent variables across six years. We then estimated choice and outcome models (Heckman 1979). In the choice model, we included two variables, hospital bed size and IT network effect because both variables are indicators of technology innovations. As a proxy of resources, bed size may influence IT implementation because large hospitals are more likely to use HIT than smaller ones (Kazley and Ozcan 2007; Menachemi et al. 2008). As a measure of network externalities, IT network effect influences technology adoption by generating network benefits with spillover effects (Lee et al. 2013; Miller and Tucker 2009). For the outcome models, we used different sets of variables to predict IQI 91 composites, experiential quality, and cost measures. We include HIT implementation variables as they impact performance. We include teaching status because compared to non-teaching hospitals, teaching hospitals are more likely to have advanced resources (Bardhan and Thouin 2013) and to treat a more complex case mix (Senot et al. 2016). Thus, teaching status may affect quality measures (Bardhan and Thouin 2013) and cost measures (Senot et al. 2016). We include bed size because can potentially influences performance outcomes (Menachemi et al. 2008). Being a member of a health system has been associated with healthcare performance (Bazzoli et al. 2000, Carey 2003), hence we include it in our analysis. Previous research shows market competition influences both experiential measures (Rego et al. 2013) and cost measures (Gaynor and Town 2012). Prior literature also shows female gender is a significant risk factor for adverse drug events (Rommers et al. 2007), which is associated with increased cost. Hence, we used percentage of female patients to predict cost measures. Overall, for IQI 91 composite quality outcome models, we used HIT implementation, teaching status, hospital size, and system member indicator; for experiential quality outcome models, we used HIT implementation, teaching status, hospital size,

system member indicator, and market share; for cost outcome models, we included HIT implementation, teaching status, hospital size, system member indicator, market share, and percentage of female patients. Our Heckman selection model results are presented in Table 2E1. We find no evidence of selection bias based on the results of the likelihood-ratio tests of independence.

To account for the potential reverse causality, we used lagged one-year dependent variables to predict HIT implementation levels. The results presented in Tables 2E2-E4 indicate that we can rule out the possible existence of reverse causality.

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Table 2E1. Heckman Selection Models

VARIABLES	Model 1 IQI 91 Chronic Composite	Model 2 IQI 91 Acute Composite	Model 3 Communication score	Model 4 Rating Score	Model 5 Recommendation score	Model 6 IQI 91 Chronic Cost	Model 7 IQI 91 Acute Cost	Model 8 Cost Per Discharge
Outcome Model								
DS	0.1774*	0.0428+	-0.0064	-0.0228	-0.0437	-0.0360	-0.0326+	-0.0607**
	(0.071)	(0.025)	(0.017)	(0.028)	(0.034)	(0.023)	(0.018)	(0.022)
TE	0.0659	0.0446*	-0.0104	-0.0015	0.0120	-0.0030	0.0082	0.0174
	(0.062)	(0.022)	(0.015)	(0.024)	(0.030)	(0.020)	(0.016)	(0.019)
Support IT	-0.1228*	-0.0762***	0.0524***	0.1046***	0.1338***	0.0042	-0.0048	0.0128
	(0.060)	(0.022)	(0.015)	(0.024)	(0.029)	(0.020)	(0.016)	(0.019)
Teaching	0.2656+	0.1782***	0.0694*	0.0981+	0.1542*	0.2557***	0.1386***	0.1239**
	(0.138)	(0.049)	(0.035)	(0.057)	(0.069)	(0.047)	(0.038)	(0.045)
Hospital Size (log)	-0.1789***	-0.1768***	-0.1145***	-0.1287***	-0.1103***	0.2115***	0.0365*	0.0298+
	(0.015)	(0.006)	(0.014)	(0.023)	(0.029)	(0.019)	(0.015)	(0.018)
System Member	-0.2296**	-0.0608*	-0.0132	0.0145	-0.0209	-0.0052	-0.0498*	-0.0123
	(0.081)	(0.029)	(0.020)	(0.033)	(0.040)	(0.027)	(0.022)	(0.026)
HHI			0.3987***	0.4644***	0.6235***	-0.2300**	-0.2421***	-0.1213
			(0.064)	(0.103)	(0.126)	(0.085)	(0.068)	(0.080)
Female						-0.5202*	0.3156	-2.0117***
						(0.263)	(0.210)	(0.249)
Choice Model								
Hospital Size (log)	0.2632***	0.2569***	0.2301***	0.2406***	0.2347***	0.2401***	0.2429***	0.2408***
	(0.067)	(0.066)	(0.065)	(0.065)	(0.065)	(0.063)	(0.064)	(0.064)
IT Network Effect	-0.0011*	-0.0011*	-0.0015**	-0.0013*	-0.0014**	-0.0014**	-0.0013*	-0.0013*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
# Observations	866	866	866	866	866	866	866	866
# Censored	121	121	121	121	121	121	121	121
rho	0.233	0.220	-0.281	-0.0597	-0.191	-0.293	-0.0383	-0.0585
sigma	1.082	0.386	0.260	0.423	0.513	0.353	0.278	0.330
lambda	0.252	0.0848	-0.0730	-0.0253	-0.0979	-0.103	-0.0107	-0.0193
chi^2	316.8	1765	156.8	86.71	76.03	327.8	63.12	123.2
Independent Test (chi^2)	0.99	0.67	1.07	0.04	0.35	0.97	0.02	0.06
Independent Test (p Value)	0.3188	0.4134	0.3020	0.8417	0.5569	0.3239	0.8978	0.8043

*** p<0.001, ** p<0.01, * p<0.05, + p<0.1

Table 2E2. Reverse Causality Test: DS Model Results

VARIABLES	Model 1 IQI 91 Chronic Composite	Model 2 IQI 91 Acute Composite	Model 3 Communication score	Model 4 Rating Score	Model 5 Recommendation score	Model 6 IQI 91 Chronic Cost	Model 7 IQI 91 Acute Cost	Model 8 Cost Per Discharge
DV_{t-1}	-0.0619	-0.5476^{+}	-0.7186	-0.2704	-0.1476	0.2996	1.1070^{+}	-0.1125
	(0.146)	(0.332)	(0.633)	(0.246)	(0.220)	(0.628)	(0.628)	(0.678)
DS_{t-1}	0.4252**	0.4345**	0.3973**	0.4094**	0.4199**	0.4260**	0.4094**	0.4273**
	(0.146)	(0.147)	(0.139)	(0.143)	(0.146)	(0.146)	(0.144)	(0.147)
DS_{t-2}	0.1245	0.1274	0.1144	0.1191	0.1248	0.1263	0.1241	0.1246
	(0.094)	(0.093)	(0.091)	(0.093)	(0.094)	(0.094)	(0.093)	(0.094)
IT Network Effect $_t$	-0.0012	-0.0014	-0.0013	-0.0012	-0.0013	-0.0012	-0.0011	-0.0012
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
HHI $_t$	-1.9727	-1.6192	-1.8120	-2.1019	-1.8679	-1.6897	-1.4647	-1.8332
	(3.341)	(3.460)	(3.216)	(3.154)	(3.162)	(3.238)	(3.103)	(3.214)
Hospital Size (log) $_t$	-0.4269	-0.4184	-0.4544	-0.4019	-0.4268	-0.4254	-0.4721	-0.4265
	(0.394)	(0.391)	(0.398)	(0.402)	(0.393)	(0.391)	(0.367)	(0.397)
Teaching $_t$	0.2328	0.2232	0.2334	0.2373	0.2511	0.2305	0.2271	0.2389
	(0.521)	(0.516)	(0.513)	(0.532)	(0.534)	(0.518)	(0.513)	(0.519)
Not-For-Profit $_t$	-0.5192	-0.5210	-0.4737	-0.4756	-0.5240	-0.5388	-0.5638	-0.5057
	(0.503)	(0.503)	(0.517)	(0.507)	(0.505)	(0.520)	(0.462)	(0.515)
Medicare $_t$	-5.7825**	-5.2741**	-5.6363**	-5.9365**	-5.8387**	-5.7256**	-5.4610**	-5.7617**
	(1.835)	(1.878)	(1.828)	(1.819)	(1.818)	(1.842)	(1.828)	(1.834)
Medicaid $_t$	-5.5564*	-5.4993*	-5.4348*	-5.6167*	-5.6691*	-5.3908*	-5.1622*	-5.6048*
	(2.444)	(2.466)	(2.398)	(2.427)	(2.445)	(2.404)	(2.408)	(2.445)
System Member $_t$	0.1151	0.1161	0.1569	0.1206	0.1305	0.1072	0.0778	0.1127
	(0.346)	(0.339)	(0.346)	(0.337)	(0.345)	(0.349)	(0.341)	(0.346)
# Observations	384	384	384	384	384	384	384	384
# Hospital	252	252	252	252	252	252	252	252
Degree of Freedom	13	13	13	13	13	13	13	13
Chi-square	50.95	50.19	52.58	53.80	52.16	50.62	52.59	50.69

(1) Robust standard errors in parentheses (2) *** p<0.001, ** p<0.01, * p<0.05, + p<0.1 (3) Constant is included

Table 2E3. Reverse Causality Test: TE Model Results

VARIABLES	Model 1 IQI 91 Chronic Composite	Model 2 IQI 91 Acute Composite	Model 3 Communication score	Model 4 Rating Score	Model 5 Recommendation score	Model 6 IQI 91 Chronic Cost	Model 7 IQI 91 Acute Cost	Model 8 Cost Per Discharge
DV_{t-1}	-0.0686	-0.1415	0.4044	0.1090	0.0174	-0.7187	-0.3865	0.0939
	(0.135)	(0.335)	(0.527)	(0.210)	(0.163)	(0.493)	(0.462)	(0.262)
TE_{t-1}	0.4900**	0.4923**	0.4989**	0.4907**	0.4858**	0.4641*	0.4839**	0.4845**
	(0.185)	(0.187)	(0.183)	(0.183)	(0.184)	(0.184)	(0.184)	(0.184)
TE_{t-2}	0.0844	0.0839	0.0866	0.0826	0.0823	0.0727	0.0803	0.0819
	(0.098)	(0.098)	(0.098)	(0.098)	(0.098)	(0.098)	(0.097)	(0.098)
IT Network Effect $_t$	0.0022+	0.0021	0.0023+	0.0022+	0.0022+	0.0022+	0.0021+	0.0022+
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
HHI $_t$	7.6419*	7.8473*	7.7923*	7.8781*	7.7575*	7.2552*	7.6111*	7.7383*
	(3.407)	(3.437)	(3.526)	(3.529)	(3.493)	(3.496)	(3.449)	(3.502)
Hospital Size (log) $_t$	-0.3021	-0.3002	-0.2858	-0.3132	-0.3017	-0.3024	-0.2842	-0.3020
	(0.375)	(0.374)	(0.376)	(0.370)	(0.373)	(0.366)	(0.374)	(0.373)
Teaching $_t$	-0.1071	-0.1053	-0.1001	-0.1012	-0.1025	-0.0818	-0.0975	-0.1014
	(0.135)	(0.141)	(0.136)	(0.139)	(0.137)	(0.133)	(0.136)	(0.137)
Not-For-Profit $_t$	-1.0756*	-1.0689*	-1.0884*	-1.0765*	-1.0583*	-0.9683+	-1.0362*	-1.0624*
	(0.501)	(0.491)	(0.506)	(0.495)	(0.492)	(0.510)	(0.497)	(0.488)
Medicare $_t$	-1.0270	-0.8708	-1.0235	-0.8980	-0.9782	-1.0067	-1.0555	-0.9940
	(1.769)	(1.785)	(1.752)	(1.775)	(1.773)	(1.762)	(1.779)	(1.754)
Medicaid $_t$	0.3288	0.3388	0.2695	0.3536	0.3363	-0.0418	0.2150	0.3458
	(2.569)	(2.573)	(2.570)	(2.578)	(2.573)	(2.487)	(2.582)	(2.554)
System Member $_t$	0.1747	0.1715	0.1430	0.1666	0.1690	0.1845	0.1837	0.1708
	(0.300)	(0.304)	(0.303)	(0.298)	(0.300)	(0.297)	(0.297)	(0.300)
# Observations	384	384	384	384	384	384	384	384
# Hospital	252	252	252	252	252	252	252	252
Degree of Freedom	13	13	13	13	13	13	13	13
Chi-square	74.70	73.06	73.79	72.97	73.28	80.79	74.84	72.94

(1) Robust standard errors in parentheses (2) *** p<0.001, ** p<0.01, * p<0.05, + p<0.1 (3) Constant is included

Table 2E4. Reverse Causality Test: Support IT Model Results

VARIABLES	Model 1 IQI 91 Chronic Composite	Model 2 IQI 91 Acute Composite	Model 3 Communication score	Model 4 Rating Score	Model 5 Recommendation score	Model 6 IQI 91 Chronic Cost	Model 7 IQI 91 Acute Cost	Model 8 Cost Per Discharge
DV_{t-1}	-0.0543	-0.2528	0.6116	0.1115	0.1005	0.4535	0.5373	-0.4372
	(0.119)	(0.297)	(0.485)	(0.253)	(0.171)	(0.514)	(0.458)	(0.365)
$Support_{t-1}$	0.4943**	0.4969**	0.5133**	0.4980**	0.4927**	0.4893**	0.4721**	0.5067**
	(0.161)	(0.163)	(0.160)	(0.158)	(0.160)	(0.161)	(0.158)	(0.163)
$Support_{t-2}$	0.1974*	0.2014*	0.2036*	0.2004*	0.1970*	0.2047*	0.1945*	0.1974*
	(0.098)	(0.098)	(0.099)	(0.098)	(0.098)	(0.098)	(0.097)	(0.098)
IT Network Effect $_t$	-0.0005	-0.0006	-0.0004	-0.0005	-0.0005	-0.0005	-0.0005	-0.0006
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
HHI $_t$	-3.1903	-2.9841	-3.1203	-2.9816	-3.0858	-2.8416	-2.9032	-3.0187
	(2.344)	(2.346)	(2.354)	(2.338)	(2.297)	(2.294)	(2.297)	(2.302)
Hospital Size (log) $_t$	-0.5865	-0.5825	-0.5661	-0.5967	-0.5863	-0.5815	-0.6030	-0.5905
	(0.394)	(0.401)	(0.407)	(0.387)	(0.396)	(0.390)	(0.385)	(0.397)
Teaching $_t$	-0.7512	-0.7561	-0.7537	-0.7493	-0.7565	-0.7548	-0.7396	-0.7488
	(0.640)	(0.652)	(0.637)	(0.633)	(0.627)	(0.636)	(0.629)	(0.640)
Not-For-Profit $_t$	-0.5514	-0.5447	-0.5777	-0.5543	-0.5299	-0.5727	-0.5515	-0.5393
	(0.578)	(0.566)	(0.597)	(0.578)	(0.580)	(0.556)	(0.552)	(0.588)
Medicare $_t$	-0.8127	-0.5443	-0.8032	-0.6945	-0.7159	-0.7169	-0.6574	-0.7798
	(1.285)	(1.325)	(1.257)	(1.270)	(1.261)	(1.291)	(1.297)	(1.300)
Medicaid $_t$	0.7692	0.8058	0.7366	0.7937	0.8398	0.9985	0.8955	0.6829
	(1.852)	(1.843)	(1.835)	(1.851)	(1.852)	(1.836)	(1.849)	(1.860)
System Member $_t$	-0.1802	-0.1826	-0.2285	-0.1879	-0.1960	-0.1886	-0.1940	-0.1833
	(0.269)	(0.268)	(0.264)	(0.270)	(0.266)	(0.267)	(0.264)	(0.273)
# Observations	384	384	384	384	384	384	384	384
# Hospital	252	252	252	252	252	252	252	252
Degree of Freedom	13	13	13	13	13	13	13	13
Chi-square	43.83	43.64	45.40	44.98	46.02	44.38	45.27	45.77

(1) Robust standard errors in parentheses (2) *** p<0.001, ** p<0.01, * p<0.05, + p<0.1 (3) Constant is included

Appendix 2F: Robustness Checks

Table 2F1. Results for SUR Models: Simultaneous Complementarity

	(1) IQI 91 Chronic Composite	(2) IQI 91 Chronic Cost	(3) IQI 91 Acute Composite	(4) IQI 91 Acute Cost	(5) Communication Score	(6) Rating Score	(7) Recommendation score	(8) Cost per Discharge
Part I. Models for DS_{t-1}, TE_{t-1}, and $Support_{t-1}$								
$DS_{t-1} \times Support_{t-1}$	-0.0045	-0.0001	0.0059	-0.0057	0.0022	0.0086	-0.0111	**-0.0085***
	(0.013)	(0.005)	(0.007)	(0.005)	(0.004)	(0.009)	(0.011)	**(0.004)**
$TE_{t-1} \times Support_{t-1}$	-0.0045	-0.0066	0.0012	-0.0003	0.0064	0.0095	0.0133	-0.0086
	(0.016)	(0.006)	(0.008)	(0.006)	(0.006)	(0.011)	(0.014)	(0.005)
$DS_{t-1} \times TE_{t-1}$	0.0031	-0.0074	-0.0075	0.0009	0.0006	0.0006	0.0022	0.0013
	(0.013)	(0.005)	(0.007)	(0.005)	(0.005)	(0.009)	(0.012)	(0.004)
$DS_{t-1} \times TE_{t-1} \times Support_{t-1}$	**-0.0226+**	0.0052	-0.0078	-0.0011	0.0063	0.0141	0.0000	-0.0029
	(0.013)	(0.005)	(0.007)	(0.005)	(0.005)	(0.009)	(0.012)	(0.004)
# Observations	2,054	2,054	2,054	2,054	2,049	2,049	2,049	2,049
Breusch-Pagan test (p Value)	0.1238		0.0000				0.0000	
Part II. Models for DS_{t-2}, TE_{t-2}, and $Support_{t-2}$								
$DS_{t-2} \times Support_{t-2}$	0.0142	0.0021	0.0015	0.0000	0.0050	**0.0177+**	-0.0032	-0.0067
	(0.015)	(0.005)	(0.008)	(0.005)	(0.005)	**(0.010)**	(0.014)	(0.005)
$TE_{t-2} \times Support_{t-2}$	**-0.0477***	**-0.0187****	-0.0055	**-0.0187****	0.0029	-0.0010	-0.0086	0.0064
	(0.020)	**(0.007)**	(0.010)	**(0.007)**	(0.006)	(0.013)	(0.018)	(0.007)
$DS_{t-2} \times TE_{t-2}$	**0.0259+**	-0.0004	0.0052	0.0004	-0.0047	-0.0120	0.0004	**-0.0093+**
	(0.016)	(0.005)	(0.008)	(0.005)	(0.005)	(0.011)	(0.014)	**(0.006)**
$DS_{t-2} \times TE_{t-2} \times Support_{t-2}$	-0.0115	-0.0026	0.0051	-0.0060	**0.0099***	0.0113	**0.0242+**	0.0018
	(0.016)	(0.005)	(0.008)	(0.005)	**(0.005)**	(0.011)	**(0.014)**	(0.006)
# Observations	1,548	1,548	1,548	1,548	1,541	1,541	1,541	1,541
Breusch-Pagan test (p Value)	0.7327		0.0000				0.0000	

(1) Robust standard errors in parentheses (2) *** p<0.001, ** p<0.01, * p<0.05, + p<0.1 (3) Direct IT effect is included (4) All control variables including hospital-level variables (e.g., size, profit status, and teaching status), IT network effect, market competition effect, and year effect are included (5) Constant is included

Table 2F2. Results for SUR Models: Temporal Complementarity of Support IT

	(1) IQI 91 Chronic Composite	(2) IQI 91 Chronic Cost	(3) IQI 91 Acute Composite	(4) IQI 91 Acute Cost	(5) Communication Score	(6) Rating Score	(7) Recommendation score	(8) Cost per Discharge
Part I. Models for DS_{t-1}, TE_{t-1}, and $Support_{t-2}$								
$DS_{t-1} \times Support_{t-2}$	0.0082	**-0.0104**$^{+}$	0.0005	-0.0034	-0.0039	0.0090	**-0.0266**$^{+}$	**-0.0109**$^{+}$
	(0.018)	**(0.006)**	(0.009)	(0.006)	(0.006)	(0.012)	**(0.015)**	**(0.006)**
$TE_{t-1} \times Support_{t-2}$	-0.0024	0.0017	-0.0017	-0.0009	**0.0125**$^{+}$	-0.0195	0.0251	0.0037
	(0.021)	(0.008)	(0.011)	(0.007)	**(0.007)**	(0.014)	(0.018)	(0.007)
$DS_{t-1} \times TE_{t-1}$	0.0087	-0.0024	**-0.0176**$^{+}$	0.0043	0.0043	0.0117	-0.0065	0.0003
	(0.017)	(0.006)	**(0.009)**	(0.006)	(0.005)	(0.011)	(0.014)	(0.006)
$DS_{t-1} \times TE_{t-1} \times Support_{t-2}$	-0.0300	-0.0074	-0.0025	**-0.0126**$^{+}$	-0.0006	0.0255*	-0.0118	-0.0092
	(0.020)	(0.007)	(0.010)	**(0.007)**	(0.006)	(0.013)	(0.016)	(0.007)
# Observations	1,191	1,191	1,191	1,191	1,188	1,188	1,188	1,188
Breusch-Pagan test (p Value)	0.1238		0.0000		0.0000			
Part II. Models for DS_{t-2}, TE_{t-2}, and $Support_{t-1}$								
$DS_{t-2} \times Support_{t-1}$	0.0005	0.0063	-0.0000	0.0039	0.0061	0.0068	0.0009	-0.0015
	(0.018)	(0.006)	(0.009)	(0.006)	(0.006)	(0.012)	(0.015)	(0.006)
$TE_{t-2} \times Support_{t-1}$	-0.0051	-0.0021	0.0145	0.0022	**-0.0124**$^{+}$	-0.0077	-0.0242	0.0038
	(0.020)	(0.007)	(0.011)	(0.007)	**(0.006)**	(0.014)	(0.017)	(0.007)
$DS_{t-2} \times TE_{t-2}$	0.0031	**-0.0103**$^{+}$	0.0086	**-0.0100**$^{+}$	0.0015	-0.0008	0.0059	-0.0084
	(0.017)	**(0.006)**	(0.009)	**(0.006)**	(0.005)	(0.011)	(0.014)	(0.006)
$DS_{t-2} \times TE_{t-2} \times Support_{t-1}$	0.0225	-0.0034	-0.0115	-0.0066	0.0130*	0.0073	0.0225	0.0001
	(0.018)	(0.006)	(0.009)	(0.006)	(0.006)	(0.012)	(0.015)	(0.006)
# Observations	1,191	1,191	1,191	1,191	1,188	1,188	1,188	1,188
Breusch-Pagan test (p Value)	0.7865		0.0000		0.0000			

(1) Robust standard errors in parentheses (2) *** p<0.001, ** p<0.01, * p<0.05, + p<0.1 (3) Direct IT effect is included (4) All control variables including hospital-level variables (e.g., size, profit status, and teaching status), IT network effect, market competition effect, and year effect are included (5) Constant is included

Table 2F3. Results for SUR Models: Temporal Complementarity of TE

	(1) IQI 91 Chronic Composite	(2) IQI 91 Chronic Cost	(3) IQI 91 Acute Composite	(4) IQI 91 Acute Cost	(5) Communication Score	(6) Rating Score	(7) Recommendation score	(8) Cost per Discharge
Part I. Models for DS_{t-1}, TE_{t-2}, and $Support_{t-1}$								
$DS_{t-1} \times Support_{t-1}$	-0.0048	0.0024	-0.0005	0.0032	0.0009	0.0089	-0.0140	-0.0073
	(0.017)	(0.006)	(0.009)	(0.006)	(0.005)	(0.011)	(0.014)	(0.006)
$TE_{t-2} \times Support_{t-1}$	0.0152	-0.0044	0.0172	-0.0019	-0.0062	-0.0056	-0.0068	0.0063
	(0.020)	(0.007)	(0.010)	(0.007)	(0.006)	(0.013)	(0.016)	(0.007)
$DS_{t-1} \times TE_{t-2}$	-0.0169	0.0010	-0.0072	0.0011	-0.0007	-0.0033	-0.0040	-0.0094
	(0.017)	(0.006)	(0.009)	(0.006)	(0.005)	(0.011)	(0.014)	(0.006)
$DS_{t-1} \times TE_{t-2} \times Support_{t-1}$	0.0137	-0.0041	-0.0026	-0.0076	**0.0161****	**0.0225***	0.0036	0.0069
	(0.017)	(0.006)	(0.009)	(0.006)	**(0.005)**	**(0.011)**	(0.014)	(0.006)
# Observations	1,191	1,191	1,191	1,191	1,188	1,188	1,188	1,188
Breusch-Pagan test (p Value)	0.8667		0.0000		0.0000			
Part II. Models for DS_{t-2}, TE_{t-1}, and $Support_{t-2}$								
$DS_{t-2} \times Support_{t-2}$	0.0071	-0.0040	0.0011	-0.0073	0.0066	0.0178	-0.0021	-0.0078
	(0.017)	(0.006)	(0.009)	(0.006)	(0.005)	(0.011)	(0.014)	(0.006)
$TE_{t-1} \times Support_{t-2}$	-0.0192	-0.0026	-0.0051	-0.0043	0.0073	-0.0013	0.0071	-0.0034
	(0.018)	(0.006)	(0.010)	(0.006)	(0.006)	(0.012)	(0.015)	(0.006)
$DS_{t-2} \times TE_{t-1}$	0.0101	-0.0048	0.0008	-0.0017	-0.0039	-0.0140	-0.0122	-0.0008
	(0.015)	(0.005)	(0.008)	(0.005)	(0.005)	(0.010)	(0.012)	(0.005)
$DS_{t-2} \times TE_{t-1} \times Support_{t-2}$	-0.0218	-0.0047	-0.0024	-0.0049	**0.0155****	**0.0195**$^{+}$	0.0156	-0.0019
	(0.016)	(0.005)	(0.008)	(0.005)	**(0.005)**	**(0.010)**	(0.013)	(0.005)
# Observations	1,191	1,191	1,191	1,191	1,188	1,188	1,188	1,188
Breusch-Pagan test (p Value)	0.8746		0.0000		0.0000			

(1) Robust standard errors in parentheses (2) *** p<0.001, ** p<0.01, * p<0.05, + p<0.1 (3) Direct IT effect is included (4) All control variables including hospital-level variables (e.g., size, profit status, and teaching status), IT network effect, market competition effect, and year effect are included (5) Constant is included

Table 2F4. Results for SUR Models: Temporal Complementarity of DS

	(1) IQI 91 Chronic Composite	(2) IQI 91 Chronic Cost	(3) IQI 91 Acute Composite	(4) IQI 91 Acute Cost	(5) Communication Score	(6) Rating Score	(7) Recommendation score	(8) Cost per Discharge
Part I. Models for DS_{t-2}, TE_{t-1}, and $Support_{t-1}$								
$DS_{t-2} \times Support_{t-1}$	0.0059	0.0081	0.0072	0.0053	0.0014	0.0083	-0.0021	0.0008
	(0.017)	(0.006)	(0.009)	(0.006)	(0.005)	(0.011)	(0.014)	(0.006)
$TE_{t-1} \times Support_{t-1}$	-0.0104	0.0041	0.0062	0.0053	0.0036	0.0124	-0.0093	-0.0074
	(0.020)	(0.007)	(0.010)	(0.007)	(0.006)	(0.013)	(0.016)	(0.007)
$DS_{t-2} \times TE_{t-1}$	-0.0019	**-0.0110**$^{+}$	-0.0001	-0.0068	-0.0022	**-0.0217**$^{+}$	-0.0099	-0.0013
	(0.017)	**(0.006)**	(0.009)	(0.006)	(0.005)	**(0.011)**	(0.014)	(0.006)
$DS_{t-2} \times TE_{t-1} \times Support_{t-1}$	-0.0030	0.0009	-0.0074	-0.0016	**0.0105**$^{+}$	**0.0232***	0.0118	-0.0030
	(0.017)	(0.006)	(0.009)	(0.006)	**(0.005)**	**(0.011)**	(0.014)	(0.006)
# Observations	1,191	1,191	1,191	1,191	1,188	1,188	1,188	1,188
Breusch-Pagan test (p Value)	0.9211		0.0000		0.0000			
Part II. Models for DS_{t-1}, TE_{t-2}, and $Support_{t-2}$								
$DS_{t-1} \times Support_{t-2}$	0.0079	-0.0065	-0.0041	-0.0013	-0.0001	-0.0004	-0.0217	-0.0093
	(0.017)	(0.006)	(0.009)	(0.006)	(0.005)	(0.011)	(0.014)	(0.006)
$TE_{t-2} \times Support_{t-2}$	-0.0288	**-0.0262*****	-0.0022	**-0.0251*****	**0.0122**$^{+}$	0.0138	0.0134	-0.0002
	(0.021)	**(0.007)**	(0.011)	**(0.007)**	**(0.007)**	(0.014)	(0.017)	(0.007)
$DS_{t-1} \times TE_{t-2}$	0.0059	0.0058	0.0048	0.0069	-0.0058	-0.0035	-0.0043	-0.0032
	(0.016)	(0.006)	(0.009)	(0.005)	(0.005)	(0.011)	(0.013)	(0.005)
$DS_{t-1} \times TE_{t-2} \times Support_{t-2}$	-0.0142	0.0022	-0.0098	-0.0046	**0.0109**$^{+}$	0.0053	-0.0031	0.0015
	(0.019)	(0.006)	(0.010)	(0.006)	**(0.006)**	(0.012)	(0.015)	(0.006)
# Observations	1,191	1,191	1,191	1,191	1,188	1,188	1,188	1,188
Breusch-Pagan test (p Value)	0.9766		0.0000		0.0000			

(1) Robust standard errors in parentheses (2) *** p<0.001, ** p<0.01, * p<0.05, + p<0.1 (3) Direct IT effect is included (4) All control variables including hospital-level variables (e.g., size, profit status, and teaching status), IT network effect, market competition effect, and year effect are included (5) Constant is included

Table 2F5. Results for Fixed Effect Models with Saidin Index: Simultaneous Complementarity

	(1) IQI 91 Chronic Composite	(2) IQI 91 Acute Composite	(3) Communication Score	(4) Rating Score	(5) Recommendation score	(6) IQI 91 Chronic Cost	(7) IQI 91 Acute Cost	(8) Cost per Discharge
Part I. Models for DS_{t-1}, TE_{t-1}, and $Support_{t-1}$								
$DS_{t-1} \times Support_{t-1}$	0.0020	0.0063	-0.0003	0.0079	-0.0172	-0.0013	-0.0049	-0.0060
	(0.011)	(0.006)	(0.005)	(0.009)	(0.011)	(0.005)	(0.004)	(0.004)
$TE_{t-1} \times Support_{t-1}$	-0.0037	-0.0004	0.0060	0.0034	0.0138	-0.0003	0.0028	-0.0045
	(0.015)	(0.008)	(0.006)	(0.010)	(0.013)	(0.005)	(0.005)	(0.005)
$DS_{t-1} \times TE_{t-1}$	0.0054	-0.0073	0.0015	0.0037	0.0055	-0.0073	0.0012	-0.0004
	(0.012)	(0.008)	(0.005)	(0.009)	(0.011)	(0.006)	(0.006)	(0.004)
$DS_{t-1} \times TE_{t-1} \times Support_{t-1}$	**-0.0223***	-0.0066	0.0049	0.0117	-0.0006	0.0010	-0.0029	-0.0019
	(0.011)	(0.006)	(0.004)	(0.008)	(0.010)	(0.004)	(0.004)	(0.004)
# Observations	2,054	2,054	2,049	2,049	2,049	2,054	2,054	2,054
# Hospital	715	715	713	713	713	715	715	715
R^2	0.044	0.044	0.373	0.119	0.038	0.129	0.124	0.229
Part II. Models for DS_{t-2}, TE_{t-2}, and $Support_{t-2}$								
$DS_{t-2} \times Support_{t-2}$	-0.0032	0.0035	0.0032	0.0082	-0.0154	0.0019	0.0022	-0.0070
	(0.015)	(0.008)	(0.005)	(0.010)	(0.015)	(0.005)	(0.004)	(0.005)
$TE_{t-2} \times Support_{t-2}$	**-0.0382***	-0.0062	-0.0005	-0.0012	-0.0057	**-0.0160***	**-0.0164***	0.0015
	(0.017)	(0.010)	(0.005)	(0.011)	(0.015)	**(0.008)**	**(0.008)**	(0.006)
$DS_{t-2} \times TE_{t-2}$	**0.0273***	0.0064	-0.0035	-0.0105	0.0002	0.0000	0.0005	**-0.0076+**
	(0.014)	(0.008)	(0.004)	(0.009)	(0.011)	(0.009)	(0.009)	**(0.004)**
$DS_{t-2} \times TE_{t-2} \times Support_{t-2}$	-0.0115	-0.0004	**0.0079***	0.0089	**0.0255***	-0.0017	-0.0045	0.0025
	(0.014)	(0.008)	**(0.004)**	(0.009)	**(0.012)**	(0.007)	(0.007)	(0.005)
# Observations	1,548	1,548	1,541	1,541	1,541	1,548	1,548	1,548
# Hospital	646	646	644	644	644	646	646	646
R^2	0.045	0.041	0.327	0.092	0.025	0.123	0.119	0.174

(1) Robust standard errors in parentheses (2) *** p<0.001, ** p<0.01, * p<0.05, + p<0.1 (3) Direct IT effect is included (4) All control variables including hospital-level variables (e.g., size, profit status, and teaching status), IT network effect, market competition effect, and year effect are included (5) Constant is included

Table 2F6. Results for Fixed Effect Models with Saidin Index: Temporal Complementarity of Support IT

	(1) IQI 91 Chronic Composite	(2) IQI 91 Acute Composite	(3) Communi -cation Score	(4) Rating Score	(5) Recommendation score	(6) IQI 91 Chronic Cost	(7) IQI 91 Acute Cost	(8) Cost per Discharge
Part I. Models for DS_{t-1}, TE_{t-1}, and $Support_{t-2}$								
$DS_{t-1} \times Support_{t-2}$	0.0034	0.0003	-0.0074	-0.0026	**-0.0308***	-0.0049	0.0020	-0.0073
	(0.016)	(0.009)	(0.006)	(0.012)	**(0.014)**	(0.006)	(0.005)	(0.005)
$TE_{t-1} \times Support_{t-2}$	-0.0149	-0.0038	**0.0110+**	-0.0167	0.0178	-0.0021	-0.0027	0.0025
	(0.022)	(0.012)	**(0.007)**	(0.016)	(0.015)	(0.007)	(0.007)	(0.006)
$DS_{t-1} \times TE_{t-1}$	0.0085	**-0.0172+**	0.0042	0.0151	-0.0030	-0.0030	0.0030	-0.0019
	(0.013)	**(0.009)**	(0.005)	(0.012)	(0.014)	(0.005)	(0.005)	(0.004)
$DS_{t-1} \times TE_{t-1} \times Support_{t-2}$	-0.0175	-0.0014	0.0027	0.0229	-0.0005	-0.0043	**-0.0098+**	-0.0058
	(0.016)	(0.009)	(0.005)	(0.015)	(0.014)	(0.006)	**(0.005)**	(0.005)
# Observations	1,191	1,191	1,188	1,188	1,188	1,191	1,191	1,191
# Hospital	499	499	499	499	499	499	499	499
R^2	0.042	0.042	0.324	0.109	0.038	0.108	0.108	0.169
Part II. Models for DS_{t-2}, TE_{t-2}, and $Support_{t-1}$								
$DS_{t-2} \times Support_{t-1}$	-0.0047	0.0009	0.0051	0.0044	-0.0055	0.0033	0.0037	0.0001
	(0.015)	(0.009)	(0.005)	(0.010)	(0.015)	(0.006)	(0.006)	(0.008)
$TE_{t-2} \times Support_{t-1}$	-0.0010	0.0147	-0.0088	-0.0059	-0.0163	0.0033	0.0037	0.0055
	(0.018)	(0.009)	(0.005)	(0.010)	(0.014)	(0.006)	(0.007)	(0.006)
$DS_{t-2} \times TE_{t-2}$	0.0016	0.0083	0.0010	-0.0007	0.0061	-0.0098	-0.0086	**-0.0084+**
	(0.013)	(0.007)	(0.004)	(0.009)	(0.012)	(0.007)	(0.007)	**(0.005)**
$DS_{t-2} \times TE_{t-2} \times Support_{t-1}$	0.0128	**-0.0158***	**0.0088***	0.0053	0.0164	-0.0044	-0.0083	-0.0027
	(0.014)	**(0.008)**	**(0.004)**	(0.012)	(0.012)	(0.006)	(0.006)	(0.005)
# Observations	1,191	1,191	1,188	1,188	1,188	1,191	1,191	1,191
# Hospital	499	499	499	499	499	499	499	499
R^2	0.044	0.041	0.323	0.093	0.035	0.109	0.110	0.173

(1) Robust standard errors in parentheses (2) *** p<0.001, ** p<0.01, * p<0.05, + p<0.1 (3) Direct IT effect is included (4) All control variables including hospital-level variables (e.g., size, profit status, and teaching status), IT network effect, market competition effect, and year effect are included (5) Constant is included

Table 2F7. Results for Fixed Effect Models with Saidin Index: Temporal Complementarity of TE

	(1) IQI 91 Chronic Composite	(2) IQI 91 Acute Composite	(3) Communication Score	(4) Rating Score	(5) Recommendation score	(6) IQI 91 Chronic Cost	(7) IQI 91 Acute Cost	(8) Cost per Discharge
Part I. Models for DS_{t-1}, TE_{t-2}, and $Support_{t-1}$								
$DS_{t-1} \times Support_{t-1}$	-0.0052	-0.0041	0.0008	0.0092	-0.0137	0.0017	0.0020	-0.0047
	(0.013)	(0.008)	(0.005)	(0.010)	(0.014)	(0.005)	(0.005)	(0.005)
$TE_{t-2} \times Support_{t-1}$	0.0111	0.0134	-0.0067	-0.0120	0.0010	0.0010	0.0001	0.0061
	(0.017)	(0.011)	(0.006)	(0.013)	(0.015)	(0.007)	(0.007)	(0.006)
$DS_{t-1} \times TE_{t-2}$	-0.0154	-0.0047	-0.0000	0.0008	-0.0027	-0.0010	0.0009	**-0.0097***
	(0.012)	(0.009)	(0.005)	(0.011)	(0.013)	(0.007)	(0.007)	**(0.004)**
$DS_{t-1} \times TE_{t-2} \times Support_{t-1}$	0.0102	-0.0037	**0.0127****	0.0194	-0.0051	-0.0037	-0.0069	0.0036
	(0.012)	(0.007)	**(0.004)**	(0.014)	(0.012)	(0.006)	(0.006)	(0.004)
# Observations	1,191	1,191	1,188	1,188	1,188	1,191	1,191	1,191
# Hospital	499	499	499	499	499	499	499	499
R^2	0.041	0.034	0.322	0.097	0.031	0.103	0.103	0.175
Part II. Models for DS_{t-2}, TE_{t-1}, and $Support_{t-2}$								
$DS_{t-2} \times Support_{t-2}$	-0.0088	0.0014	0.0048	0.0104	-0.0059	-0.0039	-0.0057	-0.0082
	(0.016)	(0.008)	(0.005)	(0.011)	(0.013)	(0.006)	(0.005)	(0.005)
$TE_{t-1} \times Support_{t-2}$	-0.0208	-0.0048	0.0035	-0.0036	0.0007	-0.0030	-0.0027	-0.0013
	(0.016)	(0.009)	(0.005)	(0.009)	(0.012)	(0.006)	(0.007)	(0.006)
$DS_{t-2} \times TE_{t-1}$	0.0114	0.0008	-0.0033	-0.0138	-0.0121	-0.0044	-0.0024	-0.0016
	(0.014)	(0.008)	(0.004)	(0.009)	(0.012)	(0.007)	(0.007)	(0.005)
$DS_{t-2} \times TE_{t-1} \times Support_{t-2}$	-0.0187	-0.0063	**0.0124****	0.0147	0.0170	-0.0020	-0.0035	-0.0007
	(0.015)	(0.009)	**(0.004)**	(0.011)	(0.012)	(0.006)	(0.006)	(0.004)
# Observations	1,191	1,191	1,188	1,188	1,188	1,191	1,191	1,191
# Hospital	499	499	499	499	499	499	499	499
R^2	0.048	0.038	0.335	0.107	0.038	0.108	0.107	0.168

(1) Robust standard errors in parentheses (2) *** p<0.001, ** p<0.01, * p<0.05, + p<0.1 (3) Direct IT effect is included (4) All control variables including hospital-level variables (e.g., size, profit status, and teaching status), IT network effect, market competition effect, and year effect are included (5) Constant is included

Table 2F8. Results for Fixed Effect Models with Saidin Index: Temporal Complementarity of DS

	(1) IQI 91 Chronic Composite	(2) IQI 91 Acute Composite	(3) Communication Score	(4) Rating Score	(5) Recommendation score	(6) IQI 91 Chronic Cost	(7) IQI 91 Acute Cost	(8) Cost per Discharge
Part I. Models for DS_{t-2}, TE_{t-1}, and $Support_{t-1}$								
$DS_{t-2} \times Support_{t-1}$	0.0063	0.0103	0.0008	0.0023	-0.0043	0.0064	0.0055	0.0038
	(0.014)	(0.007)	(0.005)	(0.011)	(0.015)	(0.006)	(0.006)	(0.007)
$TE_{t-1} \times Support_{t-1}$	-0.0123	0.0019	0.0038	0.0092	-0.0085	0.0050	0.0033	-0.0048
	(0.017)	(0.008)	(0.005)	(0.010)	(0.015)	(0.005)	(0.005)	(0.007)
$DS_{t-2} \times TE_{t-1}$	-0.0039	0.0000	-0.0007	**-0.0195**$^{+}$	-0.0076	-0.0088	-0.0057	-0.0027
	(0.014)	(0.007)	(0.005)	**(0.010)**	(0.012)	(0.005)	(0.005)	(0.004)
$DS_{t-2} \times TE_{t-1} \times Support_{t-1}$	-0.0045	**-0.0115**$^{+}$	0.0061	0.0178	0.0065	-0.0019	-0.0037	-0.0027
	(0.012)	**(0.006)**	(0.004)	(0.011)	(0.012)	(0.005)	(0.005)	(0.005)
# Observations	1,191	1,191	1,188	1,188	1,188	1,191	1,191	1,191
# Hospital	499	499	499	499	499	499	499	499
R^2	0.044	0.040	0.323	0.096	0.036	0.111	0.106	0.172
Part II. Models for DS_{t-1}, TE_{t-2}, and $Support_{t-2}$								
$DS_{t-1} \times Support_{t-2}$	-0.0023	-0.0027	-0.0063	-0.0082	**-0.0307***	-0.0039	0.0027	-0.0073
	(0.016)	(0.010)	(0.005)	(0.011)	**(0.012)**	(0.005)	(0.005)	(0.005)
$TE_{t-2} \times Support_{t-2}$	-0.0278	-0.0034	0.0102	0.0139	0.0202	**-0.0219***	**-0.0220***	-0.0020
	(0.022)	(0.013)	(0.007)	(0.016)	(0.016)	**(0.009)**	**(0.010)**	(0.005)
$DS_{t-1} \times TE_{t-2}$	0.0065	0.0056	-0.0040	-0.0013	-0.0037	0.0053	0.0064	-0.0035
	(0.013)	(0.009)	(0.005)	(0.010)	(0.012)	(0.008)	(0.008)	(0.004)
$DS_{t-1} \times TE_{t-2} \times Support_{t-2}$	-0.0084	-0.0097	**0.0103***	0.0053	-0.0003	0.0015	-0.0051	0.0011
	(0.013)	(0.009)	**(0.005)**	(0.016)	(0.012)	(0.007)	(0.007)	(0.004)
# Observations	1,191	1,191	1,188	1,188	1,188	1,191	1,191	1,191
# Hospital	499	499	499	499	499	499	499	499
R^2	0.041	0.036	0.329	0.105	0.039	0.120	0.126	0.168

(1) Robust standard errors in parentheses (2) *** p<0.001, ** p<0.01, * p<0.05, + p<0.1 (3) Direct IT effect is included (4) All control variables including hospital-level variables (e.g., size, profit status, and teaching status), IT network effect, market competition effect, and year effect are included (5) Constant is included

Table 2F9. Results for Fixed Effect Models with Extra Control Variables: Simultaneous Complementarity

	(1) IQI 91 Chronic Composite	(2) IQI 91 Acute Composite	(3) Communication Score	(4) Rating Score	(5) Recommendation score	(6) IQI 91 Chronic Cost	(7) IQI 91 Acute Cost	(8) Cost per Discharge
Part I. Models for DS_{t-1}, TE_{t-1}, and $Support_{t-1}$								
$DS_{t-1} \times Support_{t-1}$	-0.0052	0.0060	0.0021	0.0089	-0.0107	-0.0005	-0.0056	**-0.0094***
	(0.012)	(0.006)	(0.005)	(0.010)	(0.011)	(0.005)	(0.004)	**(0.004)**
$TE_{t-1} \times Support_{t-1}$	-0.0024	0.0018	0.0064	0.0100	0.0138	-0.0063	-0.0003	-0.0087
	(0.016)	(0.008)	(0.006)	(0.010)	(0.014)	(0.006)	(0.006)	(0.006)
$DS_{t-1} \times TE_{t-1}$	0.0022	-0.0074	0.0007	-0.0001	0.0011	-0.0069	0.0011	0.0014
	(0.013)	(0.008)	(0.005)	(0.009)	(0.012)	(0.006)	(0.006)	(0.004)
$DS_{t-1} \times TE_{t-1} \times Support_{t-1}$	**-0.0220+**	-0.0079	0.0064	0.0144	0.0005	0.0051	-0.0012	-0.0026
	(0.013)	(0.007)	(0.005)	(0.010)	(0.011)	(0.005)	(0.004)	(0.004)
# Observations	2,054	2,054	2,049	2,049	2,049	2,054	2,054	2,054
# Hospital	715	715	713	713	713	715	715	715
R^2	0.050	0.048	0.373	0.121	0.041	0.135	0.126	0.233
Part II. Models for DS_{t-2}, TE_{t-2}, and $Support_{t-2}$								
$DS_{t-2} \times Support_{t-2}$	0.0124	0.0008	0.0056	**0.0180+**	-0.0015	0.0021	0.0002	-0.0069
	(0.015)	(0.008)	(0.005)	**(0.010)**	(0.015)	(0.005)	(0.005)	(0.005)
$TE_{t-2} \times Support_{t-2}$	**-0.0458***	-0.0046	0.0022	-0.0014	-0.0106	**-0.0187***	**-0.0189***	0.0054
	(0.018)	(0.011)	(0.005)	(0.011)	(0.015)	**(0.009)**	**(0.010)**	(0.007)
$DS_{t-2} \times TE_{t-2}$	**0.0258+**	0.0054	-0.0048	-0.0126	0.0000	-0.0006	0.0003	**-0.0093+**
	(0.015)	(0.008)	(0.004)	(0.009)	(0.012)	(0.009)	(0.010)	**(0.005)**
$DS_{t-2} \times TE_{t-2} \times Support_{t-2}$	-0.0108	0.0057	**0.0099***	0.0112	0.0245+	-0.0030	-0.0057	0.0020
	(0.016)	(0.009)	**(0.004)**	(0.010)	(0.013)	(0.008)	(0.008)	(0.006)
# Observations	1,548	1,548	1,541	1,541	1,541	1,548	1,548	1,548
# Hospital	646	646	644	644	644	646	646	646
R^2	0.048	0.046	0.334	0.098	0.030	0.137	0.126	0.187

(1) Robust standard errors in parentheses (2) *** p<0.001, ** p<0.01, * p<0.05, + p<0.1 (3) Direct IT effect is included (4) All control variables including hospital-level variables (e.g., size, profit status, and teaching status, female patient percentage, percentages of Medicare and Medicaid patient, and health system affiliation), IT network effect, market competition effect, and year effect are included (5) Constant is included

Table 2F10. Results for Fixed Effect Models with Extra Control Variables: Temporal Complementarity of Support IT

	(1) IQI 91 Chronic Composite	(2) IQI 91 Acute Composite	(3) Communi-cation Score	(4) Rating Score	(5) Recommendation score	(6) IQI 91 Chronic Cost	(7) IQI 91 Acute Cost	(8) Cost per Discharge
Part I. Models for DS_{t-1}, TE_{t-1}, and $Support_{t-2}$								
$DS_{t-1} \times Support_{t-2}$	0.0093	0.0005	-0.0038	0.0099	**-0.0256**$^{+}$	**-0.0111**$^{+}$	-0.0033	**-0.0120**$^{+}$
	(0.016)	(0.009)	(0.006)	(0.015)	**(0.015)**	**(0.006)**	(0.006)	**(0.006)**
$TE_{t-1} \times Support_{t-2}$	-0.0040	-0.0025	**0.0127**$^{+}$	-0.0202	0.0249	0.0016	-0.0015	0.0032
	(0.021)	(0.013)	**(0.007)**	(0.018)	(0.016)	(0.008)	(0.008)	(0.008)
$DS_{t-1} \times TE_{t-1}$	0.0083	**-0.0177**$^{+}$	0.0042	0.0113	-0.0072	-0.0017	0.0047	0.0001
	(0.013)	**(0.010)**	(0.006)	(0.013)	(0.014)	(0.006)	(0.006)	(0.005)
$DS_{t-1} \times TE_{t-1} \times Support_{t-2}$	**-0.0301**$^{+}$	-0.0017	-0.0011	0.0252	-0.0132	-0.0070	**-0.0122**$^{+}$	-0.0089
	(0.016)	(0.011)	(0.006)	(0.017)	(0.016)	(0.008)	**(0.007)**	(0.007)
# Observations	1,191	1,191	1,188	1,188	1,188	1,191	1,191	1,191
# Hospital	499	499	499	499	499	499	499	499
R^2	0.047	0.045	0.322	0.109	0.044	0.119	0.113	0.181
Part II. Models for DS_{t-2}, TE_{t-2}, and $Support_{t-1}$								
$DS_{t-2} \times Support_{t-1}$	0.0001	0.0002	0.0060	0.0061	-0.0001	0.0070	0.0043	-0.0022
	(0.016)	(0.008)	(0.005)	(0.011)	(0.015)	(0.006)	(0.006)	(0.008)
$TE_{t-2} \times Support_{t-1}$	-0.0034	**0.0149**$^{+}$	**-0.0123***	-0.0068	-0.0228	-0.0019	0.0024	0.0033
	(0.018)	**(0.009)**	**(0.006)**	(0.012)	(0.016)	(0.007)	(0.008)	(0.007)
$DS_{t-2} \times TE_{t-2}$	0.0032	0.0091	0.0012	-0.0009	0.0053	-0.0101	-0.0097	**-0.0084**$^{+}$
	(0.014)	(0.007)	(0.004)	(0.010)	(0.013)	(0.008)	(0.008)	**(0.005)**
$DS_{t-2} \times TE_{t-2} \times Support_{t-1}$	0.0204	-0.0121	**0.0130****	0.0063	0.0211	-0.0032	-0.0072	-0.0003
	(0.016)	(0.008)	**(0.004)**	(0.014)	(0.015)	(0.007)	(0.007)	(0.006)
# Observations	1,191	1,191	1,188	1,188	1,188	1,191	1,191	1,191
# Hospital	499	499	499	499	499	499	499	499
R^2	0.051	0.045	0.327	0.096	0.042	0.120	0.113	0.179

(1) Robust standard errors in parentheses (2) *** p<0.001, ** p<0.01, * p<0.05, + p<0.1 (3) Direct IT effect is included (4) All control variables including hospital-level variables (e.g., size, profit status, and teaching status, female patient percentage, percentages of Medicare and Medicaid patient, and health system affiliation), IT network effect, market competition effect, and year effect are included (5) Constant is included

Table 2F11. Results for Fixed Effect Models with Extra Control Variables: Temporal Complementarity of TE

	(1) IQI 91 Chronic Composite	(2) IQI 91 Acute Composite	(3) Communication Score	(4) Rating Score	(5) Recommendation score	(6) IQI 91 Chronic Cost	(7) IQI 91 Acute Cost	(8) Cost per Discharge
Part I. Models for DS_{t-1}, TE_{t-2}, and $Support_{t-1}$								
$DS_{t-1} \times Support_{t-1}$	-0.0045	-0.0005	0.0009	0.0095	-0.0134	0.0020	0.0032	**-0.0085**$^{+}$
	(0.015)	(0.008)	(0.005)	(0.011)	(0.014)	(0.006)	(0.006)	**(0.005)**
$TE_{t-2} \times Support_{t-1}$	0.0156	0.0175	-0.0062	-0.0053	-0.0062	-0.0039	-0.0020	0.0051
	(0.017)	(0.011)	(0.006)	(0.013)	(0.016)	(0.008)	(0.008)	(0.006)
$DS_{t-1} \times TE_{t-2}$	-0.0168	-0.0066	-0.0011	-0.0040	-0.0051	0.0017	0.0016	**-0.0087**$^{+}$
	(0.014)	(0.010)	(0.005)	(0.012)	(0.014)	(0.008)	(0.008)	**(0.004)**
$DS_{t-1} \times TE_{t-2} \times Support_{t-1}$	0.0139	-0.0031	**0.0164*****	0.0230	0.0044	-0.0047	-0.0078	0.0068
	(0.013)	(0.008)	**(0.004)**	(0.014)	(0.014)	(0.007)	(0.008)	(0.004)
# Observations	1,191	1,191	1,188	1,188	1,188	1,191	1,191	1,191
# Hospital	499	499	499	499	499	499	499	499
R^2	0.050	0.041	0.326	0.100	0.037	0.113	0.108	0.183
Part II. Models for DS_{t-2}, TE_{t-1}, and $Support_{t-2}$								
$DS_{t-2} \times Support_{t-2}$	0.0061	0.0007	0.0065	0.0176	-0.0027	-0.0045	-0.0074	**-0.0093**$^{+}$
	(0.017)	(0.008)	(0.005)	(0.011)	(0.014)	(0.007)	(0.006)	**(0.006)**
$TE_{t-1} \times Support_{t-2}$	-0.0203	-0.0054	0.0074	-0.0018	0.0065	-0.0024	-0.0045	-0.0040
	(0.018)	(0.010)	(0.005)	(0.009)	(0.012)	(0.008)	(0.008)	(0.007)
$DS_{t-2} \times TE_{t-1}$	0.0106	0.0007	-0.0038	-0.0136	-0.0115	-0.0053	-0.0017	-0.0006
	(0.015)	(0.008)	(0.004)	(0.009)	(0.012)	(0.007)	(0.007)	(0.005)
$DS_{t-2} \times TE_{t-1} \times Support_{t-2}$	-0.0219	-0.0019	**0.0153*****	**0.0193**$^{+}$	0.0151	-0.0040	-0.0049	-0.0006
	(0.016)	(0.009)	**(0.004)**	**(0.011)**	(0.013)	(0.007)	(0.007)	(0.005)
# Observations	1,191	1,191	1,188	1,188	1,188	1,191	1,191	1,191
# Hospital	499	499	499	499	499	499	499	499
R^2	0.048	0.041	0.337	0.113	0.044	0.119	0.112	0.178

(1) Robust standard errors in parentheses (2) *** p<0.001, ** p<0.01, * p<0.05, + p<0.1 (3) Direct IT effect is included (4) All control variables including hospital-level variables (e.g., size, profit status, and teaching status, female patient percentage, percentages of Medicare and Medicaid patient, and health system affiliation), IT network effect, market competition effect, and year effect are included (5) Constant is included

Table 2F12. Results for Fixed Effect Models with Extra Control Variables: Temporal Complementarity of DS

	(1) IQI 91 Chronic Composite	(2) IQI 91 Acute Composite	(3) Communication Score	(4) Rating Score	(5) Recommendation score	(6) IQI 91 Chronic Cost	(7) IQI 91 Acute Cost	(8) Cost per Discharge
Part I. Models for DS_{t-2}, TE_{t-1}, and $Support_{t-1}$								
$DS_{t-2} \times Support_{t-1}$	0.0055	0.0075	0.0012	0.0075	-0.0032	0.0091	0.0057	-0.0002
	(0.015)	(0.007)	(0.005)	(0.011)	(0.013)	(0.006)	(0.006)	(0.007)
$TE_{t-1} \times Support_{t-1}$	-0.0081	0.0064	0.0040	0.0142	-0.0068	0.0033	0.0055	-0.0079
	(0.020)	(0.009)	(0.006)	(0.012)	(0.016)	(0.006)	(0.006)	(0.009)
$DS_{t-2} \times TE_{t-1}$	-0.0025	-0.0005	-0.0022	**-0.0220***	-0.0101	**-0.0116***	-0.0069	-0.0017
	(0.016)	(0.008)	(0.005)	**(0.011)**	(0.013)	**(0.005)**	(0.005)	(0.005)
$DS_{t-2} \times TE_{t-1} \times Support_{t-1}$	-0.0020	-0.0072	**0.0107***	**0.0242+**	0.0131	0.0011	-0.0018	-0.0015
	(0.015)	(0.008)	**(0.005)**	**(0.013)**	(0.013)	(0.005)	(0.005)	(0.005)
# Observations	1,191	1,191	1,188	1,188	1,188	1,191	1,191	1,191
# Hospital	499	499	499	499	499	499	499	499
R^2	0.050	0.043	0.325	0.101	0.041	0.122	0.110	0.178
Part II. Models for DS_{t-1}, TE_{t-2}, and $Support_{t-2}$								
$DS_{t-1} \times Support_{t-2}$	0.0078	-0.0048	0.0002	0.0001	-0.0209	-0.0075	-0.0014	**-0.0104***
	(0.017)	(0.010)	(0.006)	(0.013)	(0.014)	(0.005)	(0.006)	**(0.005)**
$TE_{t-2} \times Support_{t-2}$	-0.0273	-0.0007	0.0118	0.0142	0.0135	**-0.0251***	**-0.0247***	-0.0009
	(0.025)	(0.015)	(0.008)	(0.017)	(0.018)	**(0.011)**	**(0.011)**	(0.006)
$DS_{t-1} \times TE_{t-2}$	0.0063	0.0053	-0.0060	-0.0038	-0.0048	0.0066	0.0073	-0.0027
	(0.014)	(0.009)	(0.005)	(0.010)	(0.012)	(0.008)	(0.009)	(0.004)
$DS_{t-1} \times TE_{t-2} \times Support_{t-2}$	-0.0156	-0.0106	**0.0111+**	0.0047	-0.0040	0.0015	-0.0047	0.0014
	(0.017)	(0.011)	**(0.006)**	(0.018)	(0.015)	(0.009)	(0.009)	(0.005)
# Observations	1,191	1,191	1,188	1,188	1,188	1,191	1,191	1,191
# Hospital	499	499	499	499	499	499	499	499
R^2	0.045	0.038	0.327	0.106	0.041	0.133	0.127	0.179

(1) Robust standard errors in parentheses (2) *** p<0.001, ** p<0.01, * p<0.05, + p<0.1 (3) Direct IT effect is included (4) All control variables including hospital-level variables (e.g., size, profit status, and teaching status, female patient percentage, percentages of Medicare and Medicaid patient, and health system affiliation), IT network effect, market competition effect, and year effect are included (5) Constant is included

CHAPTER 3 A BIVARIATE DYNAMIC LATENT DIFFERENCE SCORE MODEL FOR LONGITUDINAL DATA ANALYSIS

Abstract

This research introduces a BDLDSM to analyze the dynamic lead-lag association between predictor and outcome variables in a longitudinal framework. The BDLDSM is a powerful tool for IS researchers aiming to use a panel data set to explore longitudinal theories related to change. In contrast to traditional longitudinal analysis techniques, BDLDSM allows IS researchers to (1) examine dynamic lead-lag associations between two variables over time; (2) simultaneously model change trajectories in both variables over time; (3) test for a reciprocal relationship between two variables over time; and (4) identify different types of dynamic effects.

Here, we first review the longitudinal analysis techniques most commonly applied in the IS field from 2008–2017, and then compare BDLDSM with these widely applied techniques. Second, we discuss the need for BDLDSM in the IS field and introduce BDLDSM with both linear and nonlinear functional forms of change. Third, we apply BDLDSM in a HIT impact context and unveil the dynamic interplay between different HIT functions and various dimensions of hospital performance. We next compare BDLDSM using linear and nonlinear functional forms and compare BDLDSM with latent growth modeling. We conclude with a discussion of BDLDSM's implications for longitudinal data analysis in the IS field.

Keywords: Bivariate Dynamic Latent Difference Score Model, Latent Growth Model, Quality of Care, Cost of Care, Health Information Technology (HIT), Business Value of IT, Longitudinal Research

3.1 Introduction

In recent years, an increasing number of empirical papers in the IS field have been using traditional longitudinal data analysis techniques, such as linear unobserved effects panel data models (e.g., fixed/random effects models), random-coefficient models, and structural equation modeling (SEM) (Zheng et al. 2014). However, these traditional panel data models suffer from two major drawbacks. First, they fail to incorporate time-dependent changes in the variables, despite the fact that IS phenomena often have two constantly changing variables in a dynamic relationship. For example, IT usage may evolve over time such that its mean trajectory is nonlinear, while IT usage's impact on task performance may also evolve, but with a linear mean trajectory (Benlian 2015). Traditional panel data analyses, such as fixed-effects modeling, can neither support trajectory change assessment nor answer research questions such as *How does the nonlinear change in IT usage impact the linear change in task performance?* Research examining time-dependent changes in variables, however, is important in theory building—both to understand change patterns and to explore the longitudinal and dynamic relationships among variables (Zheng et al. 2014).

LGM, which was recently introduced into IS, addresses the time-dependent change issue, and researchers can use it to model how the change process evolves (Zheng et al. 2014). For example, some researchers have used LGM to evaluate how trust in a new IT artifact develops over time (Söllner et al. 2016) or to examine the longitudinal dynamics of knowledge artifacts (Babik et al. 2015). LGM has also been used to develop longitudinal theories. For instance, it has been applied to examine how employee job characteristics change during an enterprise system implementation (Bala and Venkatesh 2013); to uncover feature-level changes in IT usage over time, as well as the impact of those changes on an individual's task performance (Benlian 2015);

and to test the relationship between competitive repertoire and performance over time (Li et al. 2015). Taken together, we can infer that LGM use has enabled IS researchers to make inroads into developing change-associated theories.

LGM does not, however, address the second drawback of traditional panel data models—namely, their inability to examine the reciprocal relationship, or feedback loop, between variables over time. IT researchers could benefit from an analysis technique that addressed this issue. For example, while the IT business value literature has established that IT investment can improve productivity, recent research suggests that such improvements also lead to subsequent IT investment (Baker et al. 2017). Neither traditional panel data models nor LGM can examine whether a positive feedback loop exists between IT investment and productivity improvement in a single model while incorporating the time-dependent changes.

This study addresses the two drawbacks mentioned above and introduces a more comprehensive and advanced LGM—a BDLDSM, also known as a *latent change score model*—to understand how variable relationships evolve over time. BDLDSM both answers the research questions LGM addresses and lets IS researchers test the reciprocal relationship and the dynamic feedback loop between variables to examine *dynamic* lead-lag associations between two variables over time. It does this by testing how previous changes in both variables can be used to predict an outcome variable's subsequent changes and to decompose that variable's dynamic effects (Grimm et al. 2016a).

Here, we illustrate BDLDSM application in the HIT context by investigating the longitudinal relationship between different HIT functions and various hospital performance measures. The rationale is that extant HIT research largely relies on a static framework to examine the relationship between HIT implementation and healthcare performance, and such a

framework might be unable to reveal the dynamic relationship between HIT and healthcare performance. Further, the few studies that have applied a dynamic framework have overlooked the influence of the variables' trajectory change and the dynamic lead-lag associations between HIT and healthcare performance (Furukawa et al. 2010; Menon and Kohli 2013; Sharma et al. 2016). Considering the trajectory changes for both the HIT implementation and healthcare performance is important when examining the time-dependent dynamic lead-lag association between them because this trajectory change can be either linear or nonlinear. Moreover, HIT implementation and healthcare performance may have different functional forms of trajectory change. Overlooking the trajectory change forms could lead the model to inaccurately estimate the causal relationship between predictor and outcome variables. Furthermore, HIT implementation and healthcare performance might have a dynamic, reciprocal relationship over time. Understanding how HIT implementation and healthcare performance evolve over time has practical importance, yet researchers have never studied this dynamic association. Exploring this complex relationship in a dynamic change rate framework provides a more comprehensive account of the interplay between HIT implementation and healthcare performance.

This study aims to make two major contributions to the IS literature. First, it extends current understanding of LGM in the IS field and gives IS researchers guidelines for developing a BDLDSM, which is a model ideally suited to studying the dynamic, longitudinal relationship between variables while incorporating their change trajectories. Despite its significant potential for confirming longitudinal theoretical models, BDLDSM has not, to our knowledge, been applied in the IS literature. Second, we extend the current literature on HIT impact on healthcare performance by offering a dynamic, nonlinear growth rate perspective. Emphasizing the role of context (Banger and Graber 2015), we examine two types of healthcare cost measures

(experiential and clinical quality) and three types of HIT functions (ECD, CPOE, and DS) to develop a more comprehensive understanding of the relationship between HIT implementation and healthcare performance.

3.2 Literature Review

3.2.1 Review of Longitudinal Research in the IS Field

Longitudinal, or *panel*, data refers to data collected through repeated observations over time on the same cross-sectional units (Frees 2004; Wooldridge 2010) such as individuals, households, firms, or countries. To uncover state-of-the-art analysis techniques in longitudinal analysis, we began by reviewing the longitudinal research published in the AIS website's "Senior Scholars' Basket of Journals." The journals we reviewed for 2008–2017 included *European Journal of Information Systems* (EJIS), *Information Systems Journal* (ISJ), *Information Systems Research* (ISR), *Journal of the Association for Information Systems* (JAIS), *Journal of Information Technology* (JIT), *Journal of Management Information Systems* (JMIS), *MIS Quarterly* (MISQ), and *Journal of Strategic Information Systems* (JSIS). We started the search process using the keyword "longitudinal" on the ISI Web of Science database, initially identifying 170 articles with "longitudinal" in the title, abstract, or keywords. We then scanned these papers to determine whether they were longitudinal research papers. Of these, we identified 164 papers as longitudinal research papers; they included 77 quantitative papers, 73 qualitative papers, 2 design science papers, 9 review papers, and 3 method papers.

For our study, we examined only the 77 quantitative longitudinal papers, the majority of which were published in MISQ (28 papers) and ISR (24 papers). Of the remaining papers, 8 were published in EJIS, 8 in JAIS, 5 in JMIS, 2 in JSIS, 1 in JIT, and 1 in ISJ. Of the 77 papers, 29 were published from 2008–2012, while 48 were published from 2013–2017, suggesting an

increased interest in longitudinal research. We coded the articles based on four dimensions: research question, hypotheses, time span of collected data, and analysis techniques used. The collected data's time span ranged from 75 minutes to 28 years. As Table 3.1 shows, the three most common analysis techniques used were SEM (24 papers), linear unobserved effects panel data model (12 papers), and random-coefficient model (11 papers). We now discuss the advantages and disadvantages of these and other quantitative research techniques used in the longitudinal papers.

Table 3.1 Review of Longitudinal Papers in the IS Field

Research Technique	IS Papers from 2008 – 2017
SEM/PLS	Wu et al. (2017); Zhang and Venkatesh (2017); Sykes and Venkatesh (2017); Sun and Fang (2016); Steinbart et al. (2016); Boss et al. (2015); Bhattacherjee and Lin (2015); Barnett et al. (2015); Hu et al. (2015); Sykes (2015); Bhattacherjee and Park (2014); Tsai and Bagozzi (2014); Ou et al. (2013); Sun (2013); Venkatesh and Sykes (2013); Venkatesh and Windeler (2012); Goh and Wasko (2012); Venkatesh et al. (2011a); Venkatesh et al. (2011b); Chengalur-Smith et al. (2010); Kim (2009); Kim et al. (2009); Sykes et al. (2009); Venkatesh et al. (2008)
Linear Unobserved Effects Model	Baker et al. (2017); Atasoy et al. (2016); Luo et al. (2016)； Kim et al. (2016); Yan et al. (2015); Peng et al. (2014); Parker and Weber (2014); Menon and Kohli (2013); Dedrick et al. (2013); Wang et al. (2013); Butler and Wang (2012); Hahn et al. (2009)
Random-Coefficient Models	Angst et al. (2017); Zhang (2017); Safi and Yu (2017); Venkatesh et al. (2016); Ma et al. (2014); Sasidharan et al. (2012); Setia et al. (2012); Ko and Dennis (2011); Goes et al. (2010); Lu and Ramamurthy (2010); Rai et al. (2009)

The SEM method is a multivariate statistical analysis technique that analyzes causal relationships among latent variables (Bollen 2011). SEM has been widely adopted by IS researchers over the past two decades. However, SEM, whether based on linear equations or covariance structures, collects data at a single time point and thus cannot be used to establish causality, and it cannot handle nonlinearities (Zheng and Pavlou 2010). IS researchers therefore attempt to use longitudinal data to overcome the causality inference limitation. A common

approach here is to collect the predictor and outcome variables at different time points. To study technology adoption's impact and the effectiveness of system use, for example, IS researchers can collect data at separate time points for pre-adoption intention, actual adoption usage, and post-adoption proficiency or performance variables (Sun 2013; Sykes et al. 2009; Venkatesh et al. 2011a; Venkatesh et al. 2011b). Yet, most papers collect the predictor and outcome variables only at single, separate time points, and thus the predictors are measured at a point in time that precedes measurement of the outcome variable(s). While such an approach deals with temporal precedence, it does not lend itself to tracking changes in the predictor or outcome variables over time. To examine the change trajectory of predictor and outcome variables, IS researchers apply LGM in the SEM framework (Bala and Venkatesh 2013; Benlian 2015); we discuss LGM in detail later.

Another longitudinal analysis technique commonly applied in the IS field is the *linear unobserved effects panel data model*. In this model, unobserved effects from time-constant variables capture the features of individual units that do not change over time (Wooldridge 2010). Two commonly used linear unobserved effects models are the fixed-effects model and the random-effects model. In the *fixed-effects model*, the unobserved effects are treated as fixed effects, which lets unobserved effects arbitrarily correlate with the predictors (Wooldridge 2010). For example, to control the arbitrary dependence between unobserved effects and the independent variables, Butler and Wang (2012) employed a fixed-effect analysis technique at the newsgroup level to test content boundary reshaping's effect on member dynamics and community responsiveness, while Luo et al. (2016) applied a fixed-effects model at the firm level to examine the impact of technologies on cross-channel capabilities and managerial actions. In the *random-effects model*, the unobserved effects are treated as random effects, which does

not let unobserved effects arbitrarily correlate with the predictors (Wooldridge 2010). Random-effects models are used when unobserved effects are uncorrelated with independent variables (e.g. Baker et al. (2017) or when time-invariant estimators are important (e.g., Langer et al. (2014). While both fixed- and random-effects models can examine whether a certain relationship between the predictor and outcome variables exists over time, these models fail to address the change trajectories in variables over time.

The third longitudinal analysis technique commonly used in the IS field is *random-coefficient models*, which allow slopes to differ across individuals. This technique is usually applied to analyze hierarchically nested data; over the past 10 years, hierarchical linear modeling (HLM) has been the most popular random-coefficient model applied in the IS field. Researchers can use HLM to study the relationships within and between hierarchical units. For example, with a multilevel longitudinal dataset, Rai et al. (2009) used HLM to study the impact of relational factors on strategic offshore IS project success, using cultural differences framing at two levels—the project-leader level and the project level. Venkatesh et al. (2016) applied HLM to examine how ICT interventions can improve high infant mortality with variables at the village level and the infant level. Although HLM can test hypotheses related to hierarchical units, it also fails to incorporate the change trajectories in variables over time.

In addition to these three commonly used longitudinal analysis techniques, IS researchers also use other models and techniques to analyze longitudinal datasets. To study the *change rate*'s impact on the relationship between predictor and outcome variables, IS researchers may collect data from multiple time points, analyze the data from each time point in the same structural model, and then compare the results. For example, Peng and Eunni (2011) analyzed data from 1984, 1989, 1993, 1997, 2001, and 2003 in the same research model to study the change of wage

premium for employees with computer skills. They found that the wage premium increased from 1984–1993, remained the same in 2001, and decreased in 2003, concluding that the change in wage premium followed an inverted-U shape over time. As another example, to study the trajectory changes in the evolution of content management systems, Vitari and Ravarini (2009) collected data at three phases of that evolution. However, this technique fails to incorporate the variables' within-unit changes in the model over time.

To study the duration of time until one event happens, IS researchers have applied survival analysis. For example, Yaraghi et al. (2015) used this approach with an accelerated failure-time model to test hypotheses related to the time it takes to adopt health information exchanges, while Scherer et al. (2015) applied survival analysis using Cox's proportional hazard model to study customer defection in self-service settings. This approach is not relevant for our research questions, however, as we do not focus on research questions related to time duration.

3.2.2 Review of LGM Research in the IS Field

While IS researchers have widely implemented traditional SEM, their use of LGM has been limited (Li et al. 2015b; Zheng et al. 2014). LGM's major advantage over other traditional SEM, however, is that it offers precise information on longitudinal inter-unit change patterns—that is, on the change trajectories in variables over time (Benlian 2015; Zheng et al. 2014) which are important from a theoretical perspective. Zheng et al. (2014) have discussed the importance of introducing LGM in the IS field from both theoretical and practical perspectives, and provided analysis guidelines to help IS researchers better describe, measure, analyze, and theorize longitudinal change. They have also discussed LGM's advantages and limitations compared to other longitudinal approaches, such as repeated-measures ANOVA, fixed or random effects, time-series analysis techniques, functional data analysis, and traditional SEM models (Zheng et

al. 2014). A few IS researchers have applied LGM in their research. Bala and Venkatesh (2013) used LGM analysis techniques to develop a job characteristic change model during an enterprise system implementation and found that job characteristic changes are associated with employee job satisfaction. To measure the functional forms of change, they considered four different types of growth models: a no-growth model, a linear growth model, a quadratic model, and an optimal growth model. As another example, Benlian (2015) adopted LGM and tested three functional forms of change in IT usage, including a no-growth model, a linear model, and a free-form model; he found that IT usage at the feature level increases nonlinearly over time, but with diminishing growth rates, which suggests that employee IT system usage is different at early and later stages. This research gives researchers and practitioners a dynamic view of feature-level IT usage and its impact on individuals' task performance.

Despite its benefits, LGM has three limitations. First, it cannot uncover the reciprocal relationship or feedback loop between variables over time, which is important to IS analysis. In the IT business value research area, Baker et al. (2017) tried to examine a positive feedback loop between IT investment and a firm's productivity over time. The authors applied a linear unobserved effects panel data model to examine whether improved productivity leads to additional IT investment, but they failed to examine whether additional IT investment improved productivity in the same model. To test the feedback loop between IT investment and a firm's productivity, researchers need a dynamic, reciprocal analysis framework. The need to examine reciprocal relationships or reciprocity behaviors is not uncommon in IS research. For instance, Ou et al. (2013) studied *guanxi*—the Chinese term for a close relationship based on a reciprocal favor—in a computer-mediated communication platform in an online marketplace context. *Reciprocal favor* refers to positive benefits that come from the interaction between buyers and

sellers (Ou et al. 2013). Untangling the positive feedback loop between buyers and sellers in an online marketplace makes it possible to test nuanced hypotheses about these reciprocal favors. As another example, in the IS field, the norm of reciprocity is studied as a relational factor within a dyadic relationship in the knowledge exchange context (Beck et al. 2014). If we can open the black box of the norm of reciprocity, we can unveil the dynamic exchange relationship between knowledge seeker and knowledge contributor. Reciprocity can also play an important role in the application of social network theories (Bapna et al. 2017; Goh et al. 2016), as revealing reciprocal behaviors among social network members can help IS researchers understand the network's dynamics.

Second, LGM captures only the time-invariant, or *static*, associations between these two constructs, although it can be used to simultaneously model the time-contingent changes in both the dependent and independent variables (Grimm et al. 2016a). This static association between constructs cannot be used to examine effects related to subsequent change or movement. This can lead to an inadequate development of dynamic change theories. For instance, Zheng et al. (2014) used LGM to examine the relationship between word-of-mouth (WOM) communication and book sales over time. They found a negative correlation between the slope (individual rate of change) of WOM communication and the slope of Amazon sales rank, indicating that products with a slower growth of WOM communication *tend to* see a faster decrease in sales compared to other products studied. This negative association is a static between-person association; that is, it fails to unveil the dynamic association between the predictor and outcome variables by examining whether changes in the predictor variable precede changes in the outcome variable (Grimm et al. 2016a). For example, LGM cannot be used to examine whether the changes in WOM communication precede the changes in the sales rank, and thus cannot be used to conclude

that a slower growth of WOM communication is *predicted* to lead to a faster decrease in book sales.

Third, LGM cannot decompose the dynamic change effect from the time-variant variables. For example, changes in the dependent variable may be influenced by the prior state of the dependent and independent variables and by the dependent variable's overall mean change trajectory over time. Likewise, the independent variable's change may be influenced by the prior state of the independent and dependent variables and the independent variable's overall mean change trajectory over time. To comprehensively understand the relationship between independent and dependent variables, we must consider all of the dynamic effects that determine the relationship between dependent and independent variables in a single model.

To uncover the reciprocal relationship between variables over time, to examine the dynamic association between the predictor and outcome variables over time, and to decompose the dynamic change effect from the outcome variable, we must extend our current understanding of LGM and introduce an advanced dynamic LGM—that is, BDLDSM. Figure 3.1 presents the relationships between SEM, LGM, and BDLDSM: SEM comprises LGM, while LGM comprises BDLDSM.

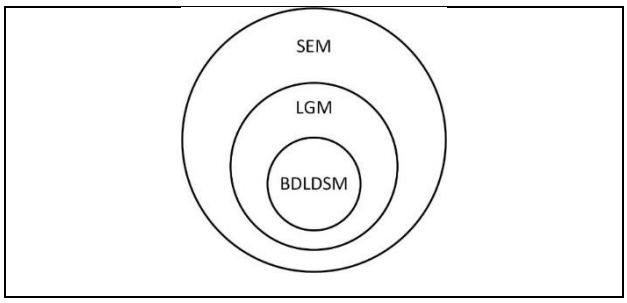


Figure 3.1 Relationship Diagram for SEM, LGM, and BDLDSM

3.2.3 The Choice of Statistics Techniques in Longitudinal Research

We created four guidelines for IS researchers to determine which statistical techniques to use when conducting longitudinal research. First, researchers should identify the role of time in the theory-building process and ensure that their paper's design and analysis align with the theory (George and Jones 2000; Mitchell and James 2001). If researchers want to address the time lag between the predictor variable *X* and the outcome variable *Y* for causal inference, they can use SEM, a linear unobserved effects model, or a random-coefficients model. If they want to incorporate the mean trajectory change of *X* or *Y* in the longitudinal model, they can use either LGM or BDLDSM. If researchers want to examine the dynamic interrelations or reciprocal relationship between *X* and *Y*, they can use BDLDSM. Also, if they want to decompose the dynamic effect of variables, they can use BDLDSM. Or, if researchers want to study other aspects of time—such as frequency, cycles, intensity, and duration—they can use other specific analysis techniques to examine time's role. For example, if researchers want to study when events occur by using time duration as an outcome, they can use survival analysis techniques.

Second, researchers should consider how many waves of repeated measures are collected. While linear unobserved effects models and random-coefficients models need at least two time points of repeated measures, LGM and BDLDSM need at least three time points of data (Zheng et al. 2014). At least three waves of data are needed to identify and conceptualize the trajectory of change (Bala and Venkatesh 2013; Chan 1998), while at least four points of repeated measures are needed to distinguish nonlinearities in LGM and BDLDSM (Raudenbush 2001). Third, researchers should consider whether they need to test multilevel hypotheses. If so, they need to use either a random-coefficients model or multi-level SEM/LGM/BDLDSM. Fourth, researchers should consider the hypothesized underlying the model of change and choose a

research analysis technique accordingly (Ferrer and McArdle 2003). For example, if identifying growth in each variable is important in the hypotheses and may be detected in the data, they can use LGM or BDLDSM. If identifying growth is not important to the hypotheses or the theory, researchers do not need to use growth analysis techniques. Table 3.2 compares the characteristics of the longitudinal models.

Table 3.2 Model Characteristic Comparison

	SEM		**LGM**	**BDLDSM**	**Linear Unobserved Effects Model**	**Random Coefficient Model**
Time periods	1	>=2	>=3	>=3	>=2	>=2
Within-unit Change	No	No	Yes	Yes	Yes	Yes
Between-unit Change	No	Yes	Yes	Yes	Yes	Yes
Change of Mean Trajectory	No	No	Yes	Yes	No	No
Dynamic Relationship	No	No	No	Yes	No	No
Dynamic Effect Identification	No	No	No	Yes	No	No
Reciprocal Relationship (X<->Y)	No	No	No	Yes	No	No

3.3 BDLDSM Model

In the following sections, we first discuss the value of and need for BDLDSM in the IS field, then introduce autoregressive models, the latent change score model, and latent growth models. After introducing BDLDSM and describing how to incorporate the functional form of change into it, we describe our modeling approach, which aligns with the structural models for multivariate longitudinal data analysis (Ferrer and McArdle 2003; Grimm et al. 2016; McArdle and Nesselroade 1994; Nesselroade and Cable 1974). Finally, we propose a four-step process to conduct BDLDSM analysis.

3.3.1 The Value of and Need for BDLDSM in the IS Field

Contemporary research on longitudinal data analysis is shifting its focus toward tracking change trajectories over time; as such, it calls for new techniques that combine features of existing

analysis techniques, including factor analysis, multivariate analyses of variance, and time series techniques (Ferrer and McArdle 2003; McArdle 2009). These new techniques help researchers better interpret longitudinal data, answer new research questions, test change-related hypotheses, and promote time-related theory development. By incorporating features of hierarchical linear models, multilevel models, random-coefficient models, LGM, linear unobserved effects models, and SEM, BDLDSM examines not only the trajectory change of each individual unit, or the *within-unit change*, but also the *between-unit change*, which describes how individual units vary in their trajectories (Raudenbush 2001). BDLDSM not only answers the research questions that LGM answers, but it can also answer more complicated and nuanced research questions about dynamic associations between two variables across time by using the change in one variable from *t-1* to time *t* as the outcome instead of directly using the variable at a given time point. Researchers can use this model to test whether prior changes, including within-unit and between-unit changes, predict subsequent changes and to examine the reciprocal relationship between variables over time.

BDLDSM has been applied in various contexts—including education, sociology, and psychology—to study the dynamic interplay between two or more constructs (Grimm et al. 2016a). For example, Grimm et al. (2016a) used BDLDSM to examine the lead-lag relationship between children's mathematics ability and their visual motor integration. They found that children with higher visual motor integration have more positive subsequent changes in their mathematics ability. To capture the dynamic interplay between students' motivation and their perceived competences during their first semester in high school, Ferrer and McArdle (2003) applied BDLDSM to examine the growth rate of and dynamic relationship between these two constructs over time and found that, while motivation has relatively flat trajectories, the

trajectories of competence scores increase over time. They discovered that, over time, motivation is the leading indicator in the interrelations between competence and motivation. BDLDSM can be applied to study developmental theories as well. Grimm (2007) studied the relationship between depression and academic achievement, implementing BDLDSM to examine how the time-dependent change of depression can be predicted by previous academic achievement scores, and vice versa. In another example, to study the relationship between two developmental processes—changes in memory performance and changes in brain size—Grimm et al. (2012) applied BDLDSM to unveil how the effects from recent changes from one developmental process led to subsequent changes in the other developmental process. They found, for example, that an increase in the lateral ventricle size leads to subsequent declines in memory performance for seniors. In the psychology field, Sbarra and Allen (2009) used BDLDSM to study development issues related to sleep and mood disturbances, while Kim and Deater-Deckard (2011) applied BDLDSM to study development issues related to dynamic changes in anger and to externalizing and internalizing problems.

BDLDSM offers IS researchers a comprehensive, dynamic view of trajectory change. IS researchers can use BDLDSM to unpack research questions that cannot be answered by traditional longitudinal research models. Those questions include the following:

1. What are the shapes of the trajectories of the outcome and predictor variables?
2. What are the dynamic lead-lag associations between two variables across time? Specifically, what is the best model for explaining the relationship between predictor (X) and outcome (Y) variables?

   (1) BDLDSM with no coupling effects

   (2) BDLDSM with a coupling effect from X to the change of Y (ΔY)

(3) BDLDSM with full coupling effects, including a coupling effect from *X* to Δ*Y* and a coupling effect from *Y* to Δ*X*

3. How can we decompose the dynamic change effects of *Y*?

3.3.2 A Brief Introduction of BDLDSM

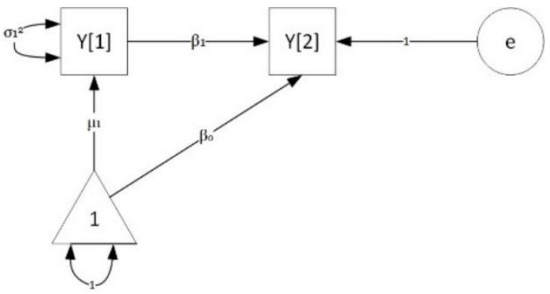
Latent change score or latent difference score models are jointly analyzed by integrating aspects of autoregressive models, the latent change score model, and LGM for longitudinal panel data analysis. Thus, we will introduce these three models before introducing BDLDSM.

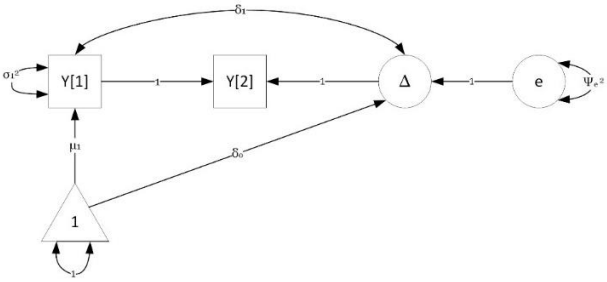
Auto-Regressive Model

Embracing a rich history across disciplines ranging from econometrics to psychology to sociology, the auto-regressive (AR) model assumes that the dependent variable in a given point in time, *t*, depends linearly on its earlier assessment (Hoyle 2012). For an observed variable, *Y*, with order of *p* at time *t*, this relationship is expressed as follows:

$$Y_t = \beta_0 + \sum_{j=1}^{p} \beta_p Y_{t-1} + \varepsilon_t.$$

Figure 3.2a, adapted from McArdle (2009), demonstrates the AR model with two waves of data. Suppose *Y*[1] and *Y*[2] are two repeated scores, with *Y*[1] preceding *Y*[2] in time. To predict *Y*[2] by *Y*[1], we then regress *Y*[2] on *Y*[1]. The figure shows all model parameters, where observed variables are in squares; the unobserved variables are in circles; the constant of 1 is in a triangle; one-headed arrows represent group or fixed effects, such as μ_1, β_0, and β_1; and two-headed arrows represent individual or random effects, such as σ_1^2 and 1.





a. Autoregression Model	b. Latent Change Score Model

Figure 3.2 Autoregressive and Change Score Models
Source: Adapted from McArdle (2009)

Latent Change Score Model

Unlike the AR model, which uses the observed variable (*Y*) as the outcome of interest, the latent change (or latent difference) score model adopts time-dependent change of the observed variable (ΔY) as the outcome of interest. The latent change score model can be applied to examine change across individual units (within-unit change) or to study time-sequential associations within and between different constructs (Grimm et al. 2016a; Grimm et al. 2016b). We specify each observed repeated measure as a function of a true score and an unobserved random error. The model is specified as

$$y_{ti} = ly_{ti} + u_{ti},$$

where y_{ti} is the observed score for individual unit *i* at time *t*, ly_{ti} is the true score for individual unit *i* at time *t*, and u_{ti} is the corresponding random errors. The latent difference score of y_{ti} (Δy_{ti}) is then specified as the differences between the true scores at time *t* and *t-1* in individual unit *i*. In this case, we can model the change of true scores in the following equation:

$$\Delta y_{ti} = ly_{ti} - ly_{t-1i},$$

where Δy_{ti} is the true change score for individual unit *i* from time *t-1* to time *t*, ly_{ti} is the true score for individual unit *i* at time *t*, and ly_{t-1i} is the true score for individual unit *i* at time *t-1*.

Figure 3.2b shows a latent change score model, adapted from McArdle (2009) using the same waves of data, *Y*[1] and *Y*[2]. The latent change (or difference) score between *Y*[1] and *Y*[2] is *Y*[2]−*Y*[1], labeled as Δ. To demonstrate the result of *Y*[2] = 1∗*Y*[1] + 1∗ Δ, we used "1" as a fixed value on the arrows to *Y*[2]. δ1 is the change score coefficient.

Latent Growth Model

To uncover the nature of the trajectory in the predictor and outcome variables, we must first use LGM to test which functional form of change is the best fit for the variables. In this section, we first introduce the no-growth model, and then present linear growth and nonlinear growth models for this purpose. We adapted the equations here from Grimm et al. (2016b).

The no-growth models have only one latent variable (the intercept), which represents the overall level of variables over time. All the no-growth and growth models are two-level models: level-1 is the individual level, while level-2 is the sample level—that is, the level for the entire sample. This two-level model not only allows individual scores to change over time, but also allows change among individual units.

We model the level-1 (individual) equation for the no-growth model as follows:

$$y_{ti} = b_{1i} + u_{ti},$$

where y_{ti} is the repeatedly measured variable at time *t* for individual unit *i*, b_{1i} is the random intercept or predicted score for individual unit *i* when t = 0, and u_{ti} is the time-dependent residual.

We model the level-2 (sample) equation by specifying the random intercept, b_{1i}, with a sample mean for the intercept, β_1, and an individual deviation from the sample mean, or *fixed effect*, d_{1i}:

$$b_{1i} = \beta_1 + d_{1i}.$$

Combining level-1 and level-2 equations, we get the following complete no-growth model equation:

$$y_{ti} = (\beta_1 + d_{1i}) + u_{ti}.$$

Unlike the no-growth models, which have only one latent variable (the intercept), the linear growth model has two latent variables: the intercept, b_{1i}, and the linear rate of change, or *random slope*, b_{2i}.

We model the level-1 linear growth model as

$$y_{ti} = b_{1i} + b_{2i} \times t + u_{ti},$$

where y_{ti} is the repeatedly measured variable at time *t* for individual unit *i*, b_{1i} is the random intercept or predicted score for individual unit *i* when t = 0, b_{2i} is the linear rate of change (linear slope) for individual unit *i* when t = 0, and u_{ti} is the time-dependent residual.

Besides specifying the random intercept, we also need to specify the linear slope for the level-2 linear growth equation, where β_2 is the sample-level mean for the linear slope and d_{2i} is the individual deviations from the sample-level mean:

$$b_{2i} = \beta_2 + d_{2i}.$$

Combining level-1 and level-2 equations, we get the following complete linear growth model equation:

$$y_{ti} = (\beta_1 + d_{1i}) + (\beta_2 + d_{2i}) \times t + u_{ti}.$$

However, if the variables are measured over a relatively long period, we will likely detect some degree of nonlinearity in their trajectories, meaning that the variables will likely change at different rates. To measure the nonlinear functional forms of change, we can apply different nonlinear growth models. There are two major types of nonlinear growth models. The first comprises growth models with nonlinearity in time; in these models, changes depend only on the known time assessment. The second type comprises growth models with nonlinearity in parameters, in which changes depend on unknown entities (Grimm et al. 2016). Examples of growth models with nonlinearity in time are quadratic and cubic models, which account for nonlinearity by adding a quadratic term of time (in the quadradic model) and both a quadratic term and a cubic term of time (in the cubic model); and spline models, which allow for separate growth models for distinct spans of time. Examples of growth models with nonlinearity in parameters are the Jenss-Bayley growth model, which combines linear and exponential trajectories, and the latent basis growth model, which allows free factor loadings of time. Here, we introduce only the growth models with nonlinearity in time, such as quadratic and cubic growth models.

We specify the level-1 quadratic growth model with three latent variables: the intercept, b_{1i}; the linear rate of change, b_{2i}; and the quadratic rate of change, b_{3i}:

$$y_{ti} = b_{1i} + b_{2i} \times t + b_{3i} \times t^2 + u_{ti}.$$

The level-2 equation for quadratic slope, b_{3i}, is written as

$$b_{3i} = \beta_3 + d_{3i},$$

where β_3 is the sample-level mean for the quadratic slope and d_{3i} is the individual deviations from the sample-level mean of the quadratic slope.

Combining level-1 and level-2 equations, we get the following complete quadratic growth model equation:

$$y_{ti} = (\beta_1 + d_{1i}) + (\beta_2 + d_{2i}) \times t + (\beta_3 + d_{3i}) \times t^2 + u_{ti}.$$

Similarly, we can specify the level-1 cubic growth model as

$$y_{ti} = b_{1i} + b_{2i} \times t + b_{3i} \times t^2 + b_{4i} \times t^3 + u_{ti},$$

where b_{4i} is the cubic change for the individual unit *i* when t = 0.

The level-2 equation for the cubic slope is

$$b_{4i} = \beta_4 + d_{4i},$$

where β_4 is the sample-level mean for the cubic slope and d_{4i} is the individual deviations from the sample-level mean of the cubic slope. Combing level-1 and level-2 equations, the cubic growth model can be specified as

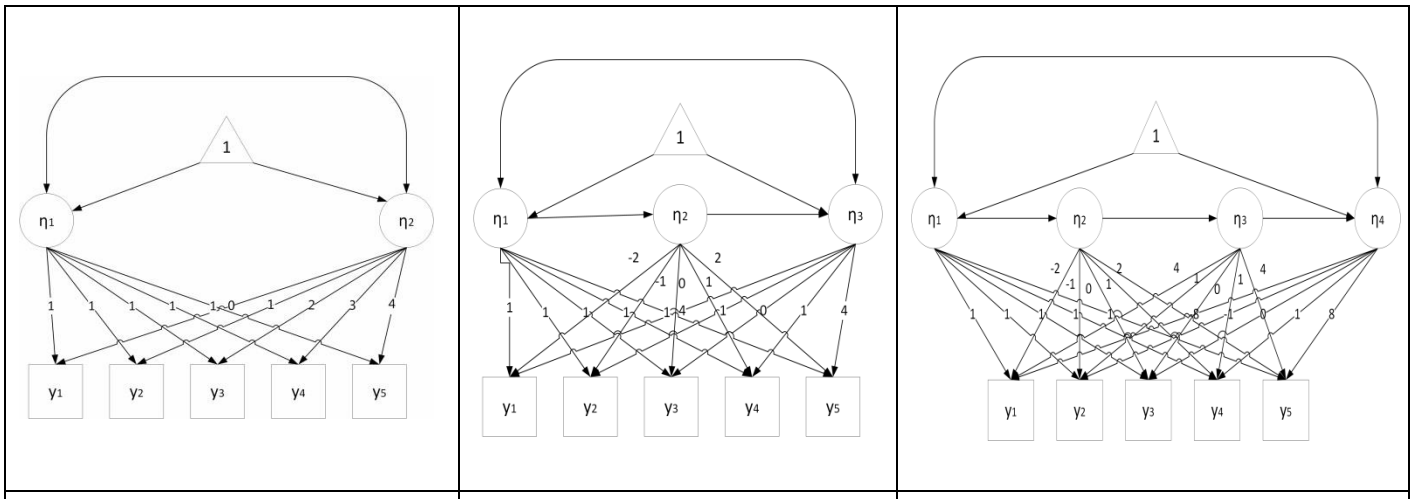
$$y_{ti} = (\beta_1 + d_{1i}) + (\beta_2 + d_{2i}) \times t + (\beta_3 + d_{3i}) \times t^2 + (\beta_4 + d_{4i}) \times t^3 + u_{ti},$$

where β_4 is sample-level mean for the cubic slope and d_{4i} is the individual deviations from the sample-level mean of the cubic slope.

To incorporate the above growth models into a structural equation modeling framework, we fitted growth models with latent variables for the intercept and slope to represent the change:

$$\boldsymbol{y_i = \Lambda \eta_i + u_i},$$

where $\boldsymbol{y}_i$ is a T × 1 vector of the repeatedly measured observed scores for individual unit *i;* T represents the number of repeated assessments based on the selected time metric; $\boldsymbol{\Lambda}$ is a T × R matrix of factor loadings defining the latent growth factors; R is the number of growth factors (R = 1 for the no-growth model, R = 2 for the linear growth model, R = 3 for the quadratic growth model, and R = 4 for the cubic growth model); and η_i is an R × 1 vector of the factor scores for the individual unit *i*. For example, the linear growth model has two factor scores: η_1 is the intercept factor score, and η_2 is the linear factor score. In addition to intercept and linear factor scores, the quadratic growth model has η_3 as the quadratic factor score, and the cubic growth model has both the quadratic factor score, η_3 , and the cubic factor score, η_4. $\boldsymbol{u}_i$ is an R × 1 vector of residual for the individual unit *i*. Figure 3.3 shows the path diagrams for the linear (Figure 3.3a), quadratic (Figure 3.3b), and cubic growth models (Figure 3.3c). In Figure 3.3, y_1 to y_5 represent the measurement of *y* in five different time periods, and the numbers in the arrows are the default fixed time score loadings. The number in the path represents time values that remain constant for the intercept (η_1), change linearly for the linear factor score (η_2), change quadratically for the quadratic factor score (η_3), and change in a cubic way for the cubic factor score (η_4).



a. Linear Growth Model	b. Quadratic Growth Model	c. Cubic Growth Model

Figure 3.3 Path Diagram of Growth Models

Source: Adapted from Grimm et al. (2016b)

BDLDSM Model

BDLDSM combines elements from AR models, latent change score models, and LGM. For BDLDSM, the specification of the latent difference (or latent change) scores must account for measurement error and time-specific, construct-irrelevant variance in the observed scores at each time point. We adapted the equations here from Ferrer and McArdle (2003) and specify that each observed repeated measure is a function of a true score and an unobserved random error. The model is specified as

$$y_{ti} = ly_{ti} + u_{ti} ,$$

$$x_{ti} = lx_{ti} + s_{ti} ,$$

where y_{ti} and x_{ti} are the observed scores for the individual unit *i* at time *t*, ly_{ti} and lx_{ti} are the true scores at time *t* for the individual unit *i*, and u_{ti} and s_{ti} are the corresponding random errors. We then specify the latent difference scores of y_{ti} (Δy_{ti}) and x_{ti} (Δy_{ti}) as the differences

between the true scores at time *t* and *t-1* in the individual unit *i*. In this case, we can model the change of true scores in the following equations:

$$\Delta y_{ti} = ly_{ti} - ly_{t-1i},$$

$$\Delta x_{ti} = lx_{ti} - lx_{t-1i},$$

where Δy_{ti} and Δx_{ti} are the true change scores for the individual unit *i* from time *t-1* to time *t*, ly_{ti} and lx_{ti} are the true scores for the individual unit *i* at time *t*, and ly_{t-1i} and lx_{t-1i} are the true scores for the individual unit *i* at time *t-1*.

The trajectory of each set of change scores over time is parameterized using a random slope factor, with loadings adjustable to reflect linear or nonlinear trajectories. The following two equations represent models that have linear mean trajectories. The latent change score at each time period is then a function of the random slope factor as well as the prior level of both y and x. That is,

$$\Delta y_{ti} = g_i + \beta_y ly_{t-1i} + \gamma_y lx_{t-1i},$$

$$\Delta x_{ti} = j_i + \beta_x lx_{t-1i} + \gamma_x ly_{t-1i},$$

where g_i and j_i are constant growth factors; β_y and β_x, called *proportional effects*, are within-variable proportional changes; and γ_y and γ_x, called *coupling effects*, are the coupling parameters that specify the cross-variable effects. From these equations, we can infer that the changes in y and x for the individual unit *i* from time *t-1* to time *t* come from three sources: the constant change components (g and j), the within-variable proportional effects (β_x and β_y), and the cross-variable coupling effects (γ_x and γ_y).

To account for the change scores' nonlinear trajectory, we first need to specify the growth models based on the latent change scores, which require the first derivative of the functional form of change with respect to time. For example, the first derivative of the level-1 cubic growth model can be written as

$$\Delta y_{ti} = b_{2i} + 2b_{3i}t + 3b_{4i}\,t^2.$$

We then incorporate the derivative function into the latent change score model:

$$\Delta y_{ti} = b_{2i} + 2b_{3i}t + 3b_{4i}\,t^2 + \beta_y\, ly_{t-1i} + \gamma_y\, lx_{t-1i},$$

where b_{2i}, b_{3i}, and b_{4i} are latent growth factors for the latent changes scores. $b_{2i}\,is$ the constant growth factor (same as g_i), b_{3i} is the linear growth factor, and b_{4i} is the quadratic growth factor. β_y represents within-variable proportional changes and γ_y represents the cross-variable coupling parameters.

This BDLDSM can be extended to multiple-group settings to explore group differences in the relationship; it can also be extended to multilevel modeling to study how changes proceed in different subsamples.

3.3.3 The Four Steps of Modeling BDLDSM

Following prior research (Chan 1998; Grimm et al. 2016b), we propose a four-step process to develop and conduct the BDLDSM analysis.

Step 1: Establish Measurement Invariance over Time

This step is a prerequisite to latent growth or change model analysis because we must ensure that the same construct is measured using the same metric with the same precision at each wave (Bala and Venkatesh 2013; Benlian 2015; Grimm et al. 2016b; McArdle 2009).

Measurement invariance allows the interpretation of growth trajectories in direct, meaningful ways and ensures that observed changes reflect changes in individual units, but not changes in measurement (Chan 1998; Grimm et al. 2016b). The two types of measurement invariance are configural invariance and factorial invariance. *Configural invariance* indicates that the construct operationalized by measured variables remains the same across different data waves. *Configural invariance* is established if the same number of factors is obtained at each wave with the same factor loadings on each factor (Bala and Venkatesh 2013; Bentein et al. 2005; Chan 1998). *Factorial invariance* indicates that the relationship between different measures and their corresponding construct are invariant across waves. Factorial invariance is established if the factor loadings corresponding to the same items remain the same over time (Bala and Venkatesh 2013; Bentein et al. 2005; Chan 1998). However, the test of measurement invariance is underpowered if the sample size is small (Grimm et al. 2016b). In other words, we must ensure that the measurement invariance test includes a sufficient number of observations.

Step 2: Modeling Growth Trajectories

To determine the nature of growth trajectories in the predictor and outcome variables, we examine the predictor and outcome variables in LGMs, such as the no change model, linear change model, and nonlinear change model. We then compare these models using the chi-square difference test to identify the LGM model with the best fit.

Step 3: Modeling BDLDSM

Next, we incorporate step 2's functional forms of change for predictor and outcome variables into the BDLDSM model. To better understand the dynamic relationship between predictor (X) and outcome (Y) variables, we can test four BDLDSM models:

(1) BDLDSM with no coupling effects

(2) BDLDSM with a coupling effect from X to the change of Y (ΔY)

(3) BDLDSM with a coupling effect from Y to the change of X (ΔX)

(4) BDLDSM with full coupling effects, including coupling effects from X to ΔY and Y to ΔX

From a theory development perspective, however, we suggest testing and comparing only the no-coupling effect model, the coupling effect from X to ΔY model, and the full coupling effect model (models 1, 2, and 4). We then compare these three models using the chi-square difference test to select the model with the best model specification.

Step 4: Model Estimation and Result Interpretation

In this step, we estimate the BDLDSM model based on the best model specification (step 3) and interpret the result.

3.4 An Example of BDLDSM

We now illustrate the application of BDLDSM to examine the dynamic, longitudinal relationship between HIT implementation level and hospital performance, which we measure in terms of healthcare quality and cost. We chose to use BDLDSM because the association between HIT implementation and hospital performance is complex and may be reciprocal. Several studies have examined the impacts of HIT implementation on healthcare performance; however, their findings have been mixed and inconclusive. Indeed, empirical results suggest that HIT may have positive (Amarasingham et al. 2009; Buntin et al. 2011; Lee et al. 2013), negative (Ash et al. 2004; Nebeker et al. 2005), or little to no significant impact (Agha 2014; Parente and

McCullough 2009) on healthcare quality. The same is true for healthcare costs, where empirical results suggest that HIT may decrease (Bardhan and Thouin 2013), increase (Agha 2014), or have little to no significant impact (Furukawa et al. 2010; Sharma et al. 2016). These conflicting results underscore the need for further research to examine the relationship between HIT and healthcare performance using a more advanced analysis technique and a fine-grained dataset. In addition, the literature has yet to sufficiently explore whether the relationship between HIT implementation levels and healthcare performance is reciprocal; it may be that an increased HIT implementation level drives healthcare performance improvement, and that hospitals that experience this improved quality and reduced cost are more likely to adopt additional HIT. We describe this dynamic and potentially reciprocal relationship between HIT implementation level and hospital performance over time in the following analysis, which we conducted using Mplus 7.

3.4.1 Sample and Data Collection

In this study, we use data from four sources. First, to obtain hospital-level clinical quality data, we use the HCUP-SID dataset, which contains 97 percent of all discharges from community hospitals in 48 U.S. states. HCUP-SID contains nonclinical variables, such as patient demographics characteristics and total charges, and clinical information, such as diagnoses, procedures, chronic indicators, admission and discharge status, the length of stay and severities related to each inpatient discharge case (HCUP 2016). We have access to an HCUP-SID dataset for seven states: California, Florida, Maryland, New Jersey, New York, North Carolina, and Washington. The datasets span six years (2008–2013) for all but California; that dataset is for 2008–2011. Second, to obtain experiential quality data, we use the HCAHPS survey data. This dataset records patients' perceptions of the quality of care they received during their inpatient

hospital stays. Third, to measure the cost, we use the Medicare cost report, which provides total cost data at the hospital level. Fourth, to obtain HIT implementation data, we use AHA's IT supplement files for 2008–2012. The AHA IT supplement database is a hospital-level database containing healthcare IT implementation-level information on three different IT functions: ECD, CPOE, and DS (AHA 2016). After mapping the four datasets, our resulting dataset is an unbalanced panel data set consisting of 835 hospital-level observations from 2008–2013.

3.4.2 Measures

Healthcare Quality and Cost

To access healthcare quality levels at each wave, we used both clinical and experiential quality measures to analyze healthcare quality. For the clinical quality measures, we obtained inpatient quality indicators (IQI) from AHRQ. IQI measures are risk-adjusted, validated quality measures that are used to compare quality across hospitals (Encinosa and Bernard 2005; Miller et al. 2005; Weiner et al. 2006) and to study HIT impact on quality (Menachemi et al. 2008; Menachemi et al. 2007). We chose to use *mortality* for selected conditions (IQI91). This measure comprises mortality indicators for certain diagnostic conditions for which 1) mortality varies substantially across institutions, and 2) evidence suggests that high mortality may be associated with deficiencies in the quality of care. IQI91 is a "weighted average of the reliability-adjusted ratios for the mortality indicators for patients" and "the reliability-adjusted ratio is a weighted average of the risk-adjusted ratio and the reference population ratio, where the weight is determined empirically" (AHRQ 2011).

We used the communication score to measure experiential quality. This score is calculated using responses to four questions in the HCAHPS survey: (1) How often did nurses communicate well with patients? (2) How often did doctors communicate well with patients? (3)

How often did staff explain about medications before giving them to patients? (4) Were patients given information about what to do during their recovery at home? The response categories for Questions 1–3 are "never/sometimes," "usually," or "always," and the response categories for Question 4 are "yes" or "no." To measure the communication score, we used the percentage of respondents who answered "always" for Question 1–3 and "yes" for Question 4 (Senot et al. 2016) and calculated the average score for these four items. In keeping with recent research (Chandrasekaran et al. 2012; Senot et al. 2016; Sharma et al. 2016) and statistical theory (Collett 2003), we applied a logit transformation on the computed average score. The following equation gives the communication score, with *i* as the individual hospitals and *Q* as the average score for four items:

$$Communication\ Score_i = Ln\left[\frac{Q_i}{1-Q_i}\right].$$

To obtain the healthcare cost, we used the cost per discharge, which is measured by a hospital's total inpatient charge, as indicated in the CMS cost report, divided by the number of discharges calculated from the HCUP database. We then log transformed the cost per discharge to satisfy the normality requirement for further analysis (Senot et al. 2016; Sharma et al. 2016).

HIT Implementation

To assess the levels of HIT function implementation at each wave, we used a total of 18 items to create three HIT constructs: ECD, which lets care providers access and record patient information; CPOE, which facilitates task execution by letting care providers give instructions to nurses and technicians; and DS, which supports decision making by giving care providers access to information that helps them accurately diagnose patient conditions, consult the latest evidence, and provide patient-specific care. Although the original items were measured on a six-point

ordinal scale, we coded each item on a four-point scale so that a single lowest category would reflect all forms of non-implementation. The resulting ordered IT implementation scheme is as follows: 0 (no implementation), 1 (beginning to implement in at least one unit), 2 (fully implemented in at least one unit), and 3 (fully implemented across all units), with full implementation indicating that IT has completely replaced paper record functionally. We derived and validated the hypothesized three-factor structure—ECD, CPOE, and DS—using categorical factor analysis.

Control Variables

To account for other factors that may influence HIT impact on hospital performance, our analysis included four control variables: hospital bed size, profit status, teaching status, and hospital market competition. We obtained the first three variables from AHA survey datasets and measured market competition using the HHI. For a focal hospital, we operationalized market competition at the hospital referral region (HRR) level and aggregated hospitals into HRRs.

3.4.3 Data Analysis and Results

Establish Measurement Invariance over Time

To ensure that the same HIT construct is measured using the same metric with the same precision at each wave, we test measurement invariance for HIT measures over time. We confirmed both configural invariance and factorial invariance of the three-factor structure. Consequently, we computed the resultant factors score for each hospital at each wave and used them as the HIT implementation variables in the subsequent joint longitudinal models.

Modeling Growth Trajectories

To examine the mean trajectories of HIT and healthcare performance variables, we first plotted the variables' trajectories over time (2008–2013) as Figure 3.4 shows. We found that both the trajectories of HIT and healthcare performance variables were not exactly linear. Consequently, we fit the HIT and healthcare performance variables into three types of growth models—a linear growth model, a quadratic growth model, and a cubic growth model—to identify the best functional form of change. Since all variable trajectories were clearly either increasing or decreasing over time, there was no need to test a no-growth model in this case.

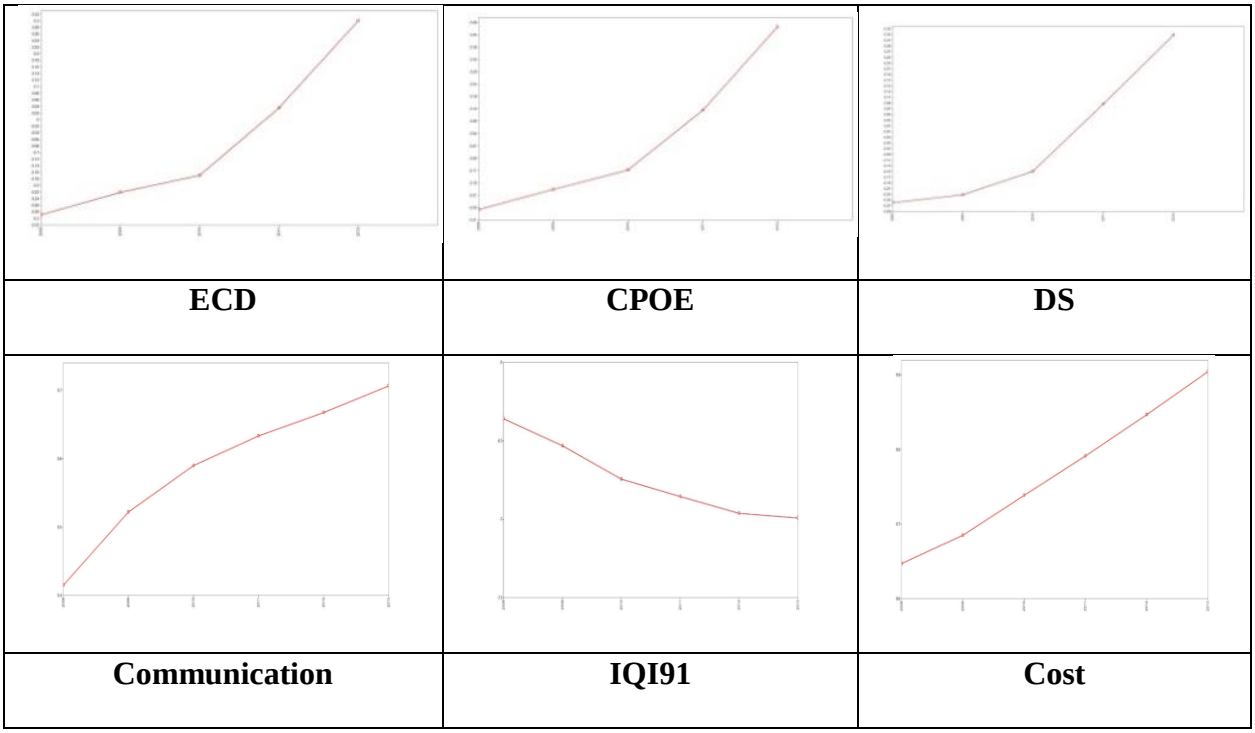


Figure 3.4 Mean Trajectory of HIT and Healthcare Performance

We used five fit indices to access model fit: (1) the chi-square goodness of fit test; (2) the root mean square error of approximation (RMSEA); (3) the comparative fit index (CFI); (4) Tucker-Lewis index (TLI), sometimes referred to as *NNFI*; and (5) the standardized root mean square residual (SRMR). Table 3.3 shows the linear growth model's fit statistics and growth

factors. Tables 3.4 and 3.5 show the two nonlinear—quadratic and cubic—growth models, respectively. We also compared these three latent growth models using chi-square difference tests (see Table 3.6). As Table 3.6 shows, HIT measures have the best-fit statistics on the quadratic growth models, while the healthcare performance variables have the best-fit statistics on the cubic growth models.

Table 3.3 Linear Growth Model

	Independent Variables (HIT Functions)			**Dependent Variables (Healthcare Performance)**		
	ECD	CPOE	DS	Communication	IQI91	Cost
$\chi 2$	92.155	111.951	74.908	126.859	53.409	56.311
DF	10	10	10	16	16	16
RMSEA	0.1	0.111	0.089	0.093	0.057	0.056
CFI	0.871	0.811	0.878	0.969	0.987	0.963
TLI	0.871	0.881	0.878	0.97	0.988	0.965
SRMR	0.089	0.095	0.073	0.047	0.022	0.156
η_1	-0.364***	-0.375***	-0.361***	0.868***	-0.64***	9.639***
η_2	0.144***	0.188***	0.155***	0.046***	-0.015***	0.052***
*** p<0.001, ** p<0.01, * p<0.05						

Table 3.4 Quadratic Growth Model

	Independent Variables (HIT Functions)			**Dependent Variables (Healthcare Performance)**		
	ECD	CPOE	DS	Communication	IQI91	Cost
$\chi 2$	8.544	11.082	4.156	69.596	22.33	75.766
DF	6	6	6	12	12	12
RMSEA	0.023	0.032	0	0.078	0.03	0.082
CFI	0.997	0.992	1	0.99	0.999	0.989
TLI	0.995	0.987	1.005	0.987	0.998	0.986
SRMR	0.02	0.025	0.017	0.045	0.008	0.094
η_1	-0.148***	-0.087***	-0.131***	0.961***	-0.673***	9.738***
η_2	0.14***	0.178***	0.149***	0.047***	-0.016***	0.05***
η_3	0.04***	0.05***	0.042***	-0.001	0.002	0.002**
*** p<0.001, ** p<0.01, * p<0.05						

Table 3.5 Cubic Growth Model

	Independent Variables (HIT Functions)			**Dependent Variables (Healthcare Performance)**		
	ECD	CPOE	DS	Communication	IQI91	Cost
$\chi 2$	3.642	2.012	2.164	34.967	9.191	17.674
DF	1	1	1	7	7	7
RMSEA	0.057	0.035	0.038	0.071	0.021	0.044
CFI	0.997	0.998	0.998	0.995	1	0.998
TLI	0.97	0.985	0.982	0.99	0.999	0.996
SRMR	0.011	0.009	0.01	0.033	0.004	0.081
η_1	-0.152^{***}	-0.089^{***}	-0.13^{***}	0.96^{***}	-6.729^{***}	9.736^{***}
η_2	0.117^{***}	0.147^{***}	0.158^{***}	0.048^{***}	-0.169^{***}	0.053^{***}
η_3	0.04^{***}	0.049^{***}	0.042^{***}	-0.001	0.016	0.003^{***}
η_4	0.008	0.009	-0.003	0	0.003	-0.001
*** p<0.001, ** p<0.01, * p<0.05						

Table 3.6 Model Comparison of Change Form

	Independent Variables (HIT Functions)			**Dependent Variables (Healthcare Performance)**		
	ECD	CPOE	DS	Communication	IQI91	Cost
Linear Growth Model vs Quadratic Growth Model						
$\Delta\chi 2$	83.611	100.869	70.752	57.263	31.079	19.455
ΔDF	4	4	4	4	4	4
p	**p<0.001**	**p<0.001**	**p<0.001**	p<0.001	p<0.001	p<0.001
Linear Growth Model vs Cubic Growth Model						
$\Delta\chi 2$	88.513	109.939	72.744	91.892	44.218	38.637
ΔDF	9	9	9	9	9	9
p	p<0.001	p<0.001	p<0.001	p<0.001	p<0.001	p<0.001
Quadratic Growth Model vs Cubic Growth Model						
$\Delta\chi 2$	4.902	9.07	1.992	34.629	13.139	58.092
ΔDF	5	5	5	5	5	5
p	p<0.5	p<0.5	p<0.5	**p<0.001**	**p<0.05**	**p<0.001**

Modeling BDLDSM

Next, to test the causal relationship between HIT and healthcare performance, we evaluated the following three models:

Model 1: BDLDSM with no coupling effects

Model 2: BDLDSM with a coupling effect from HIT to the change of healthcare performance (ΔPerformance)

Model 3: BDLDSM with full coupling effects

Because healthcare performance measures have the best fit in the cubic growth model and HITs have the best fit in the quadratic models, we fit the healthcare performance measures into BDLDSM with the first derivative cubic growth function and fit the HITs into BDLDSM with the first derivative quadratic growth function. Table 3.7 displays the chi-square model comparison among the three models. Models with no coupling effects best represented the dynamic association between IQI91 and the three HIT functions, as well as between cost and CPOE. This indicates that there is no dynamic association between IQI91 and HIT variables or between cost and CPOE when we incorporate their mean trajectory functional forms of change into the models. Models with the coupling effects from HIT to the ΔPerformance best represented the dynamic association between communication and CPOE, between cost and ECD, and between cost and DS. The full coupling models best represented the dynamic associations between communication and ECD and between communication and DS. We will now analyze the BDLDSM model with the best model fit.

Table 3.7 Model Comparison of BDLDSM (Nonlinear Change Function)

		M1: No Coupling	M2: IV to ΔDV	M3: Full Coupling	M1 vs M2	M1 vs M3	M2 vs M3	Best Model
Communication and ECD	χ^2	132.445	112.999	106.505	p<0.001	p<0.001	p=0.0108	M3: Full Coupling
	DF	77	76	75				
Communication and CPOE	χ^2	141.648	115.523	114.047	p<0.001	p<0.001	p=0.2244	M2: IV to ΔDV
	DF	77	76	75				
Communication and DS	χ^2	133.79	104.476	98.962	p<0.001	p<0.001	p=0.0189	M3: Full Coupling
	DF	77	76	75				
IQI91 and ECD	χ^2	107.706	107.7	104.865	p=0.9383	p=0.2416	p=0.0922	M1: No Coupling
	DF	77	76	75				
IQI91 and CPOE	χ^2	121.735	121.086	120.768	p=0.4205	p=0.6166	p=0.5728	M1: No Coupling
	DF	77	76	75				
IQI91 and DS	χ^2	105.447	105.374	104.444	p=0.7870	p=0.6056	p=0.3349	M1: No Coupling
	DF	77	76	75				
Cost and ECD	χ^2	368.897	363.316	362.021	p=0.0182	p=0.0321	p=0.2551	M2: IV to ΔDV
	DF	98	97	96				
Cost and CPOE	χ^2	373.559	370.04	368.569	p=0.0607	p=0.0825	p=0.2252	M1: No Coupling
	DF	98	97	96				
Cost and DS	χ^2	361.81	352.453	350.532	p=0.0022	p=0.036	p=0.1657	M2: IV to ΔDV
	DF	98	97	96				

Model Estimation and Result Interpretation

The BDLDSM with the no-coupling effect models can be written as:

$$\Delta Performance = b_{2i} + 2b_{3i}t + 3b_{4i}\,t^2 + \beta_h Performance_{i[t-1]}\,,$$

$$\Delta HIT_{it} = a_{2i} + 2a_{3i}t + \beta_{IT} HIT_{i[t-1]},$$

where b_{2i} and a_{2i} represent the constant growth factor, b_{3i} and a_{3i} represent the linear growth factor, b_{4i} represents the quadratic growth factor, and β is the self-feedback coefficient, which captures *proportional change*—that is the effect of the same variable at the previous state of the change. Since no-coupling effect models cannot reveal the dynamic relationship between predictor and outcome variables, we will not estimate those models here.

The BDLDSM with a coupling effect from HIT to the change of healthcare performance (ΔPerformance) can be written as:

$$\Delta Performance = b_{2i} + 2b_{3i}t + 3b_{4i}\,t^2 + \beta_h Performance_{i[t-1]} + \gamma_h HIT_{i[t-1]}\,,$$

$$\Delta HIT_{it} = a_{2i} + 2a_{3i}t + \beta_{IT} HIT_{i[t-1]},$$

where γ_h is the coupling coefficient, representing a coupling effect from HIT to the change of healthcare performance (ΔPerformance). Figure 3.8 shows the reported parameters and fit indices; as it shows, all the models have good overall fit, as demonstrated by the standard SEM fit indices. Model 1 in Table 3.8 presents the dynamic association between the communication score and the CPOE implementation. The change equations are

Table 3.8 Model Estimation of BDLDSM with coupling effect from HIT to Δ Performance (Nonlinear Change Function)

	Model 1 Communication and CPOE		Model 2 Cost and ECD		Model 3 Cost and DS	
Goodness of Fit						
$\chi 2$	115.523		363.316		352.453	
DF	76		97		97	
RMSEA	0.026		0.059		0.058	
CFI	0.996		0.961		0.962	
TLI	0.988		0.934		0.935	
SRMR	0.016		0.051		0.051	
Latent Means						
	Estimate	p-Value	Estimate	p-Value	Estimate	p-Value
b_{2i}	9.343	<0.001	1.152	0.032	1.187	0.026
b_{3i}	0.693	0.052	0.028	<0.001	0.031	<0.001
b_{4i}	0.091	0.186	-0.006	0.189	-0.005	0.318
a_{2i}	2.038	0.004	0.94	<0.001	0.931	<0.001
a_{3i}	0.234	0.408	0.419	<0.001	0.47	<0.001
Dynamic Coefficients						
Proportion β_h	-0.965	<0.001	-0.006	0.276	-0.006	0.24
Proportion β_{IT}	0.427	0.294	-0.050	0.054	-0.073	0.046
Coupling γ_h	-0.519	0.187	-0.009	0.018	-0.013	0.002

$$\Delta Communication = 9.343 + 1.386t + 0.273t^2 - 0.965Communication_{i[t-1]} - 0.519CPOE_{i[t-1]},$$

$$\Delta CPOE_{it} = 2.038 + 0.468t + 0.427CPOE_{i[t-1]}.$$

The proportional change effect β_h for communication is significantly negative, indicating that there is a proportional effect on changes in communication based on prior communication scores. However, the proportional change effect β_{IT} for CPOE is insignificantly negative, indicating that there is no proportional effect for CPOE. The coupling effects of γ_h are not significant, indicating that CPOE is not a significant leading indicator of subsequent changes in communication score. The constant growth factor (b_{2i}) for communication is significant at the

p<0.001 level and the linear growth factor (b_{3i}) for communication is significant at the p<0.1 level, implying that there is both a constant and a linear growth change in the changes in communication score each year. The constant growth factor (a_{2i}) for HIT is significant, indicating that there is also a constant growth change in the HIT changes each year.

Model 2 in Table 3.8 shows the relationship between healthcare cost and ECD implementation. The change equations are

$$\Delta Cost = 1.152 + 0.056t - 0.018t^2 - 0.006Cost_{i[t-1]} - 0.009ECD_{i[t-1]},$$

$$\Delta ECD_{it} = 0.94 + 0.838t - 0.050ECD_{i[t-1]}.$$

Model 3 in Table 3.8 shows the relationship between healthcare cost and DS implementation. The change equations are

$$\Delta Cost = 1.187 + 0.062t - 0.015t^2 - 0.006Cost_{i[t-1]} - 0.013DS_{i[t-1]},$$

$$\Delta DS_{it} = 0.931 + 0.94t - 0.073DS_{i[t-1]}.$$

The proportional change effect β_h for cost is insignificant in both models, indicating that changes in healthcare cost are not associated with healthcare cost in the previous year. In contrast, the proportional change effects β_{IT} for ECD and DS are weakly significant with Model 2 (at the 0.1 level) and significant in Model 3 (at the 0.5 level), implying that there is a proportional effect on changes in ECD or DS based on prior ECD or DS implementation levels. The coupling effects of γ_h are negatively significant in both models, indicating that both ECD and DS are leading indicators for the subsequent change of cost. That is, hospitals that have higher ECD or DS implementation levels show greater decreases in healthcare cost. Both the constant growth factor (b_{2i}) and the linear growth factor (b_{3i}) for cost are significant, implying

both a constant and a linear change of growth on the changes in healthcare cost each year. Similarly, both the constant growth factor (a_{2i}) and the linear growth factor (a_{3i}) for ECD and DS are significant, indicating both a constant change of growth and a linear change of growth on ECD and DS implementation levels each year.

The BDLDSM with full coupling, a coupling effect from HIT to ΔPerformance, and a coupling effect from Performance to ΔHIT can be written as

$$\Delta Performance = b_{2i} + 2b_{3i}t + 3b_{4i}t^2 + \beta_h Performance_{i[t-1]} + \gamma_h HIT_{i[t-1]},$$

$$\Delta HIT_{it} = a_{2i} + 2a_{3i}t + \beta_{IT} HIT_{i[t-1]} + \gamma_{IT} Performance_{i[t-1]},$$

where γ_{IT} is the coupling coefficient, representing the coupling effect from healthcare performance to the change of HIT implementation (ΔHIT). Table 3.9 shows the parameters and fit indices. Model 1 presents the relationship between the communication score and the ECD implementation. The change equations are

$$\Delta Communication = 12.139 + 0.934t + 0.111t^2 - 1.248Communication_{i[t-1]} - 0.251ECD_{i[t-1]},$$

$$\Delta ECD_{it} = -15.837 - 0.948t + 0.841ECD_{i[t-1]} + 2.025Communication_{i[t-1]}.$$

Model 2 presents the relationship between the communication score and DS implementation. The change equations are

$$\Delta Communication = 12.583 + 1.146t + 0.156t^2 - 1.303Communication_{i[t-1]} - 0.362DS_{i[t-1]},$$

$$\Delta DS_{it} = -13.26 - 0.75t + 0.733DS_{i[t-1]} + 1.721Communication_{i[t-1]}.$$

Table 3.9 Model Estimation of BDLDSM with Full Coupling Effect (Nonlinear Change Function)

	Model 1 Communication and ECD		Model 2 Communication and DS	
Goodness of Fit				
$\chi 2$	106.505		98.962	
DF	75		75	
RMSEA	0.023		0.02	
CFI	0.996		0.997	
TLI	0.99		0.992	
SRMR	0.015		0.016	
Latent Means				
	Estimate	p-Value	Estimate	p-Value
b_{2i}	12.139	<0.001	12.583	<0.001
b_{3i}	0.467	<0.001	0.573	<0.001
b_{4i}	0.037	0.007	0.052	0.023
a_{2i}	-15.837	0.05	-13.26	0.154
a_{3i}	-0.474	0.257	-0.375	0.449
Dynamic Coefficients				
Proportion β_h	-1.248	<0.001	-1.303	<0.001
Coupling γ_h	-0.251	0.006	-0.362	0.019
Proportion β_{IT}	0.841	0.09	0.733	0.131
Coupling γ_{IT}	2.025	0.03	1.721	0.112

First, the standard SEM fit indices show that both models have excellent overall fit. The proportional change effect β_h for the communication score is significantly negative in both models, indicating a proportional effect on changes in communication score based on prior communication scores. The proportional change effects β_{IT} for ECD is weakly significant at the p<0.1 level; for DS it is insignificant, implying a weak proportional effect on changes in ECD based on prior ECD implementation levels, but there is no proportional effect on changes in DS. The coupling effects of γ_h are negatively significant in both models, indicating that an increased implementation level of both ECD and DS are leading indicators for the subsequent decreased communication score. The coupling effects of γ_{IT} are significant in Model 1, implying that an increased communication score leads to a higher subsequent ECD implementation level. This

results in a feedback loop between ECD and communication score. Yet, the coupling effects of γ_{IT} are insignificant in Model 2, indicating that the communication score is not a leading indicator for the subsequent changes in DS implementation. For the growth scores in communication, the constant growth factor (b_{2i}), the linear growth factor (b_{3i}), and the quadratic growth factor (b_{4i}) are all significant in both models, implying a quadratic change of growth in communication score each year. The constant growth factor (a_{2i}) for ECD in Model 1 is significant, indicating a constant change of growth for ECD implementation over time.

In sum, we identified the dynamic relationship between different HIT function implementation levels and healthcare performance measures using BDLDSM. Our findings are as follows. First, we find that the mean trajectories of HIT implementation levels and healthcare performance grow in a polynomial manner. While HIT implementation levels grow in a quadratic manner over time, healthcare performance grows in a cubic manner over time. Next, we use BDLDSM to examine how the quadratic change in HIT implementation levels impact the cubic change in healthcare quality and cost. We discover that there is no causal relationship between IQI 91 and the three HIT functions, between cost and CPOE, or between communication score and CPOE. We also find that an increased DS implementation level is predicted to decrease both healthcare cost and communication score over time, while an increased ECD implementation level is predicted to reduce healthcare cost over time. Finally, we identified one feedback loop between communication score and ECD implementation, where an increased ECD implementation level is a leading indicator for a decrease in the subsequent communication score; however, increased communication score is a leading indicator for an increase in the subsequent ECD implementation level.

3.5 Model Comparison

3.5.1 Comparing Nonlinear BDLDSM with Linear BDLDSM

To draw attention to the importance of selecting the mean trajectory functional form of change, we test the BDLDSM with a linear functional form of change for both the healthcare performance and HIT implementation variables. We then compare the result with the BDLDSM models with the best-fit trajectory functional form of change.

The BDLDSM with a linear change function for both the healthcare performance and HIT are

$$\Delta Performance_{it} = \mu_{\mathrm{pi}} + \beta_h Performance_{i[t-1]} + \gamma_h HIT_{i[t-1]} ,$$

$$\Delta HIT_{it} = \mu_{\mathrm{ITi}} + \beta_{IT} HIT_{i[t-1]} + \gamma_{IT} Performance_{i[t-1]},$$

where μ_{pi} and μ_{ITi} represent the loadings associated with the constant growth factors; β_h and β_{IT} are proportional change scores that capture the effect of the same variable at the previous state of the change; and γ_h and γ_{IT} are the coupling change scores, representing the effect of the other variable at the previous state of the change.

First, we test and compare the dynamic association between HIT and healthcare performance with no coupling effect, with the coupling effect from HIT to ΔPerformance, and with the full coupling effects. Table 3.10 shows the result. Next, we select the best-fit BDLDSM with linear change forms. We then compare the best-fit BDLDSM with linear change forms with the best-fit BDLDSM incorporating the nonlinear functional form of change; as Table 3.11 shows, BDLDSMs with nonlinear functional form of change have a better model fit than BDLDSMs with linear functional form of change. Although we know BDLDSMs with the nonlinear functional form of change best represent the dynamic association between HIT

implementation and healthcare performance, we still present the result of BDLDSM with linear change forms in Tables 3.12 and 3.13 to demonstrate the importance of functional form selection. Table 3.12 shows the model estimation of BDLDSM with the coupling effect from HIT to ΔPerformance, while Table 3.13 shows the model estimation of BDLDSM with full coupling effects.

Table 3.10 Model Comparison of BDLDSM (Linear Change Function)

		M1: No Coupling	M2: IV to ΔDV	M3: Full Coupling	M1 vs M2	M1 vs M3	M2 vs M3	Best Model
Communication and ECD	χ2	604.126	547.016	543.43	p<0.001	p<0.001	p=0.0583	M2
	DF	133	132	131				
Communication and CPOE	χ2	590.955	550.898	546.405	p<0.001	p<0.001	p=0.0340	M3
	DF	133	132	131				
Communication and DS	χ2	568.671	506.982	500.878	p<0.001	p<0.001	p=0.0135	M3
	DF	133	132	131				
IQI91 and ECD	χ2	411.094	398.556	348.769	p<0.001	p<0.001	p<0.001	M3
	DF	133	132	131				
IQI91 and CPOE	χ2	398.572	398.305	394.348	p=0.6054	p=0.1210	p=0.0467	M1
	DF	133	132	131				
IQI91 and DS	χ2	356.322	349.508	348.769	p=0.0090	p=0.0331	p=0.3900	M2
	DF	133	132	131				
Cost and ECD	χ2	516.323	507.809	505.981	p=0.0035	p=0.0142	p=0.1764	M2
	DF	133	132	131				
Cost and CPOE	χ2	500.932	496.345	491.342	p=0.0322	p=0.0083	p=0.0253	M3
	DF	133	132	131				
Cost and DS	χ2	488.285	476.115	470.49	p<0.001	p<0.001	p=0.0177	M3
	DF	133	132	131				

Table 3.11 Model Comparison between Nonlinear and Linear BDLDSM

		BDLDSM with Nonlinear Change Trajectory	BDLDSM with Linear Change Trajectory	Nonlinear vs Linear BDLDSM	Better Model
Communication and ECD	$\chi 2$	106.505	547.016	p<0.001	BDLDSM with Nonlinear Change Trajectory
	DF	75	132		
Communication and CPOE	$\chi 2$	115.523	546.405	p<0.001	BDLDSM with Nonlinear Change Trajectory
	DF	76	131		
Communication and DS	$\chi 2$	98.962	500.878	p<0.001	BDLDSM with Nonlinear Change Trajectory
	DF	75	131		
IQI91 and ECD	$\chi 2$	107.706	348.769	p<0.001	BDLDSM with Nonlinear Change Trajectory
	DF	77	131		
IQI91 and CPOE	$\chi 2$	121.735	398.572	p<0.001	BDLDSM with Nonlinear Change Trajectory
	DF	77	133		
IQI91 and DS	$\chi 2$	105.447	349.508	p<0.001	BDLDSM with Nonlinear Change Trajectory
	DF	77	132		
Cost and ECD	$\chi 2$	363.316	507.809	p<0.001	BDLDSM with Nonlinear Change Trajectory
	DF	97	132		
Cost and CPOE	$\chi 2$	373.559	491.342	p<0.001	BDLDSM with Nonlinear Change Trajectory
	DF	98	131		
Cost and DS	$\chi 2$	352.453	470.49	p<0.001	BDLDSM with Nonlinear Change Trajectory
	DF	97	131		

Table 3.12 Model Estimation of BDLDSM with Coupling Effect from HIT to ΔPerformance (Linear Change Function)

	Model 1 Communication and ECD		Model 2 IQI91 and DS		Model 3 Cost and ECD	
Goodness of Fit						
$\chi 2$	547.016		349.508		507.809	
DF	132		132		132	
RMSEA	0.063		0.046		0.06	
CFI	0.942		0.976		0.945	
TLI	0.928		0.997		0.932	
SRMR	0.04		0.149		0.079	
Latent Means						
	Estimate	P-Value	Estimate	P-Value	Estimate	P-Value
μ_{pi}	1.473	<0.001	-0.36	<0.001	0.474	0.32
μ_{ITi}	1.024	<0.001	1.172	<0.001	1.012	<0.001
Dynamic Coefficients						
Proportion β_h	-0.102	<0.001	-0.032	<0.001	0	0.933
Proportion β_{IT}	0.026	<0.001	-0.012	0.009	-0.011	0.004
Coupling γ_h	-0.049	<0.001	-0.008	0.775	-0.037	0.053

Table 3.13 Model Estimation of BDLDSM with Full Coupling Effect (Linear Change Function)

	Model 1 Communication and CPOE		Model 2 Communication and DS		Model 3 IQI91 and ECD		Model 4 Cost and CPOE		Model 5 Cost and DS	
Goodness of Fit										
$\chi 2$	546.405		500.878		394.989		491.342		470.49	
DF	131		131		131		131		131	
RMSEA	0.063		0.06		0.051		0.059		0.057	
CFI	0.941		0.947		0.971		0.946		0.949	
TLI	0.925		0.933		0.964		0.932		0.936	
SRMR	0.037		0.035		0.15		0.08		0.149	
Latent Means										
	Estimate	P-Value	Estimate	P-Value	Estimate	P-Value	Estimate	P-Value	Estimate	P-Value
μ_{pi}	1.427	<0.001	1.44	<0.001	-0.37	<0.001	0.376	0.156	-0.358	<0.001
μ_{ITi}	2.02	<0.001	1.89	<0.001	0.784	<0.001	-3.456	<0.001	1.058	<0.001
Dynamic Coefficients										
Proportion β_h	-0.098	<0.001	-0.098	<0.001	-0.033	<0.001	0.001	0.594	-0.032	<0.001
Coupling γ_h	0.023	<0.001	0.032	<0.001	-0.013	0.002	-0.01	0.008	-0.011	0.02
Proportion β_{IT}	-0.055	0.034	-0.042	0.14	-0.032	0.088	-0.138	<0.001	-0.005	0.864
Coupling γ_{IT}	-0.076	0.04	-0.082	0.017	-0.039	0.046	0.047	<0.001	-0.02	0.383

After comparing the result from BDLDSM with nonlinear change forms and BDLDSM with linear change forms, we can infer the importance of selecting the mean trajectory functional form of change. This is because selecting inaccurate change trajectory functions may lead to the erroneous representation of the dynamic associations between HIT implementation and healthcare performance. For example, Model 1 in Table 3.13 shows that γ_h is positively significant, meaning that an increased CPOE implementation level will lead to the subsequent enhanced communication score. However, Model 1 in Table 3.8 shows that γ_h is insignificant, indicating CPOE is not a leading predictor of communication score. Selecting inaccurate change trajectory functions may also lead to different statistical significant levels. For example, Model 3 in Table 3.12 shows that the coupling effect (γ_h) between cost and the ECD implementation

level is negatively significant at the p<0.1 level; Model 2 in Table 3.8 shows that the coupling effect (γ_h) between cost and ECD implementation level is negatively significant at the p<0.5 level. In sum, researchers must choose the best-fit change trajectory functions before implementing BDLDSM to ensure accurate representation of the dynamic associations between predictor and outcome variables.

3.5.2 Comparing BDLDSM with LGM

We now compare our BDLDSM with bivariate LGM to demonstrate the value of our proposed research model. Because HIT measures have the best-fit statistics on quadratic growth models, and healthcare performance variables have the best-fit statistics on cubic growth models, we implement LGM with the quadratic functional form of change for HIT measures and the cubic functional form of change for healthcare performance measures. We then compare the model fit between LGM and BDLDSM. As Table 3.14 indicates, BDLDSMs have a better model fit than bivariate LGMs. Besides, as we mentioned earlier, while LGM can incorporate trajectory change forms, it cannot capture the dynamic lead-lag associations between predictor and outcome variables. For example, LGM cannot be used to examine whether the changes in the implementation level of ECD and DS precede the changes in healthcare cost, and consequently cannot be used to conclude that a slower growth of ECD and DS is *predicted* to have a faster decrease in the subsequent change in healthcare cost. Further, LGM fails to identify different dynamic effects from the overall mean trajectory change components, the within-variable proportional changes, and the cross-variable coupling effects. For example, as Model 2 in Table 3.9 shows, when using BDLDSM, we find that changes in the communication score come from overall mean trajectory change, prior communication scores, and the DS implementation level in the previous year. With LGM, however, we cannot identify such a result. Further, we cannot use

LGM to examine the reciprocal relationship between two variables. For example, employing BDLDSM, we find a feedback loop between ECD and the communication score (Model 1, Table 3.9), but this result cannot be found using LGM. In sum, BDLDSM is a better choice than LGM for researchers seeking to better understand the dynamic association between the predictor and outcome variables and to better unveil the predictors' dynamic effects.

Table 3.14 Model Comparison between LGM and BDLDSM

		BDLDSM	LGM	LGM vs BDLDSM	Better Model
Communication and ECD	$\chi 2$	106.505	261.863	p<0.001	BDLDSM
	DF	75	87		
Communication and CPOE	$\chi 2$	115.523	274.904	p<0.001	BDLDSM
	DF	76	87		
Communication and DS	$\chi 2$	98.962	214.204	p<0.001	BDLDSM
	DF	75	87		
IQI91 and ECD	$\chi 2$	107.706	223.742	p<0.001	BDLDSM
	DF	77	87		
IQI91 and CPOE	$\chi 2$	121.735	228.054	p<0.001	BDLDSM
	DF	77	87		
IQI91 and DS	$\chi 2$	105.447	181.379	p<0.001	BDLDSM
	DF	77	87		
Cost and ECD	$\chi 2$	363.316	246.11	p<0.001	BDLDSM
	DF	97	87		
Cost and CPOE	$\chi 2$	373.559	237.742	p<0.001	BDLDSM
	DF	98	87		
Cost and DS	$\chi 2$	352.453	213.798	p<0.001	BDLDSM
	DF	97	87		

3.6 Discussion

3.6.1 Key Contribution

This study makes two major contributions to the IS field. First, it methodically extends current LGM understanding and introduces a sophisticated data analysis model, BDLDSM, to examine trajectory changes and analyze the dynamic lead-lag association between the predictor and outcome variables in a longitudinal data setting. We offer guidelines to test the dynamic lead-lag

relationship between dependent and independent variables, while also considering the functional forms of change. Further, our study presents the first description of how to incorporate nonlinear change form in a BDLDSM in the IS field. For example, using BDLDSM, we identified that healthcare performance changes faster than HIT implementation levels over time. Incorporating such nonlinear trajectory changes in both healthcare performance and HIT implementation level variables, we examined the lead-lag relationship between HIT and healthcare performance. This analysis technique lets IS researchers modify the change equations of the predictor and outcome variables in different functional forms of change to represent the theory of change.

Our work also provides the first demonstration in the IS literature of quantitatively studying the reciprocal relationship between variables over time. Neither traditional panel data models nor LGM can examine this reciprocal relationship or the feedback loop between variables while incorporating time-dependent changes. Using a process or system perspective, BDLDSM can potentially be extended as an analysis tool for studying the time ordering of events in the process model or for examining the reciprocal relationships or interactions among events in the system model. As such, our proposed BDLDSM should shed light on how to empirically examine theories related to time-dependent changes and reciprocal relationships.

Second, from the HIT value perspective, we extend the current literature that studies HIT impact on healthcare performance to include a dynamic and nonlinear perspective. We find that all HIT implementation levels increase in a quadratic way over time, and healthcare performance measures grow with cubic trajectories over time. This suggests the need for researchers to examine the relationship between HIT impact on healthcare performance using a model that incorporates nonlinear functional forms of change for both the HIT and healthcare performance variables. Further, we tested dynamic lead-lag relationships between three HIT functions and

healthcare performance using BDLDSM and obtained a more comprehensive understanding of how different types of HIT functions impact changes in healthcare quality and cost. Given that prior research has conflicting findings on HIT impact on healthcare quality and cost, our research provides further empirical tests of HIT value when considering the trajectory change of both HIT and healthcare performance variables. We identified that the implementation level of ECD and DS could be used to predict subsequent changes in healthcare cost and experiential quality. However, we did not find a dynamic lead-lag relationship between healthcare technologies and clinical quality. One potential explanation is that experiential quality is an intermediate performance measure, while clinical quality that measures mortality rate is an end performance measure (Sharma et al. 2016). HIT may impact the end performance measure through intermediate performance measures, such as experiential quality. Also, factors other than HIT may influence end performance measure. Another plausible explanation for this result is that one HIT function may not impact clinical quality in isolation; we may need to test combinations of HIT functions and how their complementarity effects impact clinical quality. A third possibility is that a learning curve may exist between the HIT implementation and clinical quality improvement. If we have data over a longer time period, we may observe the HIT effects on clinical quality.

Taken together, our findings offer a comprehensive view of the longitudinal relationship between HIT functions and various healthcare performance measures. Our analysis technique can also be extended to explore other longitudinal dynamic relationships in the IS field.

3.6.2 Limitations and Suggestions for Future Research

BDLDSM has its limitations. First, its complexity may lead to difficulties in interpreting results. Researchers must not only explain the form of change for both predictor and outcome variables,

but also interpret the various BDLDSM parameters. Also, given the model's complexity, it is difficult to use graphs to illustrate BDLDSM. Consequently, we suggest that researchers use this model only if they want to probe the dynamic interplay between variables over time. Second, the causal lag examined in the BDLDSM may be limited by the data sample (Sbarra and Allen 2009). For example, we used one-year spacing between measurements, but it is likely that the causal lag between HIT and healthcare performance may be shorter than that. If the true causal lag has a lower measurement resolution, however, it will lead to inflation of the parameter estimation (Sbarra and Allen 2009). Consequently, researchers should take the causal lag into consideration when using BDLDSM. Future research may collect data using a higher resolution of the measurement. This could help researchers test the causal lag with different time spacing between measurements and identify a causal lag that is closest to the true causal lag.

Moving forward, future research can extend BDLDSM application in multiple-group settings to explore group differences in the dynamic relationship. Future research can also explore how to test the moderating effect in the dynamic relationship using BDLDSM. For example, in the healthcare setting, we can examine the moderating effect of patient safety culture in the dynamic relationship between HIT and healthcare performance by separating the sample into two groups: one with a relatively high patient safety culture score, and the other with a relatively low patient safety culture score.

CHAPTER 4 A MULTI-STATE MARKOV MODEL FOR PATIENT HEALTH STATUS PREDICTION

Abstract

This chapter focuses on an important research gap in the predictive health analytics literature in the IS field—that is, that the majority of predictive health analytics research can predict the transition only from an initial state to a single endpoint. This is called a *single-event prediction*. However, it is rare that only one event would occur in the course of hospitalization. Here, we propose multi-state models that examine multiple events to advance predictive health analytics research in the IS field. Specifically, we aim to examine various types of observable transitions (chronic to acute, acute to chronic, chronic to death, and acute to death) and underlying, unobservable transitions (minor to major disease and major disease to death) that occur as diseases progress over time, and how different HIT applications, hospital characteristics, and patient profile impact these transitions. With a rich longitudinal dataset, we apply a multi-state Markov model to examine the observable transitions and a multi-state hidden Markov model to study the underlying, unobservable transitions. We find that HIT's implementation level, hospital characteristics, and patient profile are significantly associated with the transition risk among various states. These proposed multi-state models advance current predictive health analytics research in the IS field for examining multiple events as a disease progresses over time. Additionally, studying HIT's value at a granular level provides both scholars and practitioners a more complete picture of HIT's impact.

Keywords: Predictive Healthcare Analytics, Health Information Technology (HIT), Business Value of IT, Longitudinal Research, Multi-State Model

4.1 Introduction

The widespread diffusion of HIT applications within U.S. hospitals has given researchers access to more patient-level clinical and administrative data. This increased availability of such fine-grained data has triggered an emerging stream of predictive health analytics research. Using models that predictive health analytics researchers have developed, we can better profile and identify patients with high risk and reduce the failures and delays in preventive interventions (Lin et al. 2017). The majority of predictive health analytics research predicts the transition from an initial state, such as the start of a treatment, to a single endpoint, such as readmission or death (Amarasingham et al. 2010; Bardhan et al. 2015). This transition from one state to another state is defined as an *event* (Andersen and Keiding 2002). However, it is rare that only one event would occur as a disease unfolds (Lin et al. 2017); rather, as a disease progresses over time, it is more likely that multiple events would occur. For example, patients with coronary artery disease may experience myocardial infarction, ischemic stroke, and/or hemorrhagic stroke, which may result in either a fatal cardiovascular disease or a fatal non-cardiovascular disease (Asaria et al. 2016). Given this, the transitions between these five states—myocardial infarction, ischemic stroke, hemorrhagic stroke, fatal cardiovascular disease, and fatal non-cardiovascular disease—need to be examined. In a more general case, patients may experience a series of more severe disease stages before entering the final stage, death. Researchers are interested in studying the types of events and when they occur, as well as each event's history. In the transition process, patients may either enter the adjacent disease stages or enter the death stage directly from any disease stage (Jackson 2011). If we analyze each event separately, we can neither capture the relations among different types of events nor uncover the dynamic of how patients transition among different events (Jackson 2011; Putter et al. 2006). In this chapter, we propose a

predictive model that examines multiple events to advance predictive health analytics research in the IS field.

Our first research objective is to use HIT implementation levels, hospital characteristics, and patient profiles to predict the likelihood of a future transition from a minor to a more severe state and, finally, to death. Additionally, in our predictive model, we plan to explicitly account for the transition between chronic and acute states as a disease progresses over time. We focus on this because both literature and statistical evidence suggest that the transition between chronic and acute states is a good indicator of the underlying patient health status (Bernstein et al. 2017; Greenberg 2012; Zile et al. 2008) and yet, surprisingly, no research that we know of has yet explored how to use this transition at outcome variables in predictive modeling. To address this, we suggest using a multi-state hidden Markov model, which lets us use available data to uncover a patient's unobserved and hidden health status and thus determine the patient's true state of health.

Our second research objective is to study the impact of various HIT functions on the patient-transition-level intermediate performance. *Patient-transition level* refers to the case in which the unit of analysis is at both the patient level and the transition level, while the unit of observation is only at the transition level. HIT can provide value to clinical processes by improving the workflow of the core processes, such as by enhancing communication between healthcare providers and customers and reducing patients' transition between health states during hospitalization. We refer to such impacts as *intermediate performance measures*—that is, measures of the intermediate stages in a clinical process—to differentiate them both from traditional end performance measures, such as mortality rate and healthcare cost, and from operational measures, such as capital resource utilization and clinician and administrative

efficiency (Brandyberry et al. 1999). Prior HIT value studies have typically examined HIT's impact on hospital-level end performance outcomes, which cannot capture HIT's impact on lower-level, intermediate performance outcomes. The clinical workflow enhancement that technologies facilitate (Amarasingham et al. 2009; Bardhan and Thouin 2013) and the new types of errors they introduce (Coiera et al. 2016; Kannampallil et al. 2017; Weiner et al. 2007) would likely impact this intermediate performance. Thus, it is vital to empirically study HIT's impact on lower-level outcomes and gain a clearer and deeper understanding of HIT's positive or negative effects and how these effects impact intermediate healthcare performance. This crucial area is our focus here, as we explore HIT's impact on the intermediate performance outcomes—that is, on the patient's transition between chronic and acute conditions, and the transition between minor and more severe health statuses.

Our contributions are twofold. First, our study contributes to predictive health analytics by proposing a predictive model that detects when a disease progresses from a minor to a more severe state; healthcare providers can use this information to intervene early with appropriate treatments and to slow the worsening cycle of a disease. Our model advances current predictive health analytics research in the IS field by incorporating the dynamic transitions between chronic and acute diseases in predicting patient health status and by introducing a multi-state Markov model to examine multiple events in the disease progression process.

Second, our study contributes to the HIT business value literature by examining HIT's value at the patient-transition level. We find empirical evidence that the majority of HIT functions improve patient-transition-level outcomes, and only one HIT function harms health outcomes. The assessment of how different HIT functions impact different types of transitions

can help healthcare providers effectively allocate investment across various IT resources to achieve enhanced health outcomes.

In this chapter, we first review related literature in three areas: predictive analytics on disease progression; multi-state Markov models and multi-state hidden Markov models; and HIT's value for patient-transition-level performance. We then describe our data and how we measured it, followed by a discussion of our model development and our results. Next, we discuss our study's contribution to predictive health analytics and the HIT value literature, as well as to healthcare providers and policymakers. In the final section, we present the study's limitations and future research.

4.2 Literature Review

4.2.1 Predictive Analytics on Disease Progression

Characterized by predictive—rather than explanatory—power, predictive health analytics studies use clinical and/or nonclinical data to predict the likelihood of future events or outcomes (Lin et al. 2017) such as risk of readmission (Amarasingham et al. 2010; Bardhan et al. 2015), death (Amarasingham et al. 2010), and adverse health events (Lin et al. 2017). Models developed by predictive health analytics researchers can better profile and identify patients with a high risk of readmission or death, as well as reduce failures and delays in preventive interventions.

As Lin et al. (2017) point out, predictive health analytics models can be developed in two ways. One approach, commonly used in the medical field (and discussed below in section 4.2.2), is to develop the model based on intentionally collected data in clinical trials. The other approach, commonly used in the IS field, is to develop the model based on existing and routinely collected data. We identified three gaps in extant predictive health analytics research based on existing data in the IS field. First, the extant predictive health analytics research typically

examines a two-state model that predicts only the transition from an initial state to a single endpoint. As Figure 4.1 shows, a typical two-state model research effort aims to study the probabilities of being in either an initial state—e.g., alive—or at a single endpoint, e.g., dead. For example, Tabak et al. (2013) developed a predictive model to predict mortality based on laboratory test results, patient characteristics, and hospital characteristics. Bardhan et al. (2015) used a beta geometric Erlang-2 hurdle model to predict the propensity, frequency, and timing of the readmission rate for patients with congestive heart failure. However, it is rare that only one transition or event would happen in the course of a disease (Lin et al. 2017). As a disease progresses, several events or endpoints occur at different time points. For example, as Figure 4.2 shows, a typical illness–death model has three states: disease-free (state 1), diseased (state 2), and dead (state 3) (Andersen and Keiding 2002). A patient may move from state 1 to state 2 before entering state 3, or move from state 1 to state 2 and back to state 1, and so on. If we only analyze each event separately, we cannot capture transition rates among different types of states and cannot examine which variables impact those transition rates (Jackson 2011; Putter et al. 2006).

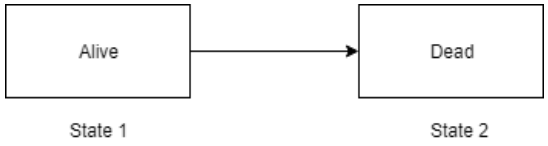


Figure 4.1 The Two-State Model

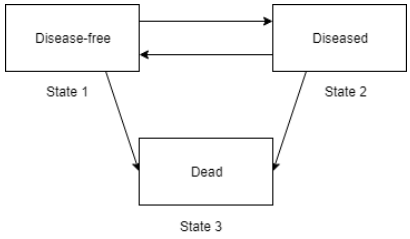


Figure 4.2 The Illness-Death Model

In the IS field, few predictive health analytics research studies have examined more than one event and considered the relationships among multiple events, and no extant research has examined the development of different patient states over time. A recently published study by Lin et al. (2017), for example, examined three adverse health events. The authors constructed an array of independent models, with each examining a specific adverse event. To account for the fact that events may correlate with each other, they created a unified framework to coordinate the models. However, their approach cannot examine the transition rate between different events, and cannot predict any subsequent event—such as death—after these three adverse events. Our proposed models differ from prior work is that they can be used to answer broader research questions related to disease evolution, including the following:

- What is a patient's risk for a certain health event at a certain time point given his or her health history?
- What is the transition rate from chronic condition to acute condition as diseases progress over time?
- How do time-constant or time-varying variables impact the transition rates?

Second, predictive health analytics researchers usually consider the chronic status of a discharge as a covariate in the model, but not as dynamic transitions over time. That is, they ignore the dynamic transitions between the chronic and the acute states. We find that both literature and statistical evidence suggest that the transition between chronic and acute conditions would be a good indicator of the underlying patient health status. They also suggest that patients that transition between chronic and acute conditions may experience deteriorate health conditions. And yet, surprisingly, no extant study explores how to use such transition information in predictive modeling. Further, the transition between chronic and acute conditions

can happen in the same body system or a different body system. These body systems include the digestive, circulatory, respiratory, nervous, and muscular systems, etc.; each system is an organized group of tissue that performs a particular function (Lysis 2018).

Literature shows that it is possible for chronic and acute conditions to transition between each other in the same body system as a disease progresses over time. For example, low back pain is a highly prevalent and costly health condition that 70–85% of adults experience at some point in their lives (Bernstein et al. 2017). Among the individuals who suffer from low back pain, 5% will develop subacute back pain, which will further develop into chronic low back pain (Bernstein et al. 2017) leading to limited functional capacity, work absenteeism, altered emotion, and high healthcare expenditure (Kamper et al. 2015). As another example, heart failure is the most common primary diagnosis for hospital admissions for patients over 65 in the United States; heart failure has a high readmission rate and a direct treatment cost of more than $34 billion per year (Desai and Stevenson 2012; Greenberg 2012). Chronic heart failure is a long-term condition that can be stabilized by treatment, but patients can experience acute decompensated heart failure, which is a symptom that signals a sudden worsening of the condition (Greenberg 2012; Lepage 2008; Zile et al. 2008). Hospitalization for acute heart failure predicts an increased risk of subsequent mortality, as well as hospitalizations for chronic heart failure (Joseph et al. 2009).

Literature also shows that it is likely for patients to transition between chronic and acute conditions among different body systems over time. For example, a patient with a chronic mental disorder may develop a nutritional disorder, which is an acute disease; in turn, the resulting nutritional deficiencies may lead to a worsening of the patient's mental illnesses (Rao et al. 2008). As another example, patients who experience acute heart attacks, which belong to

circulatory system, may further develop acquired brain injuries—a chronic disease of the nervous system and sense organ that occurs if blood flow decreases to the brain during heart attacks (Sims 2018).

As we discuss later, statistics from our dataset also confirm that the transition between chronic and acute conditions is a common activity during hospitalization and reflects a patient's health status. Capturing this transition between chronic and acute states of a disease is important; a major difference between our study and the extant literature is that we specifically account for this transition in predictive modeling.

Third, current predictive studies focus primarily on specific chronic diseases and ignore the acute patients. For example, Lin et al. (2017) and Meyer et al. (2014) studied diabetes patients because of the disease's large patient population, high medical costs, and broad societal impact. Bardhan et al. (2015) studied patients with congestive heart failure—a chronic condition that can last for years. However, patients are almost equally likely to be admitted to a hospital with either an acute or a chronic condition as their primary diagnosis. Podulka et al. (2008) analyzed patients admitted to hospitals in 15 U.S. states in 2008 and found that 4,553,900 (52%) of discharges had a chronic condition as their primary diagnosis and 4,169,800 (48%) of discharges had an acute condition as their primary diagnosis. In addition, as we mentioned above, it is very likely that chronic patients will develop acute conditions and becomes acute patients. Therefore, instead of being limited to one or more particular types of chronic disease, we find that *both* chronic and acute patients are certainly worthy of investigation. Thus, our study covers both chronic and acute patients and the transitions between these two states.

In sum, this chapter fills the three gaps in predictive health analytics research by using a multi-state framework to assess the dynamics between chronic and acute conditions in the course

of a disease unfolding, and by exploring how to apply the transition between chronic and acute conditions to uncover a patient's underlying health status. We now describe a multi-state Markov model and a multi-state hidden Markov model that enable us to study the transition dynamics between different states in a multi-state framework.

4.2.2 Multi-State Markov Model and Multi-State Hidden Markov Model

A multi-state Markov model can be used to represent continuous, multi-state processes and to study the course of disease stages. By defining various states that represent the evolution of a patient's health status over time, a multi-state Markov model captures the progression from one state to the other states. During this process, patients may advance into adjacent stages of a disease, recover from adjacent stages of a disease, or die at any stage of a disease (Jackson 2011). A multi-state Markov model can be applied to estimate transition rates between different states; researchers can then use these transition rates to obtain important insights into the relationships among different states. For example, given the transition rates among different states, researchers can estimate loco-regional recurrence and distant metastasis in breast cancer, or platelet recovery and survival in bone-marrow transplantation (Putter et al. 2006). A multi-state Markov model can also be applied to obtain predictions of the clinical prognoses for patients at certain time points within their illness or recovery process based on covariates and the occurrence of intermediate events. For example, with a given set of covariates and a post-surgery event, Putter et al. (2006) applied a multi-state Markov model to obtain a post-surgery prediction, such as the probability of a patient being in a certain state at a certain time and the probabilities of all possible future trajectories for each state.

The multi-state Markov model is widely applied in the fields of statistics and medicine to model the course of disease stages. Using a multi-state Markov model, researchers can predict

patients' clinical prognoses at certain time points in their recovery or illness process (Putter et al. 2006). For example, Longini et al. (1989) applied a multi-state Markov model to study the natural history of human immunodeficiency virus (HIV) infection. They estimated the distribution and mean length of the incubation period—that is, the period from infection to the development of clinical acquired immunodeficiency syndrome (AIDS)—for HIV-infected individuals. The researchers followed these individuals through five stages of infection: (1) infected but antibody-negative, (2) antibody-positive but asymptomatic, (3) pre-AIDS symptoms and/or abnormal hematologic indicator, (4) clinical AIDS, and (5) death due to AIDS. They estimated a mean AIDS incubation period of 9.8 years, as well as survival rates for individuals in each stage of the infection. As another example, Putter et al. (2006) examined how treatment and prognostic factors impact the course of disease for patients with breast cancer. They studied patients with early breast cancer who had either radical mastectomy or breast conserving therapy. Their study identified five states: (1) event-free after surgery, (2) loco-regional recurrence only, (3) distant metastasis only, (4) both local recurrence and distant metastasis and alive, and (5) the absorbing state, death. They estimated the transition rates between the states, and used these transition rates to obtain predictions for patients, at a certain time after surgery, based on a given event history and a set of covariates.

Researchers can apply a multi-state Markov model to estimate event history if the disease progression states are obvious and observable. However, if the disease process is hidden and unobservable, we must use a hidden Markov model to uncover the hidden states. In a hidden Markov model, the observed data are governed by probability distribution conditionally on the unobserved true state (Jackson 2011). The model was first used in a discrete-time underlying Markov chain to study speech and signal processing and biological sequence data. Applications

of the hidden Markov model in medical field, where continuous-time processes are usually more appropriate, are limited (Bureau et al. 2000; Jackson 2011). One area in which medical researchers often use a multi-state hidden Markov model is in the screening process to identify classification errors by examining the probability that true and observed states are equal (Jackson et al. 2003; Zare et al. 2014).

Extant studies that apply a multi-state Markov model and/or a multi-state hidden Markov model typically focus on proposedly collective data in clinical trials, which usually focus on a single disease with a limited sample size. For example, multi-state models have been applied in studies to screen for abdominal aortic aneurysms using data from 156 male patients (Jackson et al. 2003); to estimate the state transition probabilities for patients with early breast cancer using data from 2,795 patients (Putter et al. 2006); and to predict lifetime outcomes and costs for patients with coronary artery disease using data from 94,966 patients (Asaria et al. 2016). As we noted earlier, patients often develop diseases in different body systems over time. Developing multi-state models on a single disease fails to capture the transitions characteristics for those with diseases among different body systems. In addition, to the best of our knowledge, researchers have never applied both a multi-state Markov model and a multi-state hidden Markov model in the IS field to estimate and understand disease progressions. In this study, we use a multi-state model to model patient transition processes between chronic and acute states in continuous time, and a multi-state hidden Markov model to uncover transitions between hidden health statuses, where the states of the Markov chain are not directly observed. To develop both models, we use a large panel of 3,479,424 patients with two or more admissions and a variety of diseases in 17 different body systems.

Multi-state Markov models and multi-state hidden Markov models both support the estimation of the impact of constant or time-varying variables on the transition rates. This lets us examine how different HIT functions, along with different hospital characteristics and patient profiles, impact various types of transitions as diseases progress over time. These include observable transitions (chronic to acute, acute to chronic, chronic to death, and acute to death) and underlying and unobservable transitions (minor to major disease and major disease to death). We now discuss the importance of studying HIT's value in relation to these patient transitions.

4.2.3 HIT's Value for Patient-Transition-Level Performance

HIT improves clinical workflow efficiency, promotes medication order standardization, prevents medical errors, and leads to enhanced healthcare quality and reduced healthcare cost (Amarasingham et al. 2009; Bardhan and Thouin 2013). Meanwhile, however, HIT introduces new types of errors—called *e-iatrogenesis*—including inappropriate text entries, mismatches between newly introduced HIT and existing workflows, and problematic electronic data presentation, which lead to unintended consequences, such as incorrect or delayed treatment (Coiera et al. 2016; Kannampallil et al. 2017; Weiner et al. 2007).

Prior HIT value studies have typically examined HIT's impact on hospital-level outcomes, including quality of care (Agha 2014; Aron et al. 2011; Menachemi et al. 2008; O'Connor et al. 2011), efficiency (Watcharasriroj and Tang 2004), and financial performance (Agha 2014; Bardhan and Thouin 2013; Borzekowski 2009; Menachemi et al. 2006). For example, Menachemi et al. (2008) studied HIT's impact on various morality rates and found that hospitals that have a greater number of HIT applications have lower morality rates for several health conditions. As another example, Sharma et al. (2016) examined HIT's impact on hospital cost and found no association between HIT adoption and healthcare cost.

However, these hospital-level performance outcomes are usually end performance outcomes and cannot capture how HIT impacts lower-level, intermediate performance outcomes. The clinical workflow enhancement that technologies facilitate (Amarasingham et al. 2009; Bardhan and Thouin 2013) and the new types of errors technologies introduce (Coiera et al. 2016; Kannampallil et al. 2017; Weiner et al. 2007) would likely impact intermediate performance. Yet, to the best of our knowledge, no extant study has examined HIT's impact on patient-transition-level intermediate performance outcomes. As we noted earlier, both literature and statistical evidence suggest that patients that transition between chronic and acute conditions may experience deteriorating health conditions. Thus, it is important to examine whether HIT functions lead to reduced or increased transitions. We therefore aim, in this chapter, to empirically study the impact of various HIT functions on the patient-transition-level intermediate performance. We believe this study will provide a nuanced view of how HIT facilitates clinical workflow and/or generates unintended consequences within the intermediate clinical process.

4.3 Data and Measurement

4.3.1 Sample and Data Collection

This study uses data from three sources. First, to obtain patient-level clinical data, we use data from the HCUP-SID database, which contains 97 percent of all discharges from community hospitals in 48 U.S. states. HCUP-SID contains nonclinical variables, such as patient demographic characteristics and total charges, and clinical information, such as diagnoses, procedures, chronic indicators, admission and discharge status, length-of-stay (LOS), and severities related to each inpatient discharge case. To capture disease progression between hospital visits, we focus only on readmitted patients; we therefore use HCUP-SID data only on patients with two or more hospital admissions. We also excluded discharges related to

pregnancy, childbirth, and the puerperium, because the transition pattern between the chronic and acute statuses of women in this group is significantly different from people in other patient groups. Finally, we excluded discharges of patients under 18 years old because their treatment often differs from treatment on adults (Schmidt et al. 2014).

Second, to obtain hospital demographics and organization structure data, we use data from AHA's annual surveys of Florida and New York for 2009–2013 in conjunction with HCUP-SID data on hospitals in these two states.

Third, to obtain HIT implementation data, we use AHA's IT supplement files for 2008–2012. This hospital-level database contains healthcare IT implementation-level information on five different IT functions: DS, CPOE, ECD, RV, and telehealth (AHA 2016). DS supports the decision-making process by helping care providers accurately diagnose patient conditions, consult the latest evidence, and provide patient-specific care. CPOE facilitates task execution by allowing care providers to offer instructions to nurses and technicians. ECD lets care providers access and record patient information, while RV gives healthcare providers access to patients' prior test results. Finally, telehealth gives patients access to vital healthcare services through remote monitoring, wireless communication, video-conferencing, and electronic consults.

We mapped the three datasets with HIT variables lagged one year; the resulting dataset is an unbalanced panel data set that consists of 3,479,424 distinct patients with more than 13.4 million admissions from 338 hospitals from 2009–2013. We sampled 5% of the patients for the data analysis to keep the sample size manageable. This sample is random selected to avoid systematic bias. This sample contained 669,641 admissions that originated from 173,971 patients, among whom 43.9% had two admissions, 21.1% had three admissions, 11.9% had four admissions, and the rest had more than four admissions.

4.3.2 Measures

HIT Implementation

HIT implementation is measured on a six-point scale, where 1 indicates "fully implemented across all units," and 6 indicates "not in place and not considering implementing." Appendix 4A shows the HIT implementation items and the original measurement scale. To calculate HIT implementation levels, we first recoded the original data. Responses between 2 and 6 were recoded as 0, and we retained the original coding of 1 as 1. This coding scheme separates full implementation—that is, IT has completely replaced paper record functionality—from partial or no implementation. Next, we constructed four HIT variables (DS, CPOE, RV, and ECD) by counting the number of technologies completely implemented at a hospital in each HIT category; this approach has been widely used in both the IS and health care literature (Angst et al. 2012; Borzekowski 2009; Burke and Menachemi 2004; Menachemi et al. 2008). Telehealth is a dummy variable, for which 0 indicates no implementation and 1 indicates implementation.

Hospital Characteristics and Patient Profile Variables

To account for other factors that may influence transition intensity between different states, our model includes both hospital characteristics variables and patient profile variables. For hospital characteristics, we include hospital bed size, teaching status, and profit status, which we obtained from AHA survey datasets at the hospital level. We measure patient profiles both at the patient and discharge levels using HCUP-SID data. At the patient level, we include gender and number of total admissions, which we construct by counting the number of admissions the patient had at discharge time. At the discharge level, we include: a dummy variable that records whether the patient is an emergency or urgent admission; insurance type; discharge age; LOS; total number

of comorbidities[9] at the current admission; a dummy variable that records whether the patient was transferred from another hospital at the current admission; a dummy variable that records whether the patient's primary diagnosis is in the same body system[10] at the current admission compared to the last admission; and total number of discharges with the primary diagnosis in the same the body system as the current admission.

Summary Statistics

Table 4.1 offers an overview of our sample data. Among all patients with two or more admissions, 52.2% are female, 84.5% are emergency type or urgent admission type, 59.8% are Medicare patients, and 15.1% are Medicaid patients. The average discharge age is 64, while the average LOS is 5.8 days and the average number of hospital visits is 3.9. Among sampled patients, 24.2% transferred from another hospital at the current admission and 48.1% were diagnosed as having a disease transfer to a different body system at the current admission compare to the prior admission. Patients' primary diagnosis was in the same body system as the prior admissions two times on average; the average number for total comorbidity at the current admissions is 2.8.

[9] We include 29 different types of comorbidity in the study including congestive heart failure, valvular disease, pulmonary circulation disorders, peripheral vascular disorders, hypertension, paralysis, other neurological disorders, chronic pulmonary disease, uncomplicated diabetes, complicated diabetes, hypothyroidism, renal failure, liver disease, peptic ulcer disease excluding bleeding, acquired immune deficiency syndrome(aids), lymphoma, metastatic cancer, solid tumor without metastasis, rheumatoid arthritis/collagen vascular diseases, coagulopathy, obesity, weight loss, fluid and electrolyte disorders, blood loss anemia, deficiency anemias, alcohol abuse, drug abuse, psychoses, depression

[10] We include 17 different types of body system in the study including infectious and parasitic disease, neoplasms, endocrine, nutritional, and metabolic diseases and immunity disorders, diseases of blood and blood-forming organs, mental disorders, diseases of the nervous system and sense organs, diseases of the circulatory system , diseases of the respiratory system, diseases of the digestive system, diseases of the genitourinary system, diseases of the skin and subcutaneous tissue, diseases of the musculoskeletal system, congenital anomalies, certain conditions originating in the perinatal period, symptoms, signs, and ill-defined conditions, injury and poisoning, factors influencing health status and contact with health services

From our dataset, we find that, for patients who have two or more admissions within five years, 60.1% experienced a transition between chronic and acute diseases. We also find that patients who suffer from disease transitions between chronic and acute conditions have reduced health status and higher medical expenses. Compared with patients remaining within either a chronic or an acute status, discharges with transitions between chronic and acute status have a $7,791 higher average charge per stay, 0.97 days longer LOS, 0.37% higher death rate, and 3.7% higher probability of using emergency department services.

Table 4.1 Summary Statistics

Variables	Mean	Stdev	Min	Max
Health IT				
No. of DS (lagged)	3.282	2.377	0	6
No. of CPOE (lagged)	2.009	2.304	0	5
No. of RV (lagged)	5.061	1.247	0	6
No. of ECD (lagged)	4.035	2.144	0	7
Telehealth (lagged)	0.136	0.343	0	1
Hospital Characteristic				
No. of beds	574	513	4	2,396
Teaching	0.289	0.453	0	1
For-profit	0.198	0.399	0	1
Patient Profile				
Female	0.522	0.500	0	1
Emergency or Urgent	0.845	0.362	0	1
Medicare	0.598	0.490	0	1
Medicaid	0.151	0.358	0	1
Discharge Age	64.061	18.267	18	108
LOS	5.847	7.818	0	353
No. of Visits	3.973	5.309	1	114
Transfer Hospital	0.242	0.428	0	1
Transfer Body System	0.481	0.500	0	1
No. of same body system	2.088	3.373	1	97
No. of comorbidity	2.802	1.870	0	13

4.4 Model Development and Data Analysis

4.4.1 A Multi-State Markov Model

To estimate the transition rate between a chronic and an acute status, we developed a multi-state Markov model for disease progression in continuous time. We propose three different states: admission with a chronic condition[11] as the primary diagnosis (state 1), admission with an acute condition as the primary diagnosis (state 2), and the absorbing state, death (state 3). Patients in state 1 can move to any state, as can patients in state 2; death (state 3), however, is the absorbing state so it is impossible to go from state 3 to the other states. Figure 4.3 shows our multi-state Markov model.

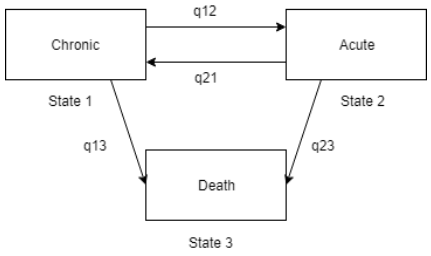


Figure 4.3 Multi-State Markov Model

We assume that the sampling scheme is non-informative—that is, that an observation made at a certain time does not provide information on that observation's value. We assume that we observe the admission state, $O(t)$, when patients visit hospitals at time t. Figure 4.4 shows an example of the sampling situation: a patient is observed on five occasions over a three-year period. The patient is observed at times 0, 1.5, 1.8, 2.5, and 3, and occupies the states of 1, 1, 2, 1, and 3, respectively. The state occupancy in between the observation times and the times of

[11] A *chronic condition* is defined as a condition that lasts 12 months or longer and meets one or both of the following tests: (a) it places limitations on self-care, independent living, and social interactions; and (b) it results in the need for ongoing intervention with medical products, services, and special equipment (https://www.hcup-us.ahrq.gov/db/vars/chronn/kidnote.jsp).

movement between the states are unobserved. Thus, the exact value for the times of changes in state is unknown, but the change occurs within a certain bounded interval—a situation referred to as *interval censored*. At the same time, unless the last observation is in state 3 (death), the remaining observations are subject to right censoring. However, right censoring does not bias our estimation because we are interested only in the transition risk between the states. We assume that censoring is *non-informative*—that is, that patients who are right censored have the same probability of experiencing a subsequent event as patients who remain in the study. In this case, the standard multi-state model likelihood is applicable.

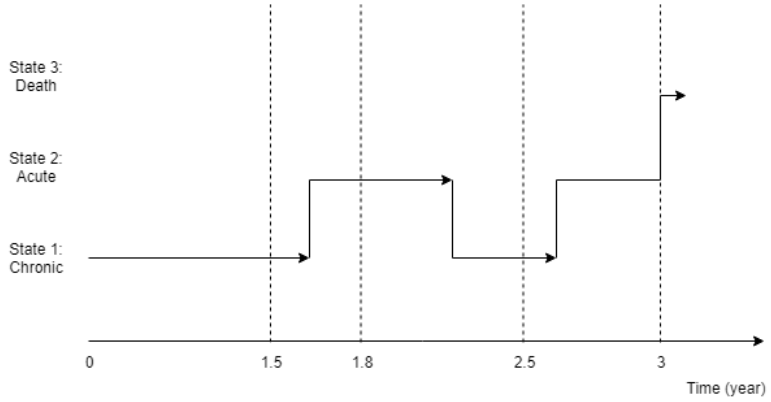


Figure 4.4 An Example of the Evolution of a Multi-State Model

The movement on the discrete state space 1,…R is governed by the transition intensities, or the *hazard rate*, which represents the instantaneous risk of progression from state *r* to state *s*, q_{rs}, which is defined as

$$q_{rs} = q_{rs}(t\,, z(t), F(t)) = \lim_{\Delta t \to 0} P(O(t + \Delta t) = s | O(t) = r, z(t), F(t))/\Delta t.$$

This hazard function q_{rs} provides the hazard rate that a patient who is at state r by time *t*, will transition to state *s* during the infinitesimally small time interval, Δt. $z(t)$ are time-dependent explanatory variables. $F(t)$ is the collection of events that represents the observation history. Because the Markov assumes that future evolution depends only on the current state,

$q_{rs}(t, z(t), F(t))$ is independent of $F(t)$. We assume that transition intensities q_{rs} depends on time only through $z(t)$. We call this a *time-inhomogeneous* model.

We model the effect of covariates on the transition from state *r* to state *s* using Cox's proportional hazards model, a commonly applied survival model, on the transition hazards. For a patient with covariates $z(t)$, the transition hazard $q_{rs}(t)$ for transition state *r* to state *s* is

$$q_{rs}(t, z(t)) = q_{rs}^{(0)} \exp(\boldsymbol{\beta}_{rs}^{T} z(t)),$$

where $q_{rs}^{(0)}$ is the baseline hazard of transition from state *r* to state *s*, $z(t)$ are time-dependent covariates specific to the transition from state *r* to state *s*, and $\boldsymbol{\beta}_{rs}^{T}$ is a vector of regression coefficients.

We include three sets of covariates in the model:

1) HIT variables (DS, CPOE, RV, ECD, and telehealth)

2) Hospital characteristics variables (bed size, teaching status, and for-profit status)

3) Patient profile variables at the patient level (female indicator and number of total admissions) and the discharge level (emergency and urgent admission indicator, insurance type, discharge age, LOS, indicator for hospital transfer, total number of comorbidities at current admission, indicator for body system transfer, number of discharges with the primary diagnosis in the same the body system as the current admission)

The transition intensities form a transition intensity matrix *Q*, where the sum of each row is zero. This means that the diagonal entries are defined by $q_{rr} = -\sum_{s \neq r} q_{rs}$. For a three-state multi-state model, the transition intensity matrix is as follows:

$$Q = \begin{pmatrix} -(q_{12} + q_{13}) & q_{12} & q_{13} \\ q_{21} & -(q_{21} + q_{23}) & q_{23} \\ 0 & 0 & 0 \end{pmatrix}.$$

Maximum likelihood estimates Q can be computed from the transition probability matrix $P_{t_1}(t_2 - t_1)$, with (r, s) entry being $p_{rs}\{t_2 - t_1, z(t)\}$. Suppose Q is constant over the interval (t_1, t_2), then $P_{t_1}(t_2 - t_1) = P(t)$, where t is the time interval between t_2 and t_1. The transition probability matrix $P(t)$ is as follows:

$$P(t) = \exp(tQ).$$

The contribution to the likelihood for a pair of successive observed disease states $S(t_j)$, $S(t_{j+1})$ at times t_j, t_{j+1} for individual i is as follows:

$$L_{i,j} = P_{S(t_{i,j})S(t_{i,j+1})}(t_{i,j+1} - t_{i,j}).$$

This likelihood is the entry of the transition matrix P(t) at the $S(t_j)$ row and $S(t_{j+1})$ column. We calculate the full likelihood using the product of transition probabilities between observed states, over all individuals i and observation times j, which is presented as follows:

$$L(Q) = \prod_i L_i = \prod_{i,j} L_{i,j} = \prod_{i,j} P_{S(t_{i,j})S(t_{i,j+1})}(t_{i,j+1} - t_{i,j}),$$

where each $L_{i,j}$ is the entry of the transition matrix P(t) at the S($t_{i,j}$) row and the S($t_{i,j+1}$) column, which is evaluated at $t = t_{i,j+1} - t_{i,j}$. The likelihood *L(Q)* is maximized in terms of log(q_{rs}) to compute the estimates of q_{rs}. We chose the quasi-Newton method as our optimization algorithm because it is often used for multi-state models and gives the greatest speed of converge (Jackson et al. 2003). We computed the standard errors from the Hessian at the optimum. We run the model with diverse sets of initial values to ensure that our model converges to a global rather than local maximum of the likelihood surface. To implement the multi-state Markov model and

the multi-state hidden Markov model, we use an open source R package called *msm* (Jackson 2011).

4.4.2 A Multi-State Hidden Markov Model

We also aim to develop a continuous-time three-state hidden Markov model to uncover the true state or the hidden state of a patient's health status. Suppose S_{it} represents the true state for patient *i* at time *t*, and it evolves as an unobserved Markov process. S_{it} is assumed to have three states: admission with minor disease (state 1), admission with major disease (state 2), and death (state 3). We assume that major disease is a more severe disease than minor disease, and is more likely to result in mortality than minor disease. The minor disease state can only go through major disease state before entering the final state, death. We therefore assume that patients with minor disease (state 1) at the current admission can stay in the current state (state 1) or move to a major disease (state 2) at the next moment. Patients with minor disease (state 1) cannot move to death (state 3) directly; they must go through the major disease (state 2) first. We also assume that patients with major disease (state 2) can advance to the next state, death (state 3), stay in the same state (state 2), or recover and move to a minor disease state (state 3). Again, death (state 3) is the absorbing state and cannot move to the other states. Figure 4.5 shows the multi-state hidden Markov model. The definition of transition intensity for a multi-state hidden Markov model is the same as for a multi-state Markov model. Thus, the transition intensity matrix for a three-state hidden Markov model is presented as follows:

$$\mathrm{Q}_H = \begin{pmatrix} -q_{12} & q_{12} & 0 \\ q_{21} & -(q_{21}+q_{23}) & q_{23} \\ 0 & 0 & 0 \end{pmatrix}.$$

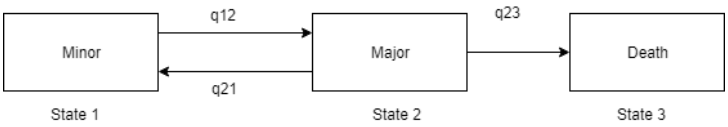


Figure 4.5 The Multi-State Hidden Markov Model

Because the exact state of health status is difficult to determine, we form the emission probability density based on the observed chronic and acute statuses for patient *i* at time *t*, $Q_{H_{it}}$. As we discussed earlier, the three observed statuses are: admission with a chronic condition (state 1), admission with an acute condition (state 2), and death (state 3).

A hidden Markov model has two types of parameters: transition probabilities and emission probabilities. As we noted earlier, maximum likelihood estimates can be computed from the transition probability matrix $P_H(t)$, with (*r*, *s*) entry from time t_1 to time t_2 as $p_{rs}\{t_2 - t_1, z(t)\}$. We include the same time-dependent covariates, $z(t)$, as we introduced above. We will now discuss the emission probabilities, with (r, s) entry for patient *i* at observation time *j*, $e_{rs} = \Pr(O(t_{ij}) = s \mid S(t_{ij}) = r)$.

Detailed emission probability density is as follows:

Because state 3 is exactly observed, we have:

$\Pr(O(t_{ij}) = 3 \mid S(t_{ij}) = 1) = \Pr(O(t_{ij}) = 3 \mid S(t_{ij}) = 2) = \Pr(O(t_{ij}) = 1 \mid S(t_{ij}) = 3) = \Pr(O(t_{ij}) = 2 \mid S(t_{ij}) = 3) = 0$

$\Pr(O(t_{ij}) = 3 \mid S(t_{ij}) = 3) = 1.$

Given that S_{ij}=1, we can observe only O_{ij}=1 or O_{ij}=2, so we also have:

$\Pr(O(t_{ij}) = 1 \mid S(t_{ij}) = 1) + \Pr(O(t_{ij}) = 2 \mid S(t_{ij}) = 1) = 1.$

Likewise, given that S_{ij}=2, we can observe only O_{ij}=1 or O_{ij}=2, so we also have:

$\Pr(O(t_{ij}) = 1 \mid S(t_{ij}) = 2) + \Pr(O(t_{ij}) = 2 \mid S(t_{ij}) = 2) = 1.$

Here, we can assume that both Pr($O_{ij} \mid S_{ij}$ =1) and Pr($O_{ij} \mid S_{ij}$ =2) follow binomial distribution, Binomial (n, p). Next, we need to set the initial values for Pr($O(t_{ij})$=1|$S(t_{ij})$=1), Pr($O(t_{ij})$=2|$S(t_{ij})$=1), Pr($O(t_{ij})$=1|$S(t_{ij})$=2), and Pr($O(t_{ij})$=2|$S(t_{ij})$=2). We assume that the closer the admission time is to the death time, the more severe the disease is. From our dataset, we find that, on first admission, 49.93% of patients had chronic conditions and 50.07% of patients had acute conditions. From this, we assume the initial value for Pr($O(t_{ij})$=1|$S(t_{ij})$=1) is 0.5 and the initial value for Pr($O(t_{ij})$=2|$S(t_{ij})$=1) is 0.5. We also find that, on the admissions closest to death, 40.04% patients had chronic conditions and 59.96% patients had acute conditions; from this, we assume the initial value for Pr($O(t_{ij})$ =1| $S(t_{ij})$ =2) is 0.4 and the initial value for Pr($O(t_{ij})$=2|$S(t_{ij})$=2) is 0.6. We also assume that several patient profile variables influence the emission distributions or hidden Markov outcome distributions, so we use these variables as covariates for the emission distributions. These variables are female indicator, number of total admissions, emergency admission indicator, insurance type, indicator for hospital transfer, total number of comorbidities at current admission, indicator for body system transfer, and number of discharges with the primary diagnosis in the same the body system as the current admission.

For discrete time hidden Markov model, researchers often use the forward-backward, or *Baum-Welch*, algorithm. Baum-Welch is the previous version of expectation-maximization (EM) algorithm, when applied to hidden Markov model, they are essentially the same. Bureau et al. (2000) proposed generalizing the Baum-Welch algorithm to continuous time, which we will follow in this essay.

The likelihood of patient *i* is given as follows:

$$L_i = \Pr(O_{i1}, \dots, O_{in_i})$$

$= \sum \Pr(O_{i1}, \dots, O_{in_i} | S_{i1} \ \dots, S_{in_i}) \ \Pr(S_{i1}, \dots, S_{in_i})$.

The assumed Markov property is

$\Pr(S_{ij} \mid S_{i,j-1,} \ \dots, S_{i1}) = \Pr(S_{ij} \mid S_{i,j-1})$.

The contribution L_i is a product of matrix:

$$L_i = \sum_{S_{i1}} \Pr(O_{i1} | S_{i1}) \Pr(S_{i1}) \sum_{S_{i2}} \Pr(O_{i2} | S_{i2}) \Pr(S_{i2} | S_{i1}) \sum_{S_{i3}} \Pr(O_{i3} | S_{i3}) \Pr(S_{i3} | S_{i2}) \dots \sum_{S_{in_i}} \Pr(O_{in_i} | S_{in_i}) \Pr(S_{in_i} | S_{in_{i-1}}),$$

where

1) $\Pr(O_{ij} | S_{ij})$ is the emission probability density.

2) $\Pr(S_{ij} \mid S_{i,j-1})$ is the transition probability (p_{rs}) of the hidden Markov chain.

4.4.3 Multi-State Markov Model Results

Table 4.2 provides the frequencies of admissions between different states. We find that 154,788 (31.1%) chronic admissions are followed by chronic admissions; 141,948 (28.36%) acute admissions are followed by acute admissions; 98,488 (19.74%) chronic admissions are followed by acute admissions; and 88,452 (17.77%) acute admissions are followed by chronic admissions. We further discover that 7,196 (1.46%) are dead after chronic admissions and 7,982 (1.58%) are dead after acute admissions.

Table 4.2 Frequencies for Transitions to the Next Stage

Initial Stage	1 = Chronic Status	2 = Acute Status	3 = Death
1	154,788 (31.10%)	98,488 (19.74%)	7,196 (1.46%)
2	88,452 (17.77%)	141,948 (28.36%)	7,982 (1.58%)
3	0	0	0

To compare the goodness of fit among the models with various covariance sets, we employed the likelihood-ratio test. The null model (Model 1) is a multi-state Markov model with

no covariates. In Model 2, we added IT variables; in Model 3, we added hospital characteristics variables; and in Model 4 we added patient profile variables. Table 4.3 presents the likelihood-ratio test for models 1–4 and shows that the likelihood-ratio test favors our proposed model (Model 4) over the other models.

Table 4.3 Likelihood-Ratio Test for Multi-State Markov Models

Model	-2*Log-Likelihood	Test	Likelihood Ratio Statistic	ΔDF	P-Value	AIC
Model 1: Null	1,002,667					1,002,676
Model 2: Add IT Variables	1,002,266	1 vs 2	401	20	**<0.0001**	1,002,314
Model 3: Add Hospital Characteristics	1,001,954	2 vs 3	312	12	**<0.0001**	1,002,026
Model 4: Add Patient Profile	315,283	3 vs 4	23747	32	**<0.0001**	978,343

Table 4.4 shows the results of the estimated hazard ratios with a 95% confidence interval (CI) on the transition intensities. We find that DS has no significant effect on any of the transitions. The hazard ratio estimate of the CPOE implementation level on the chronic-to-death transition is 1.059 (95% CI: 1.003, 1.087), implying that, for patients in state 1 (chronic), higher CPOE implementation is associated with a higher risk of progression to state 3 (death). CPOE has no significant effect on the transition from chronic to acute, acute to chronic, or acute to death. The hazard ratio estimates for the RV implementation level on the chronic-to-acute transition is 0.928 (95% CI: 0.885, 0.973) and on the acute-to-chronic transition, it is 0.916 (95% CI: 0.873, 0.961), implying that a higher level of RV implementation is associated with a lower risk of transition between chronic and acute states. RV has no significant effect on the transition from chronic to death or acute to death. ECD has no significant effect on any of the transitions. The hazard ratio estimates of the telehealth implementation level on the acute-to-death transition is 0.729 (95% CI: 0.546, 0.974), implying that a higher level of telehealth implementation is

associated with a lower risk of transition from the acute to the death state. Telehealth has no significant effect on chronic-to-acute, acute-to-chronic, or chronic-to-death transitions.

Besides HIT implementation levels, we notice that hospital characteristics and patient profile variables are also significantly associated with transition risks among various states. For example, a higher number of hospital beds is associated with a lower risk of transition from chronic to death states, but a higher risk of transition from acute to deaths states. Teaching hospitals are associated with a higher risk of transition from chronic to acute and chronic to death, but a lower risk of transition from acute to death. Female patients are associated with higher risk of transition between chronic and acute conditions, but lower risk of transition from chronic to death and from acute to death. Emergency or urgent admission type is associated with lower risk of transition between chronic and acute conditions, but higher risk of transition from chronic or acute to death. Medicare or Medicaid patients are associated with a lower risk of transition between chronic and acute and from chronic to death, but a higher risk of transition from acute to death. Higher age when admitted is associated with higher risk of transition between chronic and acute conditions and from chronic to death. Increased LOS is associated with a lower risk of transition between chronic and acute conditions but a higher risk of transition from chronic to death and acute to death. Patients who have an increased number of visits, diagnoses changed to a different body system at the current vs. last admission, or a higher number of comorbidities are associated with higher risk of transition between chronic and acute, and from chronic or acute to death. Transferring hospitals is associated with a higher risk of transition between the chronic and acute status, but a lower risk of transition from acute to death. A higher number of discharges with the primary diagnosis in the same the body system as the

current admission is associated with a higher risk of transition from chronic to death but a lower risk of transition from chronic to acute.

Table 4.4 Results for Multi-State Markov Model

Variable	State 1–State 2 Chronic–Acute	State 1–State 3 Chronic–Death	State 2–State 1 Acute–Chronic	State 2–State 3 Acute–Death
Health IT				
No. of DS	1.028 (0.997-1.060)	0.996 (0.973-1.019)	1.029 (0.998-1.061)	1.000 (0.955-1.047)
No. of CPOE	0.983 (0.957-1.011)	**1.059 (1.033-1.087)**	0.986 (0.960-1.014)	1.035 (0.980-1.093)
No. of RV	**0.928 (0.885-0.973)**	0.981 (0.939-1.024)	**0.916 (0.873-0.961)**	1.020 (0.923-1.128)
No. of ECD	1.018 (0.984-1.052)	1.001 (0.970-1.033)	1.003 (0.970-1.037)	0.972 (0.912-1.036)
Telehealth	0.937 (0.808-1.085)	0.966 (0.855-1.091)	0.927 (0.798-1.076)	**0.729 (0.546-0.974)**
Hospital Characteristic				
No. of beds（log）	1.082 (0.986-1.189)	**0.869 (0.805-0.937)**	1.094 (0.994-1.203)	**1.182 (1.016-1.375)**
Teaching	**1.220 (1.056-1.410)**	**1.193 (1.052-1.352)**	1.153 (0.995-1.336)	**0.686 (0.525-0.895)**
For-profit	1.045 (0.867-1.259)	0.924 (0.803-1.063)	1.040 (0.861-1.257)	0.939 (0.704-1.252)
Patient Profile				
Female	**1.325 (1.192-1.473)**	**0.768 (0.706-0.834)**	**1.145 (1.029-1.275)**	**0.762 (0.646-0.899)**
Emergency	**0.278 (0.236-0.328)**	**1.782 (1.523-2.085)**	**0.282 (0.238-0.333)**	**1.336 (1.015-1.758)**
Medicare	**0.691 (0.600-0.797)**	**0.829 (0.724-0.949)**	**0.737 (0.638-0.852)**	**1.441 (1.068-1.944)**
Medicaid	**0.713 (0.620-0.819)**	**0.685 (0.549-0.856)**	**0.843 (0.731-0.971)**	**1.701 (1.260-2.295)**
Discharge Age	**1.031 (1.027-1.035)**	**1.058 (1.055-1.062)**	**1.022 (1.019-1.026)**	1.005 (0.997-1.013)
LOS（log）	**0.434 (0.404-0.467)**	**1.941 (1.829-2.060)**	**0.382 (0.354-0.411)**	**1.194 (1.010-1.412)**
No. of Visits	**1.152 (1.131-1.174)**	**1.031 (1.021-1.041)**	**1.142 (1.120-1.165)**	**1.032 (1.021-1.043)**
Transfer Hospital	**1.363 (1.186-1.568)**	1.045 (0.930-1.174)	**1.437 (1.246-1.659)**	**0.795 (0.633-0.997)**
Transfer Body System	**4.292 (3.266-5.641)**	**1.185 (1.023-1.374)**	**3.714 (2.820-4.890)**	**2.682 (2.093-3.437)**
No. of same body system	**0.066 (0.055-0.080)**	**1.265 (1.097-1.457)**	**0.092 (0.076-0.111)**	1.196 (0.945-1.514)
No. of comorbidity	**1.696 (1.624-1.773)**	**1.168 (1.143-1.194)**	**1.686 (1.613-1.763)**	**1.211 (1.158-1.266)**

Note: 95% of confidence interval is reported in the parentheses

4.4.4 Multi-State Hidden Markov Model Results

To compare the goodness of fit among the models with various covariance sets, we again used the likelihood-ratio test. The null model (Model 1) is a multi-state hidden Markov model with no covariates. We added HIT variables in Model 2, hospital characteristics variables in Model 3, and patient profile variables in Model 4. Table 4.5 shows the likelihood-ratio test for models 1–4; it also shows that the likelihood-ratio test favors our proposed model (Model 4) over the other models.

Table 4.5 Likelihood-Ratio Test for Multi-State Hidden Markov Model

Model	-2*Log-Likelihood	Test	Likelihood Ratio Statistic	ΔDF	P-Value	AIC
Model 1: Null	1,302,305					1,302,315
Model 2: Add IT Variables	1,301,979	1 vs 2	326	15	**<0.0001**	1,302,019
Model 3: Add Hospital Characteristics	1,301,746	2 vs 3	233	9	**<0.0001**	1,301,804
Model 4: Add Patient Profile	369,510	3 vs 4	15,937	24	**<0.0001**	1,285,916

Table 4.6 presents the result of the estimated hazard ratios with a 95% CI on the transition intensities. We find that DS and RV have insignificant effects on both transitions. The hazard ratio estimate of CPOE implementation level on major disease to death transition is 1.056 (95% CI: 1.044, 1.068), indicating that a higher level of CPOE implementation is associated with a 5.6% higher risk of transition from major disease to death. CPOE has no significant effect on the transition from minor to major disease. Next, we find that hazard ratio estimates of the ECD and telehealth implementation levels on the transition from major disease to death is 0.977 (95% CI: 0.963, 0.990) and 0.876 (95% CI: 0.820, 0.935), implying that a higher level of ECD or telehealth implementation is associated with a lower risk of transition from major disease to death. Both ECD and telehealth have no significant effect on the transition between minor and major disease.

Besides HIT implementation level, we find that one hospital variable and most patient profile variables are also significantly associated with the transition risk among various health states. We find that teaching hospitals are associated with a higher risk of transition from minor to major disease. Female patients are associated with a lower risk of transition from major disease to death. Emergency or urgent admission type is associated with a higher risk of transition from minor to major disease and from major disease to death. Medicare patients are associated with a lower risk of transition from minor to major disease. Medicaid patients are associated with a lower risk of transition from minor to major disease, but a higher risk of transition from major disease to death. Higher age, longer LOS, and increased number of visits are associated with higher risk of transition from minor to major disease and from major disease to death. Transferring hospitals is associated with a lower risk of transition from minor to major disease but a higher risk of transition from major disease to death. Primary diagnosis changed to a different body system at the current admission compared to the last admission and a higher number of comorbidities are associated with higher risk of transition from minor to major disease and from major disease to death. A higher total number of discharges with the primary diagnosis in the same the body system as the current admission is associated with a higher risk of transition from major disease to death.

Table 4.6 Results for Multi-State Hidden Markov Model

Variable	State 1–State 2 Minor–Major	State 1–State 3 Major–Death
Health IT		
No. of DS	1.005 (0.968-1.043)	1.001 (0.988-1.013)
No. of CPOE	0.991 (0.960-1.024)	**1.056 (1.044-1.068)**
No. of RV	0.964 (0.912-1.020)	0.989 (0.970-1.008)
No. of ECD	1.009 (0.967-1.052)	**0.977 (0.963-0.990)**
Telehealth	1.013 (0.842-1.218)	**0.876 (0.820-0.935)**
Hospital Characteristic		
No. of beds（log）	0.913 (0.818-1.019)	0.990 (0.953-1.029)
Teaching	**1.298 (1.081-1.558)**	0.952 (0.893-1.016)
For-profit	1.083 (0.867-1.354)	0.965 (0.894-1.042)
Patient Profile		
Female	0.922 (0.816-1.043)	**0.678 (0.648-0.708)**
Emergency	**1.317 (1.011-1.715)**	**1.495 (1.391-1.607)**
Medicare	**0.606 (0.505-0.726)**	1.064 (0.992-1.142)
Medicaid	**0.725 (0.586-0.897)**	**1.190 (1.085-1.305)**
Discharge Age	**1.044 (1.039-1.049)**	**1.035 (1.033-1.036)**
LOS（log）	**1.422 (1.294-1.563)**	**1.658 (1.607-1.711)**
No. of Visits	**1.045 (1.032-1.058)**	**1.020 (1.014-1.027)**
Transfer Hospital	**0.776 (0.644-0.936)**	**1.060 (1.001-1.123)**
Transfer Body System	**4.227 (3.497-5.109)**	**1.319 (1.255-1.387)**
No. of same body system	0.927 (0.790-1.088)	**1.828 (1.690-1.977)**
No. of comorbidity	**1.338 (1.286-1.393)**	**1.187 (1.172-1.203)**

Note: 95% of Confidence Interval is reported in the parentheses

Figure 4.6 plots the estimated transition probabilities between states within five years. As the figure shows, we find that the transition probabilities from minor to major diseases and from major to minor disease increase over time, with the former transition probability consistently lower than the latter. We also discover that the transition probabilities from minor disease to death and from major disease to death increase over time, with the former transition probability consistently lower than the latter.

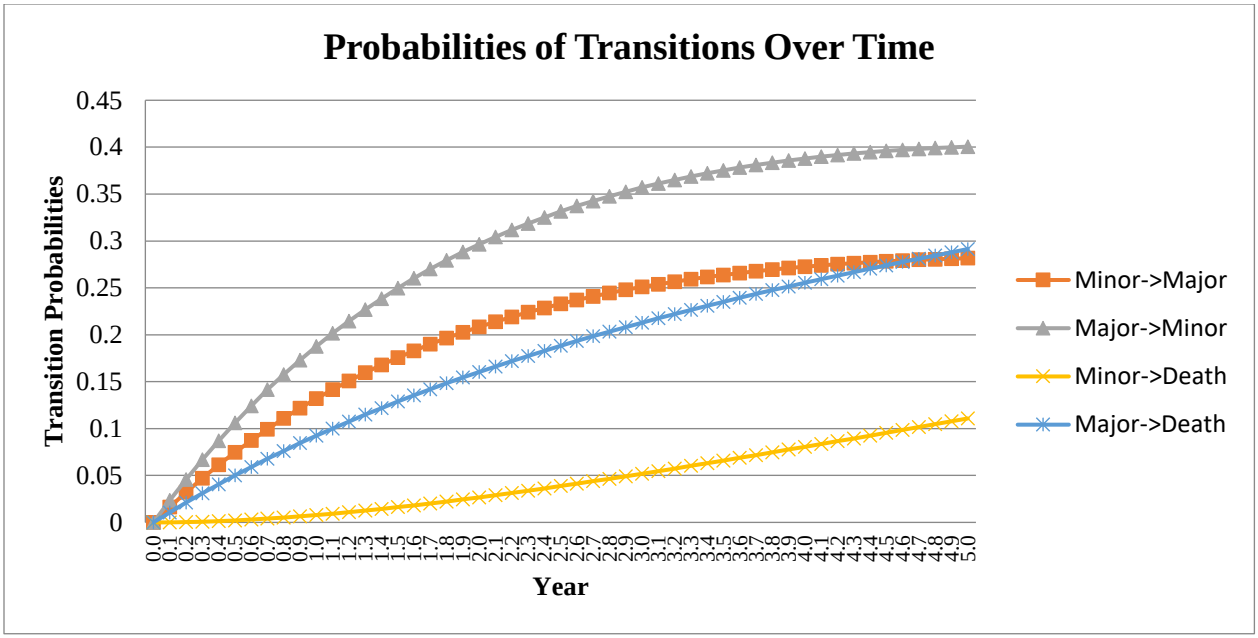


Figure 4.6 Probabilities of Transitions Over Time

4.4.5 Predictive Analytics Performance

In this section, we first assess the goodness of fit of the multi-state models and then examine the sampling variability. To assess the goodness of fit of the multi-state and multi-state hidden Markov models, we compare the observed and expected prevalence of each state over time, which is a common approach for multi-state model assessment (Jackson 2011). *Prevalence* or *prevalence rate* is the measure of disease occurrence—that is, the proportion of individuals in a population who have a particular disease or condition at a specified point in time or over a specified time period (Porta 2014). We follow the procedures suggested by prior literature to calculate the prevalence rate for both the multi-state and multi-state hidden Markov models (Gentleman et al. 1994; Titman and Sharples 2010).

For the multi-state Markov model, assuming we have a series of observations $O_{i1}, \ldots O_{in}$ at fixed set of times $t_1, \ldots, t_n$ for patients $i=1, \ldots, N$, with model parameters θ and the covariate vectors z_i, the observed and expected counts in each state are calculated as follows:

$$Observed_{jr} = \sum_{i=1}^{N} 1\{O_i(t_j) = r\}$$

$$Expected_{jr} = \sum_{i=1}^{N} p_{r_{0i}r}(0, t_j; \theta, z_i),$$

where $p_{r_{0i}r}(0, t_j; \theta, z_i) = P(O(t_j) = r | O(t_0) = r_{0i})$ and r_{0i} is the initial state at time 0 for the patient *i*.

Because the observation scheme is unbalanced, it is impossible to find a set of time that includes all patients in the study. Gentleman et al. (1994) suggest a method for calculating the observed prevalence at a common time frame: assume that patients are still in the state they were in at the last observation. Thus, we have

$$\widetilde{O}_i(t) = O(t_i^*),$$

where t_i^* is the maximum time below *t* at which patient *i* was observed. Because the choice of $t_1, \ldots, t_n$ can be important to determining a model's goodness of fit, we use a graphical generalization of prevalence counts. Instead of using $Observed_{jr}$ and $Expected_{jr}$ at a discrete set of times, we use

$$Observed_r(t) = \sum_{i=1}^{N} 1\{\widetilde{O}_i(t) = r\}$$

$$Expected_r(t) = \sum_{i=1}^{N} p_{r_{0i}r}(0, t; \theta, z_i),$$

where $Observed_r(t)$ is a step function. To obtain the prevalence rate at each state, we use prevalence counts at a particular time divided by the population at that time.

For the multi-state hidden Markov model, we use prevalence rate to assess the goodness of fit for the observed states. The calculation for observed counts of the multi-state hidden Markov model in each state is the same as the calculation for the multi-state Markov model. For the expected counts of the multi-state hidden Markov model, assuming that n(t) individuals are under observation at time t and the initial probability of occupying the true state r is f_r, the expected number of individuals in true state r at time t is the rth element of the vector n(t)fP(t) (Jackson 2018). The expected number of individuals in the observed state s is the s_{th} element of the vector n(t)fP(t)E, where E is the emission probability matrix.

To assess the predictive analytics performance for our proposed models, we randomly sampled 1% from the entire dataset, which is separate from the in-sample dataset. Figures 4.7 and 4.8 plot the graphical prevalence chart for the multi-state Markov model and the multi-state hidden Markov model, respectively. As the figures show, our models perform well in predict prevalence rate over three years.

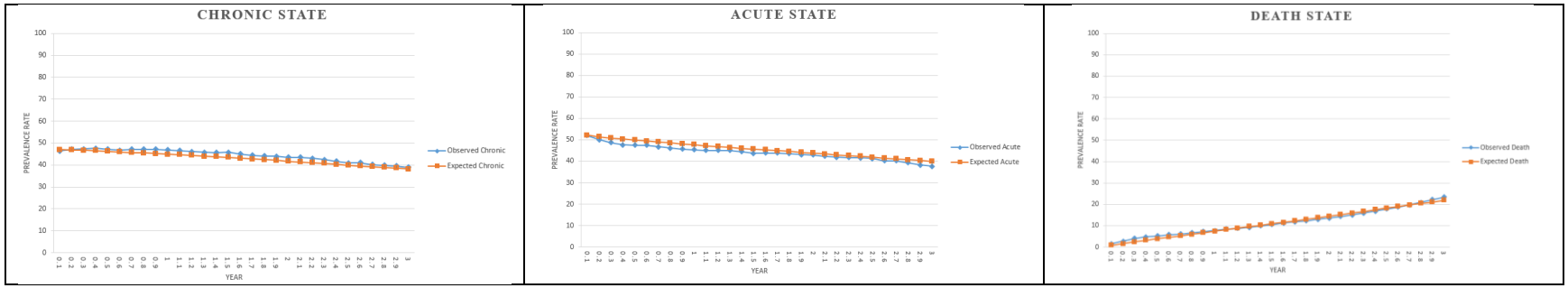


Figure 4.7 Observed and Expected Prevalence Rate for Multi-State Markov Model

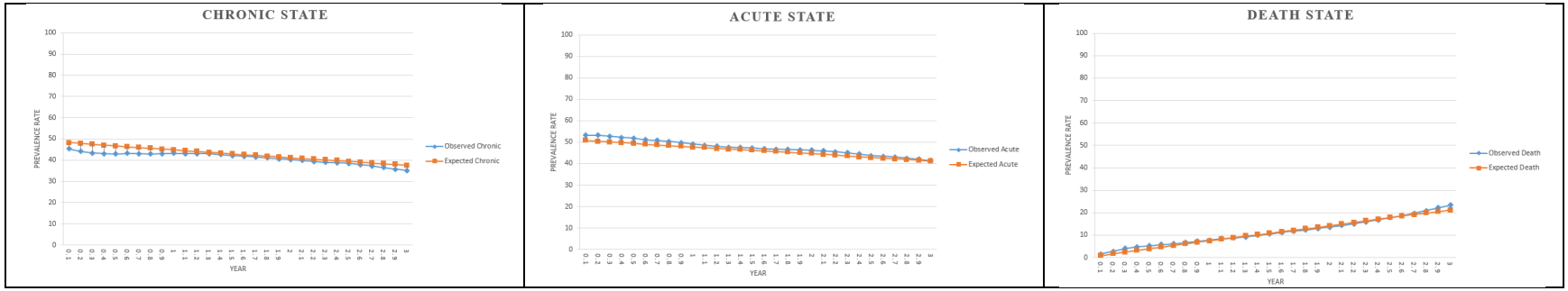


Figure 4.8 Observed and Expected Prevalence Rate for Multi-State Hidden Markov Model

Next, we test sampling variability to rule out the possibility that our estimates may vary between different random samples. To do so, we randomly select another 5% of the sample from the entire dataset, which is a separate sample from the sample selected to estimate the proposed models. We first estimate the same proposed models using the new sample. We then compare the CIs of this sample with those of the sample used to estimate the proposed model. The literature indicates that nonoverlap of two CIs implies a significant difference (Belia et al. 2005; Schenker and Gentleman 2001). Our results show that all of the CIs are overlapping between the two samples, so we find no evidence of significant difference between them in terms of CI overlap. We can therefore rule out sampling variability for the 5% random sample selected to estimate our models.

4.5 Discussion

Our study makes several research contributions to predictive health analytics research and HIT business value literature. For predictive health analytics research, our model advances current predictive health analytics research in the IS field in three ways. First, the model examines multiple events as a disease progresses over time. To the best of knowledge, this is the first predictive health analytics research in the IS field that studies event history and predicts transitions between different health events over time. Compared with existing predictive health analytics in the IS field, our models can answer a broader research questions related to disease evolution.

Second, we develop predictive health analytics models based on a variety of patient groups, including those with chronic and acute conditions in 17 body systems. Predictive models in the IS field focus primarily on a specific chronic disease and ignore the acute patients. Predictive models in the medical field are usually based on a single disease and a limited sample

size. However, it is likely that many patients will transition between acute and chronic conditions and between conditions in different body systems. Predictive models based on only chronic patients or a single disease are unlikely to capture transitions information for patients with diseases that transition between chronic and acute conditions and/or across different body systems. Our proposed models shed light on the predictive health analytics research to incorporate a variety of patient groups.

Third, extant predictive health analytics research typically considers the chronic status of a discharge as a model covariate, not as a dynamic state in a discrete state space. Our research suggests that transitions between chronic and acute states—along with HIT implementation levels, hospital characteristics, and patient profiles—are good indicators of the underlying patient health status. The predictive models we propose detect future time points at which a disease may transition between chronic and acute states and progress from a minor to a more severe state; healthcare providers can use this information to intervene early to offer appropriate treatments and slow the worsening cycle of a disease.

Our study contributes to the HIT business value literature by examining HIT's value at the patient-transition level. We find empirical evidence that the majority of HIT functions improve patient-transition-level outcomes, and that only the CPOE function increases transition risk from other states to death. Prior literature has found that CPOE has the potential to improve healthcare quality, effectiveness, and safety, but that it can also introduce significant safety issues and unintended consequences (Coiera et al. 2016; Weiner et al. 2007). However, no extant study empirically examines CPOE's impact on patient-transition-level outcomes. This study provides empirical evidence that COPE is negatively associated with patient-transition-level intermediate performance outcomes. Many other factors related to organizational, technical, or

human-machine interface also contribute to unintended consequences (Weiner et al. 2007). One plausible explanation is that human-computer interfaces may not be suitable for the highly interruptive and flexible healthcare context (Coiera et al. 2016). Issues in healthcare are usually complex and multidimensional, yet technologies are typically designed to process healthcare work in a linear manner (Ash et al. 2004; Ash et al. 2007). Misrepresenting clinical process as a linear process, however, can lead to inflexibility, workarounds, and errors in the information entered (Coiera et al. 2016). Another plausible explanation is that human-to-human communication, rather than documentation, is healthcare's primary information task as it facilitates sense-making in communication and includes the constant human diligence for error catching (Coiera 2000; Coiera et al. 2016). Technologies that are not designed to meet the needs of clinical practices and communication processes can lead to errors in both communication and coordination (Coiera et al. 2016). The unintended consequences caused by misconfigurations between workflow, users, and technologies may increase the transition risk between different health statuses.

In addition to our research contribution, our study also makes practical contributions. Assessing how different HIT functions impact different types of transitions can help healthcare providers effectively allocate investments across various IT resources to achieve enhanced health outcomes. Specifically, our findings can help healthcare providers identify which technologies to adopt to reduce different types of health-status transitions. For example, our results suggest that investments in RV will reduce the transition risk between chronic and acute conditions, while investments in ECD and telehealth will reduce the transition risk from major disease to death.

4.6 Limitations and Future Work

With a rich longitudinal dataset, this study estimates patient health status based on the transition between chronic and acute states and studies the impact of HIT implementation on these transitions. Notwithstanding our research contributions, this study has limitations and presents multiple opportunities for future research. A first limitation is that our study examines the transition information for all diseases as a whole, without separately examining each disease individually. And, as we know, different diseases may progress in various ways. Future work can extend our results and examine how HIT's value impacts individual diseases.

Second, the multi-state model we applied is a time-homogeneous model, which assumes that the transition intensity matrix is constant in time. However, we find that the transition intensity matrix changes after three years. Future work may account for this change and use a time-inhomogeneous multi-state model to examine how transition intensities change with time.

Third, we apply this Markov property in the essay—the probability of a state only depends on the probability of the previous state. However, in the future, we can relax this assumption and incorporate more event history in our states by employing a higher order Markov model, e.g., second-order Markov model that takes into account the two previous states.

Fourth, the multi-state Markov model we propose cannot be used to predict a patient's next readmission. Future work can study both one-time patients and readmitted patients and apply a hurdle model to separate one-time hospital patients from multi-visit patients and model a patient's next admission time.

Finally, our study considers only how individual HIT functions impact the transition between chronic and acute health statuses. But, very often, the complementarity effects that

improve healthcare performance come only from combining HIT functions. We encourage researchers to explore how HIT's complementarity effects impact the transitions between different health statuses in the future.

Appendix

Appendix 4A: HIT Items List and Scale (Source: AHA IT Supplement Files)

HIT implementation items are listed as follows:

1. Decision Support:

1) Clinical guidelines
2) Clinical reminders
3) Drug allergy alerts
4) Drug-drug interaction alerts
5) Drug-Lab interaction alerts
6) Drug dosing support

2. CPOE:

1) Laboratory tests
2) Radiology tests
3) Medications
4) Consultation requests
5) Nursing orders

3. Results Viewing:

1) Lab reports
2) Radiology reports
3) Radiology images
4) Diagnostic test results
5) Diagnostic test images
6) Consultant reports

4. Electronic Clinical Documentation:

1) Patient demographics
2) Physician notes
3) Nursing Notes
4) Problem lists
5) Medication lists
6) Discharge summaries
7) Advanced directive

HIT implementation is measured by a six-point scheme as follows:

1 = Fully implemented across all units

2 = Fully implemented in at least one unit

3 = Beginning to implement in at least one unit

4 = Have resources to implement in the next year

5 = Do not have resources but considering implementing

6 = Not in place and not considering implementing

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