EFFECTS OF HEALTH INFORMATION TECHNOLOGY ADOPTION ON QUALITY OF CARE AND PATIENT SAFETY IN US ACUTE CARE HOSPITALS

by

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ABSTRACT

The adoption of healthcare information technology (HIT) has been advocated by various groups as critical in addressing the growing crisis in the healthcare industry. Despite the plethora of evidence on the benefits of HIT, however, the healthcare industry lags behind many other economic sectors in the adoption of information technology. A significant number of healthcare providers still keep patient information on paper. With the recent trends of reimbursement reduction and rapid technological advances, therefore, it would be critical to understand differences in structural characteristics and healthcare performance between providers that do and that do not adopt HIT. This is accomplished in this research, first by identifying organizational and contextual factors associated with the adoption of HIT in US acute care hospitals and second by examining the relationships between the adoption of HIT and two important healthcare outcomes: patient safety and quality of care.

After conducting literature a review, the structure-process-outcome model and diffusion of innovations theory were used to develop a conceptual framework. Hypotheses were developed and variables were selected based on the conceptual framework. Publicly available secondary data were obtained from the American Hospital Association (AHA), the Health Information and Management Systems Society (HIMSS), and the Healthcare Cost and Utilization Project (HCUP) databases. The information technologies were grouped into three clusters: clinical, administrative, and strategic decision making ITs. After the data from the three sources were cleaned and merged, regression models were built to identify organizational and contextual

factors that affect HIT adoption and to determine the effects of HIT adoption on patient safety and quality of care.

Most prior studies on HIT were restricted in scope as they primarily focused on a limited number of technologies, single healthcare outcomes, individual healthcare institutions, limited geographic locations, and/or small market segments. This limits the generalizability of the findings and makes it difficult to draw definitive conclusions. The new contribution of the present study lies in the fact that it uses nationally representative latest available data and it incorporates a large number of technologies and two risk adjusted healthcare outcomes. Large size and urban location were found to be the most influential hospital characteristics that positively affect information technology adoption. However, the adoption of HIT was not found to significantly affect hospitals' performance in terms of patient safety and quality of care measures. Perhaps a remarkable finding of this study is the better quality of care performance of hospitals in the Midwest, South, and West compared to hospitals in the Northeast despite the fact that the latter reported higher HIT adoption rates.

In terms of theoretical implications, this study confirms that organizational and contextual factors (structure) affect adoption of information technology (process) which in turn affects healthcare outcomes (outcome), though not consistently, validating Avedis Donabedian's structure-process-outcome model. In addition, diffusion of innovations theory links factors associated with resource abundance, access to information, and prestige with adoption of information technology. The present findings also confirm that hospitals with these attributes adopted more technologies. The methodological implication of this study is that the lack of a single common variable and uniformity of data among the data sources imply the need for standardization in data collection and preparation. In terms of policy implication, the findings in this study indicate that a significant number of hospitals are still reluctant to use clinical HIT. Thus, even though the passage of the American Recovery and Reinvestment Act (ARRA) of 2009 was a good stimulus, a more aggressive policy intervention from the government is warranted in order to direct the healthcare industry towards a better adoption of clinical HIT.

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LIST OF ABBREVIATIONS

ADE – Adverse Drug Event
ADM – Automated Dispensing Machine
AHA – American Hospital Association
AHRQ – Agency for Healthcare Research and Quality
AMA – American Medical Association
AMI – Acute Myocardial Infarction
BCMA – Bar-Coding at Medication Administration
BCMD – Bar-Coding at Medication Dispensing
BSI – Blood Stream Infection
CBSA – Core Based Statistical Area
CDR – Clinical Data Repository
CDS – Clinical Decision Support
CHF – Congested Heart Failure
CPOE – Computerized Physician Order Entry
DBMS – Database Management System
DRG – Diagnosis Related Group
EHR – Electronic Health Record
EMAR – Electronic Medication Administration Records
EMR – Electronic Medical Record
HCUP – Healthcare Cost and Utilization Project
HHI – Herfindahl-Hirschman Index
HIMSS – Health Information and Management Systems Society
HIT – Health Information Technology
HMO – Health Maintenance Organization
IOM – Institute of Medicine
IQI – Inpatient Quality Indicator
IQI 15 – Acute Myocardial Infarction
IQI 16 – Congestive Heart Failure
IQI 20 – Pneumonia
NIS – Nationwide Inpatient Sample
PACS – Picture Archiving and Communication System
PSI – Patient Safety Indicator
PSI 2 – Death in Low Mortality DRG
PSI 3 – Decubitus (Pressure) Ulcer
PSI 6 – Iatrogenic Pneumothorax
PSI 7 – Selected Infection due to Medical Care
ROBOT – Robot for Medication Dispensing

CHAPTER 1: INTRODUCTION

The primary objectives of this research are first – to identify what organizational and contextual factors affect the adoption of health information technology (HIT) in U.S. acute care hospitals, and second – to understand the relationships between the adoption of information technology and two healthcare outcomes, i. e., patient safety and quality of care. This first chapter provides the problem statement and research questions, the significance and scope of the study, a brief explanation of the theories used, and discussions on the new contributions of the findings.

1.1 Problem Statement and Research Questions

Prior studies have pointed out several problems with the U.S. healthcare system. Though the U.S. healthcare system is the largest in the world, standing at $2.2 trillion or about 17.3% of the total GDP in 2009 and projected to increase to $4.5 trillion or about 19.3% of the GDP by 2019 (Centers for Medicare & Medicaid Services, 2009), it remains expensive, unsafe, and inefficient compared to some other developed countries (Amarasingham, Plantinga, Diener-West, Gaskin, & Powe, 2009; Chaudry et al., 2006; Hillestad et al., 2005; Poon et al., 2006). Under the current healthcare system, many healthcare providers do not keep up with up-to-date medical discoveries, follow guidelines, or measure their performance, and they coordinate minimally with each other (Bodenheimer, 2008; Taylor et al., 2005). Medical errors are estimated to kill between 44,000 and 98,000 patients every year (Institute of Medicine, 2000), while adverse drug events (ADEs) injure or kill an estimated 770,000 people annually in hospitals (Kaushal, Shojania, & Bates, 2003). Surveys also revealed that a significant portion of the public is not satisfied and does not feel safe with the quality of care they receive (Altman, Clancy, & Blendon, 2004).

Moreover, healthcare services are reported to have become overly complex in recent years, and this complexity is accompanied by substantial increases in cost (Paré & Sicotte, 2001). Since the healthcare industry typically performs in an environment of constrained resources, a challenge exists in balancing maximizing productivity and market share on the one hand and serving the actual health need of the community on the other hand (Flood, Zinn, & Scott, 2006). Taylor and colleagues (2005) predicted that with the recent trend of increasing numbers in the aged population, healthcare cost inflation will ultimately make the federal deficit unsustainable.

Policy makers, healthcare providers, and consumer groups as well as concerned organizations such as Institute of Medicine (IOM), Agency for Healthcare Research and Quality (AHRQ), and The Leapfrog Group have advocated that the adoption of healthcare information technology (HIT) could play a key role in addressing the growing crisis in the healthcare industry (Kazley & Ozcan, 2008). The adoption of one or more HIT applications is shown to improve patient safety in the following areas: reduced errors of omission (Overhage, Tierney, Zhou, & McDonald, 1997); reduced number of adverse drug effects and serious medication errors (Bates et al., 1998; Kaushal et al., 2003; Walsh, Kaushal, & Chessare, 2005); improved physician prescribing behavior (Teich et al., 2000); increased patient identification confirmation (Dean Franklin, O'Grady, Donyai, Jacklin, & Barber, 2007); reduction in fatal hospitalization

(Amarasingham et al., 2009); efficient physician time spent with patients (Pizziferri et al., 2005); and increased nurse time on direct patient care (Wang et al., 2003).

In terms of quality of care, the adoption of HIT applications may lead to improved quality of care by: providing better surveillance (Samore, Lichtenberg, Saubermann, Kawachi, & Carmeli, 1997); encouraging adherence to stricter and evidence-based guidelines (Cannon & Allen, 2000); reducing inpatient days (Mullet, Evans, Christenson, & Dean, 2001); increasing appropriateness of orders (Chen et al., 2003); enhancing integrated data review (Schnipper et al., 2008); and positively affecting medication and non-medication quality of care measures (Yu et al., 2009). Kazley and Ozcan (2008) in particular demonstrated a significant relationship between hospitals' adoption of electronic medical records (EMR) and AHRQ quality of care indicators, while Amarasingham et al. (2009) found a positive association between computerized physician order entry (CPOE), clinical decision support (CDS) systems, and lower mortality rates due to acute myocardial infarction and pneumonia. McCullough, Casey, Moscovice, and Prasad (2010) also found a significant association between treatment of heart failure and pneumonia patients and the adoption of EMR and electronic health record systems (EHR) in teaching hospitals.

Additional advantages include improving communication between physicians and other healthcare providers; integration of administrative and clinical data; reducing mortality and morbidity; providing effective solutions to adverse events by reducing the chance that they happen by enabling quick response when they happen and by providing feedback after they happen; providing access to critical patient information; assisting with clinical calculations; facilitating effective monitoring; providing decision support systems; increasing inpatient volume; addressing the problem of information asymmetry between patients and providers as well as among providers; increasing the value of the available information in the hospitals; and increasing the value of the healthcare providers in order to keep them competitive in the market (Bates & Gawande, 2003; Chaudry et al., 2006; Dexter, Perkins, Maharry, Jones, & McDonald, 2004; Overhage, Perkins, Tierney, & McDonald, 2001; Parente & McCullough, 2009; Poon et al., 2006; Teich et al., 2000; Wang, Wan, Burke, Bazzoli, & Lin, 2005).

It is also indicated that since investment in HIT enables hospitals to devote less time for the same treatment and reduce administrative time needed by nurses, it generates savings in labor costs and increases in overall profits (Parente & Van Horn, 2006). At a national level, Hillestad et al. (2005) estimated that a 90% national adoption of EMR in hospitals could cost up to a total of $98 billion, while the efficiency savings from patient care could potentially top more than a staggering $77 billion per year. At the hospital level, the cost of developing and implementing a computerized physician order entry (CPOE) system in a teaching hospital was estimated at $1.9 million with maintenance cost of $500,000 per year (Kaushal et al., 2003), while the overall savings were between $5 and $10 million per year (Teich et al., 2000).

However, even in the presence of such a large amount of evidence supporting the benefits of HIT applications, the adoption of IT systems in the healthcare industry has been only modest compared with many other industries (Hillestad et al., 2005). Instead of focusing on clinical IT systems, the healthcare industry has primarily focused on acquiring technological applications that are related to administration and financial transactions (Chaudry et al., 2006). Efficient coordination is hindered among healthcare providers simply because a considerable amount of patient records are still kept on paper. The estimate is that only 20–25% of hospitals in the

United States keep medical records electronically (Hillestad et al., 2005). Another article estimated that the proportion of general physicians using electronic record systems in the United States is 17% compared to 88% in the Netherlands (Poon et al., 2006). This is an area of concern because paper records could easily get lost and lead to treatment errors, duplications, and eventual healthcare cost increases (Kazley & Ozcan, 2008). In addition, paper-based medical records may produce a shortage of information on cost and quality of service that could otherwise enable patients to make informed decisions (Hillestad et al., 2005).

Despite such low levels of adoption, the current trend is that various stakeholders are increasingly recognizing the benefits of healthcare information systems. In fact, HIT adoption is noted as one of the relatively few areas in the current healthcare debate where a general agreement exists among the diverse groups of healthcare providers, consumers, and policy makers (Chaudry et al., 2006). The purpose of this paper, therefore, is first to identify organizational and contextual characteristics determinant in the HIT adoption of hospitals and second to understand the latest effects of HIT adoption on patient safety and quality of care. More specifically, this study aims to address the following research questions:

Question 1: What organizational and contextual factors are associated with HIT adoption in acute care hospitals?

Question 2: Is the adoption of HIT applications associated with enhanced patient safety in acute care hospitals, controlling for organizational and contextual factors?

Question 3: Is the adoption of HIT applications associated with better quality of care in acute care hospitals, controlling for organizational and contextual factors?

1.2 Significance of the Study

Prior research shows that the study of healthcare information technology would benefit from the utilization of research models that comprehensively examine the relationships between HIT adoption and healthcare outcomes. This is due to the fact that most previous studies are limited in their scope as they primarily focused on data from single sites, a very small number of technologies, or a single patient outcome. Since the healthcare industry is inherently multifaceted (Miller et al., 2005) such fragmented works could only produce overly specific parts of the solution.

This study, therefore, aims to address the concern by applying a more inclusive and consistent approach: first, by using the latest nationally representative data, it explores organizational and contextual variables that may affect HIT adoption in hospitals; second, by examining the effects of technology adoption by selecting 52 HIT applications under three technology clusters based on their potential impacts on select healthcare outcomes; third, by using the individual hospitals as the units of analysis to attempt to effectively capture the relationships between HIT adoption, patient safety and quality of care; and fourth, by using risk-adjusted estimates of widely applied patient safety and quality of care indicators to develop a more consistent measurement of healthcare outcomes. In doing so, this paper ultimately aims to contribute to the literature on HIT adoption with medical care, research, and policy implications in a hospital setting.

1.3 Scope of Study

Previous works on healthcare information technology applications in the context of hospitals are highlighted. The benefits and drawbacks of HIT adoption in hospitals, the barriers to HIT adoption, and gaps in previous studies are discussed. A theoretical framework is constructed through which specific information technology applications, hospital characteristics, and healthcare outcomes are selected for analysis. Negative binomial and multiple regression models are used on the most recent national data to generate a more comprehensive model that analyzes the relationships between HIT adoption and the selected healthcare outcomes, i.e., quality of care and patient safety. Quality of care and patient safety are analyzed as dependent variables while organizational and contextual characteristics of hospitals are analyzed as independent variables with respect to adoption of information technology. The theoretical, methodological, and policy implications of the findings, as well as the limitations of the study and recommendations for future investigation are discussed at the end.

1.4 Theoretical Construct

The structure-process-outcome model and diffusion of innovations theory are applied in this study. The structure-process-outcome model analyzes the quality of healthcare in hospitals from three perspectives: structure, process, and outcome. Structure refers to visible aspects of hospitals such as material and human resources as well as organizational and contextual characteristics. Process refers to the way healthcare is delivered. Outcome refers to changes that are products of the healthcare delivered. Diffusion of innovations theory on the other hand explains how new ideas or innovations are diffused or communicated within a social system. The theory also identifies individual and organizational characteristics that may influence the diffusion of innovation. The structure-process-outcome model is applied to conceptualize the healthcare delivery in hospitals into three distinct parts. Diffusion of innovations theory is next applied to identify specific HIT applications as well as organizational and contextual factors that may determine the course of HIT adoption in hospitals. Together these two theories are used to formulate four major hypotheses that will be discussed in Chapter 3.

1.5 New Contributions

Although much empirical studies exist on the relationships between HIT adoption and healthcare outcomes, most previous studies have primarily focused on specific technologies and healthcare concerns, limited healthcare sectors, healthcare institutions, geographic locations, and market segments, which limits the generalizability of the findings and inhibits researchers from making definitive conclusions. To my knowledge, no previous study has comprehensively examined the impacts of health information systems from both patient safety and quality of care perspectives on national data. Given the benefits of HIT adoption and the rapid advances in the sophistication of information technology systems in recent years, a more inclusive and up-to-date investigation would be beneficial to get a more complete image.

This study, therefore, uses nationally representative data and focuses on the relationships between information technology adoption and two healthcare outcomes: patient safety and quality of care. Since the case mix of the providers can significantly affect their performance, outcome estimates used in this study are risk adjusted for age, gender, DRGs, and comorbidity. In addition, this study examines the effects of a significantly large number of information technologies and identifies organizational and contextual characteristics of hospitals that may affect the adoption of the selected information technologies and healthcare outcomes. As such, it is anticipated that the findings will be beneficial to academicians, healthcare providers, and policy makers and offer a small but relevant contribution to the current debate on healthcare reform and the needs for immediate HIT adoption.

1.6 Summary

This study is motivated by the realization that the U.S. healthcare system needs immediate transformation and that a widespread adoption of HIT systems could play a critical role in addressing the issue. Evidence exists that HIT may lead to improved quality of care, reduced healthcare costs, and enhanced and efficient patient outcomes. However, the adoption of information technology in the healthcare industry has been very slow compared to other industries. This study, therefore, aims to identify the factors that influence the adoption of HIT in hospitals. Furthermore, specific attention will be targeted towards finding the latest trends in the relationships between information technology adoptions and select healthcare outcomes. This chapter provided a brief explanation on the problems with the current U.S. healthcare system and presented a case for the need of HIT adoption in hospitals. Research questions are raised within the context of this study. The significance, the scope, the theoretical framework, and the new contributions of the study are also discussed.

The next chapter provides a more in-depth literature review on the information technology applications, the healthcare outcomes, and organizational and contextual factors analyzed in this study. Chapter 3 discusses the conceptual framework and the hypotheses developed based on two theories. Chapter 4 presents the methodologies used. Chapter 5 presents the findings. Finally, Chapter 6 provides the discussion, implications, the limitations of the study, and recommendation for future research.

CHAPTER 2: LITERATURE REVIEW

The previous chapter provided an introduction to the problem statement, the research questions, the significance, the scope, the theoretical construct, and the new contributions of the study. This chapter provides the literature review conducted on the impact of IT in other industries, barriers to HIT adoption in hospitals, and limitations of HIT. This chapter also provides explanations of some of the HIT applications and the two patient outcomes, as well as the organizational and contextual factors that are used as explanatory and control variables. Information was gathered from peer-reviewed journals searched on academic online databases, including Google Scholar, MEDLINE, and Academic Search Premier. The following key words were used in various combinations to search for relevant articles: hospital, health information technology, HIT adoption, clinical IT, administrative IT, strategic, IT, organizational factors, contextual factors, patient safety, and quality of care.

2.1 IT Use in Other Industries

Since the 1980s, information technology systems have been applied widely in several economic sectors such as telecommunications, finance, and merchandising in the form of bar coding, online shopping, and ATMs (Hillestad et al., 2005; Jaana, Ward, Pare, & Wakefield, 2005). This led to what Bates and Gawande (2003) called "mass customization," which is "the efficient and reliable production of goods and services according to the highly personalized needs of individual customers" (p. 2526). Consequently, many of these industries exhibited significant efficiency and productivity growth. For instance, it is possible for customers today to browse companies' websites and purchase online from simple items such as flowers and pizzas to highly customized and sophisticated equipment without leaving the comfort of their homes. Of course, receiving proper healthcare is much more complex than online ordering of pizza. Yet, Bates and Gawande argued the unlikelihood of individualized and reliable patient care without the involvement of information technology systems. Hillestad et al. (2005) also argued that with IT attributed productivity improvement of 1.5% (as in the retail industry) the healthcare industry can decrease annual spending by $346 billion, while with a 4% improvement (as in the telecommunications industry) the healthcare industry could save $813 billion annually. However, Hillestad and colleagues cautioned that the current situation in healthcare lacks some of the qualities that these other industries have, such as strong competition, significant investment in IT infrastructure, and strong industry leaders.

2.2 Limitations of HIT

Despite the advantages of HIT systems, some limitations persist. Chaudry et al. (2006) indicated that HIT applications by themselves do not affect diseases or health conditions, because they are only tools to support healthcare activities. In addition, studies on time management savings to healthcare professionals using HIT have produced mixed results. Donyai, O'Grady, Jacklin, Barber, and Dean Franklin (2007) demonstrated that staff time requirements increased on medication-related tasks on the physicians, pharmacists, and general staff when using HIT applications, though Dean Franklin et al. (2007) showed that nursing time spent on drug rounds has decreased. Mekhjian et al. (2002) also noticed that the introduction of HIT systems could lead to major cultural changes in hospitals that could impede productivity at least at the earlier stages. Walsh et al. (2005) indicated that even though the overall error rate may be reduced, typographical or other human–machine interaction errors could still be an issue. Other limitations include the prohibitive upfront costs associated with initial implementation and the subsequent incremental costs linked to operation and maintenance.

2.3 Barriers to HIT Adoption

Despite the existence of widespread evidence that information technology applications have an enormous potential to positively affect the delivery of healthcare and lower costs, hospitals still remain less inclined to adopt information technology. The adoption of clinical IT is still at a very young stage compared to administrative and financial IT systems. Bates and Gawande (2003) as well as Hillestad et al. (2005) identified the following barriers to the widespread adoption of clinical information technology among healthcare providers: (1) financial barriers—the need for substantial investment at the implementation stage and the running cost at the operation stage are prohibitive to the majority of healthcare providers; (2) lack of standard—no guidelines or standards exist for interoperability of technology applications and clinical representation of data, and, thus, most applications are not well integrated; and (3) cultural barriers—since information technology is a relatively new field, there is reluctance on the part of clinicians to adopt and use it in the daily operations. Other barriers include unsatisfactory return on investment (ROI) (Fonkych & Taylor, 2005) and vendor immaturity (Poon et al., 2006).

2.4 Health Information Technology Applications

Dosi (1982) defines the term technology as "a set of pieces of knowledge, both directly 'practical'… and 'theoretical'… know-how, methods, procedures, experience of successes and failures and also, of course, physical devices and equipment" (pp. 151-152). HIT systems with clinical application fall into any of the following four sub-domains that often have both software and hardware aspects: (1) notes and records, (2) test results, (3) order entry, and (4) decision support (Amarasingham et al., 2009). Each of these sub-domains can be developed either in house or acquired from the market based on license fees. There is evidence that no significant differences exist in terms of cost in either case (Wang et al., 2003).

In this study, HIT applications are divided into three clusters based on the approach by Austin and Boxerman (1998). These are clinical IT, administrative IT, and strategic decision-support IT. Austin and Boxerman also identified a fourth category (electronic network applications), which in this study is folded within the Strategic IT cluster due to their inherent similarities. Based on literature review, 25 clinical, 18 administrative, and 9 strategic IT applications (a total of 52) were selected for the analysis (Bhattacherjee, Hikmet, Menachemi, Kayhan, & Brooks, 2007; Burke & Menachemi, 2004; Menachemi, Chukmaitov, Saunders, & Brooks, 2008; Wanget al., 2005). Table 1 shows a list of the technologies under each cluster.

Table 1: HIT Applications by Technology Clusters

Clinical IT	Administrative IT	Strategic IT
1. Abstracting	1. Accounts payable	1. Budgeting
2. ADM	2. ADT/Registration	2. Case mix management
3. Ambulatory EMR	3. Benefits administration	3. Contract management
4. Ambulatory PACS	4. Browser	4. Cost accounting
5. BCMA	5. Credit/collections	5. Data warehousing/mining – financial
6. BCMD	6. DBMS	6. Enterprise resource planning
7. Cardiology information system	7. Eligibility	7. Executive information system
8. Chart deficiency	8. Email	8. Nurse staffing/scheduling
9. Chart tracking/locator	9. Encoder	9. Outcomes and quality management
10. Clinical data repository	10. Enterprise master person index (EMPI)	
11. Clinical decision support	11. General ledger	
12. Computerized physician order entry (CPOE)	12. Materials management	
13. Electronic medication administration record (EMAR)	13. Patient billing	
14. In-house transcription	14. Patient scheduling	
15. Laboratory information system	15. Payroll	
16. Nursing documentation	16. Personnel management	
17. Operating room (surgery) - peri-operative	17. RFID - supply tracking	
18. Operating room (surgery) - post-operative	18. Time and attendance	
19. Operating room (surgery) - pre-operative		
20. OR scheduling		
21. Order entry (includes order communications)		
22. Pharmacy management system		
23. Radiology information system		
24. ROBOT		
25. Telemedicine - radiology		

(Source: Adapted from Burke & Menachemi, 2004; Used With Permission.)

2.4.1 Clinical IT

The clinical IT cluster refers to technologies that are directly associated with patient diagnosis, treatment, and evaluation of outcomes (Austin & Boxerman, 1998). The primary purpose of these technologies is to improve patient care. According to Wang et al. (2005), the clinical IT cluster is particularly at the core of hospital services because clinical IT applications are directly applied to provide high quality of care to patients, which is the primary goal of hospitals. Menachemi et al. (2008) also found significant associations between adoption of clinical IT and several quality of care indicators. Below are explanations on some of the clinical IT applications that have exhibited relatively higher diffusion rates among healthcare providers, that are highly associated with patient safety and quality of care, and that can have an impact at the prescribing, dispensing, and administration stages of the medication management process (Amarasingham et al., 2009; Furukawa, Ragu, Trent, & Vinze, 2008).

2.4.1.1 Electronic Medical Records (EMR)

EMR is defined as a "comprehensive database system used to store and access patients' healthcare information electronically. [EMR is] An application environment that is composed of the clinical data repository, clinical decision support, controlled medical vocabulary, order entry, computerized practitioner order entry, and clinical documentation applications" (Furukawa et al., 2008, Appendix Exhibit section, p. 2). According to Bates and Gawande (2003), clinicians' insufficient patient information is the primary cause of serious medication errors. In line with that, a recent study by Parente and McCullough (2009) singled out EMR as the only HIT application that affects patient safety at a statistically significant level by reducing medical errors and providing more convenient access and retrieval of the most up-to-date patient information. Medication errors can also be made due to illegible handwriting and orders that are insufficiently specific (Bates & Gawande, 2003). Computerized record systems, on the other hand, could minimize these problems by eliminating the need for handwritten orders and by placing stricter regulations on drug choice and dosage (Schnipper et al., 2008). In addition, by using data from Healthcare Information and Management Systems Society (HIMSS) and other sources, Hillestad and colleagues (2005) demonstrated that investment in EMR can help improve safety and efficiency of healthcare with subsequent potential cost savings approximated at $81 billion per year. Otieno, Hinako, Motohiro, Daisuke, and Keiko (2008) projected that EMR will become a critical part of healthcare delivery within the next 10 to 15 years. The term EMR is used in this study to broadly refer to technological applications such as computerized physician order entry, clinical decision support, clinical data repository, and electronic medical administration records.

2.4.1.1.1 Computerized Physician Order Entry (CPOE)

Though an error can occur at any stage of the medication processes, the majority of medication errors and adverse drug events (ADEs) occur at the stage of drug ordering and prescribing (Donyai et al., 2007; Kaushal, Bates, et al., 2001; Kaushal, Shojania, et al., 2003; Reckmann, Westbrook, Koh, Lo, & Day, 2009). According to a study by Dean Franklin, Vincent, Schachter, and Barber (2005), the incidence of prescribing errors varies between 0.3% and 39.1% of total medication orders. Computerized physician order entry systems (CPOE) are suggested as critical in preventing such errors (Kaushal et al., 2001; Walsh et al., 2005).

HIMSS Analytics (2009) defined computerized practitioner order entry, also known as computerized physician order entry or CPOE, as a software application that is “an order entry application specifically designed to assist clinical practitioners in creating and managing medical orders for inpatient acute care services or medication” (p. 10). Several advantages are attributed to CPOE systems, including: automation of the medication process, standardization, legibility, avoidance of injury, and storage (Reckmann et al., 2009); reducing prescribing errors (Donyai et al., 2007); positive impacts throughout all stages of patient stay, starting from drug selection to screening and monitoring of treatment as well as evaluating outcomes (Schiff & Rucker, 1998); increased application of proper work procedure and decreased errors of omission (Overhage et al., 1997); almost complete elimination of rule violation (Potts, Barr, Gregory, Wright, & Patel, 2004); and decreased cost of physician prescribing (Teich et al., 2000). In addition, Mekhjian et al. (2002) pointed out that CPOE systems could automatically calculate the appropriate dose, improve medication management, check for potential drug-to-drug interactions and allergies, and enable clinicians to provide complete and accurate information supported by evidence-based best practice. Moreover, since orders and medical records are typed directly on computers, illegible handwriting will not be an issue. Yu et al. (2009) also indicated that when used together with clinical decision systems, CPOE can boost patient safety and positively affect quality of care indicators.

2.4.1.1.2 Electronic Medical Administration Records (EMAR)

The medication cycle can be divided into four interdependent phases: (1) physicians place the order; (2) nurses transcribe the order; (3) the pharmacists perform the verification and dispensing; and (4) nurses administration the medication (Mekhjian et al., 2002). Within this medication cycle, EMAR systems are applied at the nurse transcription phase (HIMSS Analytics, 2009). EMAR is defined as an "electronic record keeping system that documents when medications are given to a patient during a hospital stay. This application supports the five rights of medication administration (right patient, right medication, right dose, right time, and right route of administration)" (HIMSS Analytics, 2009, p. 14). Dean Franklin et al. (2007) demonstrated that when used in a closed loop system that consists of electronic prescribing, ward-based automated dispensing, and barcode patient identification, EMARs can reduce prescribing- and administration-related errors by half. Mekhjian et al. also asserted that when EMAR systems are applied together with CPOE, transcription will not be needed, and this will heighten awareness among nurses and completely eliminate errors, at least at the nursing transcription phase.

2.4.1.1.3 Clinical Decision Support (CDS) Systems

HIMSS Analytics (2009) defined clinical decision support (CDS) system as an "application that uses pre-established rules and guidelines, that can be created and edited by the healthcare organization, and integrates clinical data from several sources to generate alerts and treatment suggestions" (p. 9). CDS systems can also be seen as software whose purpose is facilitating the decision-making process about patients (Schnipper et al., 2008). About 79% of adverse drug events take place at the medication ordering stage (Kaushal et al., 2001). Kaushal and colleagues (2003) noted that clinical decision support systems could be effective in monitoring and preventing errors and the associated adverse drug events at the medication and ordering stages. More recently, Yu et al. (2009) indicated that when used along with CPOE, CDS systems could also improve quality of care.

2.4.1.1.4 Clinical Data Repository (CDR)

Clinical data repository (CDR) refers to a "centralized database that allows organizations to collect, store, access, and report on clinical, administrative, and financial information collected from various applications within or across the healthcare organization… for accessing/viewing, managing, and reporting enterprise information" (HIMSS Analytics, 2009, p. 9). A study by Samore et al. (1997) has demonstrated that a relational database of CDR that was used to store recent and historical clinical data significantly improved quality of care activities in a teaching hospital in Boston.

2.4.1.2 Bar-Coding at Medication Administration (BCMA)

Bar-coding at medication administration (BCMA) is another HIT application that is believed to reduce medication-related errors. The term refers to "barcode technology… used by nursing services to improve the efficiency of operations such as patient identification, nurse identification, medication identification, and closed-loop medication administration process that improve patient safety" (HIMSS Analytics, 2009, p. 4). All medications used in hospitals are recently required by federal laws to be bar-coded (Walsh et al., 2005). BCMA systems match bar codes on the medications with patient bands to assure that the right medication is being administered at the right dosage to the right patient at the right time. In other words, the application of BCMA systems increases the frequency of medications' being checked before being administered to patients, and thereby reduces the chance that patients are administered (1) the wrong medication that was ordered for other patients; or (2) the right medication but at the wrong time. Thus, BCMA systems will likely help to minimize medication errors at administration, which account for about 34% of all preventable adverse drug effects (Dean Franklin et al., 2007). However, a study by Sakowski, Newman, and Dozier (2008) indicated that opportunities still exist to improve BCMA systems, because they are less effective in detecting more severe medication administration errors.

2.4.1.3 Bar-Coding at Medication Dispensing (BCMD)

Bar-coding at medication dispensing (BCMD) is defined as a "code consisting of a group of printed and variously patterned bars and spaces and sometimes numerals that are designed to be scanned and read into computer memory as identification… used by the pharmacy department for inventory control of drugs" (HIMSS Analytics, 2009, p. 4). Little information is available on the effects of bar-coding at medication dispensing on patient safety and quality. However, Bates (2000) has indicated that bar-coding could be critical in ensuring that the right drug is being administered to the right person at the right time and at the right dosage, thereby reducing the chances of making medication errors, particularly if combined with automated dispensing machines (ADMs). BCMD is also useful in tracking critical information such as expiration dates (Kuiper, McCreadie, Mitchell, & Stevenson, 2007), which otherwise can be easily overlooked by humans.

2.4.1.4 Robot for Medication Dispensing (ROBOT)

According to HIMSS Analytics (2009), robot for medication dispensing (ROBOT) is a "robotic technology used by pharmacies to conduct dispensing and cart fill functions and to deliver medications to medication cabinets for restocking" (p. 33). Walsh et al. (2005) indicated that pharmacy robot systems can be effective in addressing errors related to drug dispensing. However, Walsh and colleagues cautioned that even though the application of robots could decrease errors related to drug dispensing and dosage, errors could still occur at the human–machine interaction stage.

2.4.1.5 Automated Dispensing Machines (ADMs)

HIMSS Analytics (2009) defined automated dispensing machines (ADMs) as a "medication dispensing cabinet that automates the storing, dispensing, and tracking of narcotics, floor stock, and PRN… medications in patient care areas… interfaces with hospital ADT/billing systems to improve charge capture and materials management systems to track inventory" (p. 4). Walsh et al. (2005) pointed out the ADMs are particularly effective in addressing one of the most prevalent medication administration problems—a missed dose—which the authors define as a "dose not available for the patient within 20 minutes of the scheduled time of administration" (p. 701). When used together with BCMD (Bates, 2000) and with EMARs (Dean Franklin et al., 2007), ADMs can also be effective in reducing medication errors.

2.4.2 Administrative IT

Administrative IT applications in a hospital are not directly related to patient care activities. They are rather used in the human resource department and include "financial information systems, payroll, purchasing and inventory control, outpatient clinic scheduling, office automation, and many others" (Austin & Boxerman, 1998, p. 5). Table 1 shows the list of 18 administrative IT applications that were obtained from the HIMSS data set and used in this analysis. Wang et al. (2005) indicated that the adoption of Administrative IT in hospitals is affected by number of beds and the size of the population served by the hospital. More recently, Menachemi et al. (2008) demonstrated that the adoption of administrative IT may be negatively associated with some quality of care indicators. However, their study was based on data from a single state (Florida), and thus presents difficulties in formulating generalizations. A study by Burke, Wang, Wan, and Diana (2002) showed that adoption of administrative IT is associated with urban location and market competition. The various types of administrative IT are not discussed in detail in this study for the purpose of brevity.

2.4.3 Strategic IT

Similar to administrative IT applications, strategic IT applications are not directly related to patient care in hospitals. They are used by the management team in the hospitals to make strategic-planning and revenue-generating decisions as well as monitoring and performance evaluations. They depend on both internal data (e.g., patients' clinical experience and administrative capabilities of the hospital) and external data (e.g., changes in demography, market, and other contextual factors) sources during the decision-making process (Austin & Boxerman, 1998). The list of the 9 Strategic IT applications used in the analysis is shown in Table 1. Wang et al. (2005) indicated that hospitals' adoption of strategic IT is affected by bed-size and for-profit status, while Burke et al. (2002) indicated that adoption of strategic IT may be associated with size, for-profit status, urban location, and market competition. Menachemi et al. (2008) found that the application of strategic IT may be positively associated with some quality of care indicators.

2.5 Effects of HIT Adoption on Healthcare Delivery

2.5.1 Enhanced Patient Safety

Patient safety refers to "freedom from accidental injury caused by medical care" (Miller, Elixhauser, Zhan, & Meyer, 2001, p. 112). Error is defined as "the failure of a planned action to be completed as intended or the use of a wrong plan to achieve an aim" (Miller et al., p. 112). The highly influential publication from Institute of Medicine (IOM), *To Err Is Human: Building a Safer Health System* (2000), estimated that between 44,000 and 98,000 patients die in the United States every year due to medical errors. Isaac and Jha (2008) also indicated that significant mortality and morbidity are caused by poor medical care.

Medication errors in particular refer to "errors in drug ordering, transcribing, dispensing, administering, or monitoring" (Kaushal et al., 2001; p. 2115). Walsh et al. (2005) argued that since healthcare services are complex processes with significant interactions between a number of actors such as physicians, patients, nurses, and pharmacists, opportunities exist to make errors by any one of the actors. Consequently, patient safety could be easily compromised in the form of errors in medication-related calculations and lack of strict standards on drug choice, frequency, and dose. In addition, Sakowski et al. (2008) pointed out that medication errors are the leading causes of error-related inpatient deaths.

HIT applications are reported to have positive association with enhanced patient safety outcomes (Siegrist & Kane, 2003). Amarasingham et al. (2009) demonstrated that HIT systems could increase patient safety by reducing complications and mortality rates, as well as by minimizing medical errors. Taylor et al. (2005) estimated that the age-adjusted mortality rate could potentially be reduced by 18% while employee sick days could decrease by forty million with the application of HIT in disease prevention and management. Overhage et al. (1997) argued that HIT may lead to reduced error of omission while Walsh et al. (2005) indicated that HIT adoption may reduce the number of adverse drug effects and serious medication errors. In addition, Teich et al. (2000) demonstrated that physician prescribing behavior could improve with widespread use of information technology.

Furthermore, electronic systems can be more effective in monitoring patients, safeguarding critical information, and providing effective solutions compared to humans while it can be difficult for humans to find the right information from the piles of data on papers that are collected from patients. In short, there is always the chance to make errors at any one of the prescribing, dispensing, administration, and monitoring phases of the medication process (Reckmann et al., 2009), and the use of information technology could be one critical step in averting such costly mistakes. As adoption of HIT systems increases, it is predicted that the way healthcare is provided in hospitals will be continuously redesigned and eventually errors will be difficult to make (Hillestad et al., 2005) or better, they will be eliminated altogether (Mekhjian et al., 2002).

Other studies, however, show different results. Sakowski et al. (2008) found that a BCMA system was not able to detect serious medication errors while Bates et al. (1998) found that the use of CPOE decreased potential, not actual, adverse drug events (ADEs). Parente and McCullough (2009) also found that only EMR could significantly affect patient safety, while nurse charts and patient archiving and communication systems (PACS) did not affect patient safety significantly.

2.5.2 Better Quality of Care

The provision of a higher quality of care is one of the foremost objectives of the healthcare system (Miller et al., 2005). HIT applications are seen as key elements in increasing the quality of services in the healthcare industry. Quality of care refers to "the degree to which health services for individuals and populations increase the likelihood of desired health outcomes and are consistent with current professional knowledge" (Institute of Medicine, 2001, p. 244). Quality of care can also be more specifically defined as "doing the right thing at the right time in the right way to the right person and having the best possible results" (Agency for Healthcare Research Quality, n. d.). These definitions indicate that higher quality of care refers to the reduction or total elimination of "overuse," "underuse," or "misuse" of services and resources. The definitions also indicate that patient quality of care is inherently different from other aspects of services, also known as "amenities," such as appearance, comfort, and convenience (Romano & Mutter, 2004).

Quality of care and patient safety initiatives have been promoted by the Institute of Medicine (IOM), Agency for Healthcare Research and Quality (AHRQ), and the Leapfrog Group as well as others in recent years. HIT is being increasingly recognized to play a critical role in addressing the quality of care and patient safety concerns. As a result, states such as California have recently passed regulations that require hospitals to report their plans on how to adopt technologies (Furukawa et al., 2008). Furthermore, Poon et al. (2006) pointed out that recent efforts to meet the needs of patients and payers, such as the pay-for-quality incentives, necessitate the application of information technology systems that help measure and improve the quality of care. Thus, technology-supported quality of care improvement efforts could result in better relationships between patients and payers, which is critical, particularly in light of the recent reimbursement reduction trends.

In line with that, a number of authors have indicated that the adoption of HIT applications may lead to improved quality of care. Samore et al. (1997) found an association between HIT adoption and better surveillance, while Cannon and Allen (2000) pointed out that the use of HIT may lead to adherence to evidence-based guidelines. Mullett et al. (2001) found a link between HIT use and reduced inpatient days and Chen et al. (2003) demonstrated a positive relationship between HIT adoption and increased appropriateness of orders. In addition, McCullough et al. (2010) as well as Kazley and Ozcan (2008) found a positive association between information technology use and better performance on some AHRQ quality of care indicators. Different from these findings, however, Mekhjian et al. (2002) indicated that the introduction of HIT systems could lead to cultural changes in hospitals that could initially affect productivity and, thus, the quality of the care provided in the hospitals.

2.6 Organizational and Contextual Factors Influencing HIT Adoption and Patient Outcomes

Control variables (with regard to patient outcome), also known as explanatory variables (with regard to HIT adoption), refer to the physical, financial, and operational aspects of the hospitals that directly or indirectly affect the adoption of information technology applications and healthcare outcomes. The variables used in this study are categorized into two groups: (1) organizational factors (size, ownership, teaching status, and HMO penetration); and (2) contextual factors (urban/rural location, regional location, market competition, and payer mix). These variables are explained as follows.

2.6.1 Size

Previous works demonstrated that the level of HIT adoption in a hospital has a significant positive relationship with its size (Burke et al., 2002; Fonkych & Taylor, 2005; Parente & Van Horn, 2006; Wang et al., 2005). The reason given is that the adoption of HIT requires enormous financial commitments, in the form of both one-time implementation costs and the continuous operating and maintenance costs. Since large hospitals have the relative advantages of economies of scale and fewer financial constraints, they are better able to invest in HIT compared to smaller hospitals. In fact, Furukawa and colleagues (2008) found that large hospitals have at least three times higher HIT adoption rate compared to smaller hospitals. However, patient healthcare outcomes differed on this explanatory variable. For example, Romano et al. (2003) indicated that more patient safety events were observed in large hospitals compared to smaller hospitals, while Miller et al. (2001) associated a large number of hospital beds with patient safety incidents. In this study, size refers to the number of set-up and staffed beds in a hospital. As explained in the next chapter, the hospitals are grouped into three size categories: small, medium, and large.

2.6.2 Ownership

Prior investigations on the effects of ownership type on the adoption of information technology have produced mixed results. Fonkych and Taylor (2005) and Parente and Van Horn (2006) found that not-for-profit hospitals have considerably higher adoption rates of clinical IT applications, while for-profit hospitals have higher adoption rates of administrative and managerial IT applications. The reason for this could be that attributed to the primary objective of investor-owned hospitals, which is profit maximization. Consequently, for-profit hospitals may be less motivated to invest in clinical information technology and more motivated to adopt technologies that are helpful in increasing profitability. In addition, not-for-profit hospitals are reported to have more financial advantages over community or state/government hospitals, and as a result, they may have higher adoption rate of information technology applications (Furukawa et al., 2008). Parente and Van Horn specifically pointed out that for-profit and not-for-profit hospitals aim for different outcomes from the adoption of IT; whereas the former benefit from IT in the form of reduced number of days supplied (profit maximization), the latter benefit in the form of increased quantity of services supplied (volume maximization). On the other hand, there is evidence that the dynamics of HIT adoption has shifted over the years. Parente and Van Horn found that between 1987 and 1998 higher rate of IT adoption was observed in not-for-profit short-term acute care hospitals than in for-profit hospitals, while

Fonkych and Taylor indicated that in 2004 more for-profit hospitals made significant budget commitments to HIT.

Similarly, the findings were mixed in terms of patient outcomes. Studies by Thomas, Orav, and Brennan (2000) and Sloan, Picone, Taylor, and Chou (2001) found no major difference between for-profit and not-for-profit hospitals in terms of preventable adverse events and certain quality of care measures. On the other hand, a study by Miller et al. (2001) associated not-for-profit ownership with higher patient safety incidents, while Jha, Li, Orav, and Epstein (2005) linked not-for-profit status with better performance in terms of quality of care. Romano et al. (2003) also associated both for-profit and not-for-profit ownership of hospitals to higher incidences of patient safety events though the specific types of events varied between the two hospital types.

2.6.3 Teaching Status

Compared to non-teaching hospitals, teaching hospitals are generally characterized by large size and extensive diversity of healthcare professionals, including medical students, physicians, nurses, and assistants. Furukawa et al. (2008) indicated that teaching status is positively associated with adoption of some information technology types. Similarly, a study based on the 2006 HIMSS data set by Fonkych and Taylor (2005) indicated that academic hospitals have up to two times higher adoption rates of HIT compared to non academic hospitals. But on the other hand, a study of 1,441 metropolitan hospitals by Wang et al. (2005) indicated that teaching status of hospitals does not affect hospitals' HIT adoption.

With regard to healthcare outcomes, Thomas et al. (2000) indicated that the incidence of preventable adverse events was very small in government teaching hospitals. This finding is supported by Allison et al. (2000) and Jha et al. (2005), who found an association between teaching status and higher quality of care. On the other hand, however, Miller et al. (2001) and Romano et al. (2003) found a high incidence of patient-safety events in major teaching hospitals and urban teaching hospitals, respectively.

2.6.4 Health Maintenance Organization (HMO) Penetration

The general trend is that health maintenance organizations (HMOs) are increasingly making solid presence in hospitals (McCue, 2000). The reasons given are that HMOs enable hospitals to (1) expand their markets; (2) have control over the provider network; and (3) increase their profit margins. HMO sponsorship of hospitals is positively associated with availability of excess cash (McCue), which in turn may be associated with higher level of information technology adoption. This finding is also supported by Fonkych and Taylor (2005), who found that in particular for-profit hospitals that are involved in HMOs have a higher likelihood of adopting HIT. Contrary to the above findings, however, Wang et al. (2005) found that HMO penetration does not significantly affect hospitals' information technology adoption.

With regard to healthcare outcomes, Volpp and Buckley (2004) found that higher HMO penetration may not affect quality of care in terms of mortality rates, while Mark, Harless, McCue, and Xu (2004) indicated that increased HMO penetration may be associated with lower mortality in hospitals. The explanation they provided was that HMO patients' stay in the hospitals are generally short because of prearranged contracts, and they leave the hospitals to die in other facilities. HMO penetration is measured by the presence or absence of an HMO contract in the hospitals.

2.6.5 Urban/Rural

Since hospitals in rural areas are generally small in size and have a lower market competition, they may need only limited administrative capacity and thus lower levels of information technology adoption compared to their counterparts in urban areas. This assumption is supported by Furukawa et al. (2008) and Burke et al. (2002), who found that urban location is positively associated with higher information technology adoption. However, a study by Fonkych and Taylor (2005) indicated that when controlled for size, no significant difference exists between rural and urban hospitals in terms of EMR or CPOE adoption, while rural hospitals are likely to have lower adoption rates of PACS. In addition, Romano et al. (2003) found that patient-safety incidents were observed both in urban and rural hospitals, though the majority of the incidents occurred in urban hospitals. This finding is supported by Miller et al. (2001), who found a relationship between urban location of hospitals and patient safety events.

2.6.6 Region

The Healthcare Cost and Utilization Project (HCUP) data set (2009b) grouped the fifty states into four geographic regions: Northeast (CT, MA, ME, NH, NJ, NY, PA, RI, & VT); Midwest (IA, IL, IN, KS, MI, MN, MO, ND, NE, OH, SD, & WI); South (AL, AR, DE, FL, GA, KY, LA, MD, MS, NC, OK, SC, TN, TX, VA, & WV); and West (AZ, CA, CO, ID, MT, NM, NV, OR, UT, WA, & WY). Hospitals from DC, Alaska, Hawaii, Puerto Rico and other associated areas were excluded from the analysis.

Furukawa et al. (2008) found that in 2006 hospitals in the East Coast area exhibited higher HIT adoption rate compared to hospitals in the Western and Mountain regions. Romano et al. (2003) found very small association between regional location and patient-safety events, while Jha et al. (2005) detected better performance in Northeast and Midwest hospitals.

2.6.7 Market Competition

In today's competitive market environment, the survival of organizations depends on their market positions relative to their competitors. IT applications have been demonstrated to give organizations information, productivity, and cost advantages. In line with that, Burke et al. (2002) found that higher market competition is positively associated with overall information technology adoption. Fonkych and Taylor (2005) surprisingly indicated that not-for-profit hospitals are more likely to adopt HIT when the market is more competitive, while their for-profit counterparts are more likely to adopt information technology when the competition is lower. Wang et al. (2005) on the other hand demonstrated that higher competitive market conditions do not necessarily affect hospitals' adoption of HIT. In addition, a research by Sari (2002) associated both high and low market competition of hospitals with lower quality of care. Similarly, Cuellar and Gertler (2005) found that lower market competition does not necessarily improve quality of care.

In this study the inverse market competition is measured by the Herfindahl-Hirschman Index (HHI) of market concentration, which is calculated as: H-H index = $\sum_{i=1}^{n}$ (number of beds in a hospital / total number of beds in a county)^2, where n is the total number of hospital beds in a county (Phibbs & Robinson, 1993). Higher values of the HHI scores indicate less market competition.

2.6.8 Payer Mix

The term payer mix is used in this study to refer to the ratio of Medicare and Medicaid patients to the total number of hospital patients. Borzekowski (2002) indicated that the Prospective Payment System of Medicare has led to higher adoption rates of HIT in hospitals. The reason given was that higher payer mix required more information processing, and subsequently hospitals were likely to adopt more administrative IT systems (Wang et al., 2005). Contrary to that, it can also be argued that since Medicare and Medicaid reimbursements are relatively lower than other sources, hospitals with higher proportion of Medicare/Medicaid patients may have smaller resources to invest on technology and, thus, exhibit lower adoption rate of information technology. This is particularly true after the enactment of the 1997 Balanced Budget Act, which has significantly affected the financial performance of hospitals (Parente & Van Horn, 2006). This assumption is also supported by Furukawa et al. (2008) as well as Fonkych and Taylor (2005), who found a negative association between Medicare and Medicaid share and particularly EMR and CPOE adoption.

In terms of patient outcome, a study by Miller et al. (2001) showed a positive association between higher percentage of Medicare-insured patients and increased patient-safety events, while a study by Taylor, Whellan, and Sloan (1999) revealed that teaching hospitals that received relatively higher Medicare reimbursement performed better in some quality of care indicators.

2.7 Gaps in Previous Studies

Many of the researches reviewed in this study used empirical data and applied cutting-edge approaches. However, the majority of them were inherently contextual and thus remained narrow in scope. The findings were limited in terms of number of information technologies, sample size, hospital characteristics, healthcare outcomes, geographic locations, market segments, stakeholders, benchmark institutions, or time periods. As a result, it is difficult to draw definitive conclusions from the studies due to their limited generalizability. To my knowledge, no previous work has included a large number of technologies, hospital characteristics, and multiple health outcomes using nationally representative data sets. Table 2 shows the list of some of the pertinent literature on HIT reviewed in this study along with the technologies studied, data sources, focus areas, and significant findings.

Table 2: Sample Previous Works on Healthcare Information Technology

Authors	Technology	Data sources	Focus area	Significant findings
Amarasingham et al. (2009)	Automated notes and records, COPE, CDS	72 hospitals in Texas	Patient safety, cost	15% reduction in fatal hospitalization; up to 55% reduction in deaths from heart procedures 16% reduction in complications; lower hospital admission costs.
Anderson et al. (2006)	HIT	Qualitative analysis	Cost saving	National HIT adoption efforts could improve the position of U.S. healthcare system compared to other OECD member countries.
Ash (1997)	End user online literature searching, computer based patient record, electronic mail systems	1,335 individuals from 67 academic institutions	Infusion and diffusion of technologies	Organizational attributes (communication, participative decision making, top- management support, planning, existence of champions, and reward systems) affect diffusion of technologies; they have minimal effect on infusion.
Bates et al. (2003)	Various HIT applications	Qualitative study	Safety	HIT produces reduced errors, improved communications, access to information, better monitoring, increased medication safety.
Bates et al. (1999)	CPOE with Decision Support	A teaching hospital	Medication errors	Substantial decrease in the rate of non-missed-dose medication errors during the study period: medication error rate decreased by 81%, non-intercepted serious medication errors decreased by 86%.
Bates et al. (1998)	CPOE, a combination of CPOE and team intervention	A teaching hospital	Nonintercepted serious medication errors	Nonintercepted serious medication errors decreased by 55% during the study period, preventable ADEs declined by 17%; nonintercepted potential ADEs declined by 84%.
Bhattacherjee et al. (2007)	Administrative, clinical, and strategic IT	Florida hospitals	Hospitals' operational performance	Higher adoption rates of clinical IT were associated with better performance.

Authors	Technology	Data sources	Focus area	Significant findings
Burke et al. (2004)	Clinical, administrative, and strategic decision support systems	National data	IT munificence	A hospital's IT strategy can be observed from its IT munificence.
Burke et al. (2002)	Various IT applications	National data	Organizational and market factors	Positive association between level of IT adoption and hospital size, location, system membership, ownership, and market competition.
Cannon et al. (2000)	Computerized reminder, EMR	VA	Computer-based vs. paper-based reminder systems	Increased adherence to guidelines (25.5% higher screening rate and 94.4% more documentation) as a result of using computer-based reminders.
Chen et al. (2003)	CPOE, Decision Support	A teaching hospital	Appropriateness of order entry	Inappropriateness of orders decreased from 54% to 14.6% following implementation of computerized reminders; 13% cancellation for all antiepileptic drug (AED) tests ordered, of which 27% were redundant and 4 % were non-redundant orders.
Dean Franklin et al. (2007)	Closed-loop electronic prescribing, ADM, barcode patient identification, EMAR	A teaching hospital	Prescribing and administration errors, patient id confirmation, and staff time	1.8% and 2.7% reduction in prescription and medication administration errors respectively; 63.7% increase in patient identity confirmation before medication administration; 24 sec, 30 min/weekday, and 7.6% increases in prescription time, ward pharmacy service time, and non drug round nursing medication time respectively; 10 min reduction in time per drug administration round.
Dexter et al. (2004)	CPOE, EMR	A teaching hospital	Computerized physician standing order vs. computerized physician reminders	Patients with computerized physician standing order had increased influenza and pneumococcal vaccine administration (more than 12% and 20% respectively) compared to patients with computerized physician reminders.

Authors	Technology	Data sources	Focus area	Significant findings
Furukawa et al. (2008)	EMR, CDS, CPOE, BarD (BCMD), ROBOT, ADM, EMAR, BarA (BCMA)	National data	Patient safety	Patient safety initiatives may lead to higher adoption of HIT. Factors that affect HIT adoption include size, ownership, teaching status, system membership, payer mix, and accreditation status.
Hillestad et al. (2005)	EMR	National data	Cost saving	Widespread adoption of EMR at a national level could produce savings of $142-$371 billion in the form of efficiency, safety, and health benefits. CPOE could help save $3.5 billion per year through adverse drug event prevention.
Kaushal et al. (2003)	CPOE, CDS systems	Tertiary data	Medication safety	Reduced medication error and adverse drug effect rates, and improvements in corollary orders and prescribing behaviors.
Kazley et al. (2008)	EMR	National data	Quality of care	Significant positive associations between EMR use and certain quality indicators.
McCullough et al. (2010)	CPOE, EHR	National data	Quality of care	Hospitals that adopted CPOE and HER exhibited higher quality of care compared to those hospitals that did not adopt the technologies.
Mekhjian et al. (2002)	CPOE, EMAR	A teaching hospital	Staff time and costs	Medication turn-around, radiology, and laboratory time decreased by 64%, 43%, and 25% respectively; length of stay decreased by 0.2 days; cost per admission decreased in select services.
Menachemi et al. (2008)	Clinical, administrative, and strategic decision support systems	Florida hospitals	Quality of care	Adoption of IT was associated with better performance in some quality of care indicators.
Mongan et al. (2008)	HIT	Qualitative analysis	Cost saving	HIT could result in cost savings through enhanced coordination and efficient use tests and treatments by healthcare providers.

Authors	Technology	Data sources	Focus area	Significant findings
Mullett et al. (2001)	Pediatric antiinfective decision support system	A teaching hospital	Quality of care	59% reduction in pharmacy interventions; decrease in patient days (36% for antiinfective therapy days, 28% for excess dose days); 11.5% and 9% reduction in the number of antiinfective course orders and antiinfective costs per patients respectively.
Overhage et al. (2001)	CPOE	A teaching hospital	Staff time	Physician time spent with patients increased initially by 2.2 minutes (0.43 min if duplicate administrative tasks are excluded) as a result of CPOE implementation, time spent eventually decreased with more experience.
Overhage et al. (1997)	CPOE, EMR	A teaching hospital	Error of omission	43% of physicians who received computerized reminders prescribed suggested corollary orders while only 21.9% of physicians without reminders did the same. Computerized reminders, when used with EMR, reduce the rate of errors of omission and enhance the use of guidelines.
Parente et al. (2009)	EMR	National data	Patient safety	Statistically significant positive relationship between EMR adoption and patient safety.
Parente et al. (2006)	Various IT applications	National data	For-profit vs. not-for-profit	The marginal effects of IT adoption were reduced number of days supplied for for-profit hospitals and increased quantity of services supplied for not-for-profit hospitals.
Pizziferri et al. (2005)	EHR	5 ambulatory primary care clinics in Boston	Physician time	After the implementation of EHR, physician clinic time spent per patient fell by 0.5 min from 27.55 min to 27.05 min.

Authors	Technology	Data sources	Focus area	Significant findings
Poon et al. (2006)	Various HIT functionalities	8 stakeholders from 2 market segments (Boston and Denver)	Level of adoption	The level of HIT adoption depends more on financial factors and less on quality and safety factors.
Sakowski et al. (2008)	BarA	6 community hospitals	Medication administration errors	BarA systems fail to detect more severe medication administration errors: 91% of detected errors were benign, while only 1% were life-threatening and 8% had the potential to produce moderate effect.
Samore et al. (1997)	CDR	A teaching hospital	Surveillance	Improved hospital surveillance/monitoring and quality of care.
Schnipper et al. (2008)	EMR, CDS systems	Partners HealthCare, qualitative study	Decision support	Enabled integrated data review, clinical documentation, and decision support environment.
Taylor et al. (2005)	EMR	National data	Cost saving	\$81-\$162 billion and \$10 billion in cost savings due to enhanced healthcare delivery efficiency and transaction efficiency respectively; 18% reduction in age adjusted mortality; 40 million less annual employee sick days.
Teich et al. (2000)	CPOE	A teaching hospital	Patient safety	1 and 2 years follow up studies confirmed improvements in physician prescribing behaviors.
Walsh et al. (2005)	CPOE, ADM, BCMA	Qualitative study	Patient safety	CPOE, ADM, and BCMA help reduce medication errors.

Authors	Technology	Data sources	Focus area	Significant findings
Wang et al. (2005)	Clinical, administrative, and strategic decision support systems	National data	Market, financial, and organizational factors	Adoption pattern of IT applications was affected by market, organizational, and financial factors. A positive association exists between operating revenue and HIS adoption.
Wang et al. (2003)	A third-generation ICU information system	VA	Nurse time	Following the installation of the ICU information system, the time spent on documentation decreased by 10.9%. Time spent providing direct patient care and doing patient assessment increased by 8.8% and 5.4% respectively.
Welch et al. (2007)	EHR	54 physician practices	Quality and Cost of care	Mixed result for the quality of care measures, no significant impact for short-term cost per episode.
Wu et al. (2007)	Mobile healthcare systems (MHS)	Nine hospitals in Taiwan	Acceptance and perception	User's acceptance is determined by the perceived usefulness, ease of use, and compatibility of the systems.
Yu et al. (2009)	CPOE	National data	Quality of care	CPOE implementation has a positive association with medication and non-medication quality of care measures.

Note: ADM = Automated Dispensing Machines; BCMA = Bar-Coding at Medication Administration; BCMD = Bar-Coding at Medication Dispensing; CDR = Clinical Data Repository; CDS = Clinical Decision Support; CPOE = Computerized Physician Order Entry; EHR = Electronic Health Record; EMAR = Electronic Medical Administration Records; EMR = Electronic Medical Record; ROBOT = Robot for Medication Dispensing

This study, therefore, aims to fill the gap and propose and validate multiple regression models that examine these factors. The following approach was used on publicly available national data sets: (1) theoretically supported conceptual and analytical frameworks were constructed to provide guidance to the study; (2) organizational and contextual factors that may affect HIT adoption were identified based on the theoretical frameworks; (3) specific technologies were identified based on literature review; and (4) the effects of the technologies on the selected healthcare outcomes were then assessed after risk adjusting for gender, age, and comorbidity categories of the provider. The findings were then used to put forward theoretical, methodological, and policy implications as well as suggestions for future studies. As such, this study aims to contribute a new and broader insight on hospital information technology adoption and its effect on healthcare outcomes based on the most recent nationally representative hospital data.

2.8 Summary

This chapter provided a literature review on the current state of HIT adoption in U.S. acute care hospitals. IT applications are being widely adopted in other industries and have produced significant gains. However, they have been of limited use in the healthcare industry despite their evidence-based potential to improve cost, safety, quality, and efficiency. Financial, regulatory, and cultural barriers that created such low levels of HIT adoption and the limitations of HIT were discussed. The literature review revealed that effects of the adoption of one or more of the clinical IT applications on patient safety and quality of care in acute care hospitals has been demonstrated, though the effects of the adoption of administrative and strategic IT on patient safety has not be as thoroughly documented. Previous findings on select technologies, patient outcomes, and organizational and contextual factors were also discussed. The next chapter describes the theories used to develop the conceptual framework and the hypotheses.

CHAPTER 3: THEORETICAL FRAMEWORK AND CONCEPTUAL MODEL

The previous chapter provided a literature review on the adoption of technologies and patient outcomes in a hospital setting. The literature review revealed that electronic clinical information is necessary in providing higher quality of care in hospitals. Similarly, electronic forms of administrative and strategic information may help hospitals to operate efficiently and survive the financial environment that is becoming increasingly tight. Organizational and contextual factors that may affect the adoption of information technology were discussed. The structure-process-outcome model and diffusion of innovations theory are used in this chapter to explain the structure and outcomes of the information technology adoption process as well as what factors are particularly detrimental to the adoption of technologies by hospitals. The conceptual framework of the model is also discussed.

3.1 The Structure-Process-Outcome Model

Avedis Donabedian's (1980) structure-process-outcome model is a widely used approach in the study of hospital quality of care. This approach analyzes quality of healthcare from three dimensions: structure, process, and outcome. It assumes that a probabilistic relationship exists among the structure, process, and outcome dimensions of healthcare organizations (Marathe, Wan, Zhang, & Sherin, 2007; Wan, 1995, 2002). Under this framework, individual characteristics of healthcare providers are examined independently to measure the quality of care provided to patients. Each variable is associated with other observed indicator variables and/or latent theoretical constructs. The purpose of the research determines which specific observed variables and/or theoretical latent constructs are included in the analysis.

The structure dimension is particularly influential in contributing to or impeding the effectiveness of the overall healthcare provision and refers to tangible aspects of hospitals, such as material resources, human resources, and organizational characteristics (Donabedian, 2003). Specific examples of structural dimension include the nature and location of the facility, the types of equipment used, and the number, qualification, coordination, and organization of the healthcare providers working in the hospital as well as non-medical infrastructure (Birkmeyer, Dimick, & Birkmeyer, 2004; Ganz, Litwin, Hays, & Kaplan, 2007). In short, structure refers to community, organization, provider, and population characteristics within the healthcare industry (McGlynn, 2007).

The application of structural dimensions in the assessment of quality of care is justified because this information can be relatively easy to acquire from administrative data (Birkmeyer et al., 2004). In addition, there is evidence that causal relationships do exist between structure and outcome (Halm, Lee, & Chassin, 2002). However, Romano and Mutter (2004) cautioned that one has to be careful when using structural measures in a model, because (1) structural aspects of hospitals are sometimes very difficult to modify, and (2) the quality of care provided in hospitals can sometimes become independent of the structure of the hospitals. This means two hospitals may find themselves in different structural dimensions but provide the same level of quality of care.

Process measures, on the other hand, broadly refer to the actual healthcare provision activities by healthcare professionals (Donabedian, 2003). They also refer to the patient-provider interaction (Ganz et al., 2007; McGlynn, 2007) or more specifically the way patients are treated and evaluated by healthcare providers (Romano & Mutter, 2004). These definitions imply that process measures can easily be manipulated by providers in order to achieve better outcomes. Donabedian stressed that process measures are affected not only by providers but also by patients and their families. There is evidence of a positive relationship between process measures and improved patient outcomes (Birkmeyer et al., 2004). Some process measures, however, are not scientifically tested but are dopted based on observations and consensus. Process measures may have drawbacks; since they sometimes come from medical records and patients through surveys, interviews, and observations, they may be expensive to collect. But unlike structure measures, it is possible to take action on process measures, and, thus, they can be seen as more reliable indicators of quality of care.

Donabedian (2003) defined outcome measures as “changes (desirable or undesirable) in individuals and populations that can be attributed to healthcare” (p. 46). These changes may be in the form of health status, knowledge, or behavior of patients and their families. Outcomes may also include the satisfaction that patients experience due to the care they received. Outcome measures, according to Romano and Mutter (2004), are easier to be understood by patients and other non-clinicians because at the end of the day what really matters to patients is the result of what healthcare providers do. Outcomes could be influenced by both structure and process, though a study by Hoenig et al. (2002) indicated that outcomes are influenced less by structure and more by process measures. Outcome measures can easily be captured from published administrative data sets such as the HCUP data set. It is recommended to use risk adjusted data because some important aspects that affect patient outcomes, such as severity of illness, are not caught in normal administrative data (Donabedian, 2003; Romano & Mutter, 2004). In this study a modified version of the structure-process-outcome model is used (see Figure 1), which, unlike Donabedian's original model, assumes a direct association between structure and outcome.

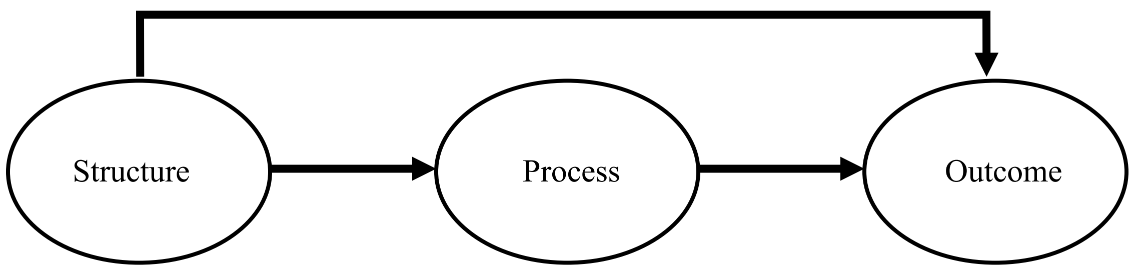


Figure 1: The Modified Structure-Process-Outcome Model

The structure-process-outcome model reportedly has some limitations. Donabedian (2003) acknowledged the difficulty in establishing causal relationship between process and outcome, and even when deemed possible, the probability that process could affect outcome is often very small. As a solution, Donabedian suggested using a large number of cases to ascertain that the outcome is the result of the process. Another limitation is that patients vary in terms of physical, social, financial, genetic, and other characteristics that may affect the outcomes of the healthcare provided to them. This problem can be alleviated by applying case-mix adjustment. However, there is no single case-mix adjustment procedure that is universally accepted. Despite these limitations, however, the structure-process-outcome model is widely used to conceptualize the quality of care provided in hospitals.

3.2 Diffusion of Innovations Theory

The terms *diffusion* and *innovation* are the core of the diffusion of innovations theory. Everett Rogers (2003), who is perhaps the most influential figure in the study of diffusion of innovations theory, defined diffusion as “the process in which an innovation is communicated through certain channels over time among the members of a social system” (p. 5). Rogers also defined innovation as “an idea, practice, or object that is perceived as new by an individual or other unit of adoption” (p.12). Communication refers to a two-way process in which two employees of the same or different levels interact with each other within or outside of the organization in order to transfer a message and achieve mutual understanding (Ash, 1997). Diffusion is one special type of communication. However, diffusion is distinct from other communication types because it primarily focuses on new ideas. Innovation is a multiphase process, and not a single event occurring at a single point of time (Pierce & Delbecq, 1977). Since innovative ideas are new, they entail a degree of uncertainty, risk, and a journey to the unfamiliar (Teece, 1996). The social systems through which the innovation diffuses are important parts of this theory (Ash, Lyman, Carpenter, & Fourier, 2001). Ultimately successful new ideas lead to social changes in which the structure of social systems is altered.

An idea that is perceived as new is generally referred to as an innovation. The term *new* does not necessarily reflect the length of time since an idea was discovered; it refers only to the point of decision by individuals to adopt it. In other words, organizations may have known about an innovation for some time, but the innovation becomes new only when the organizations decide to use it for the first time (Weiner, Helfrich, & Hernandez, 2006).

Studies show that innovations, which could take either a technical or administrative form, enhance the performance of organizations (Naranjo-Gil, 2009). Once organizations decide to use a new technology that is proven to be successful, the likelihood that they will reverse their decision is minimal, regardless of how inexpensive or convenient the old technologies may be

(Teece, 1996). For example, the probability that abacuses will replace modern digital calculators is close to zero.

Individual and organizational determinants in the process of innovation adoption are the questions that diffusion of innovations theory aims to address. An important aspect that should be stressed is that the degree to which an innovation is adopted by users depends on how successfully it meets the needs of potential users. Technological advancements or financial advantages alone may not be enough to guarantee the success of an innovation.

Timing is another very important aspect of diffusion of innovation. Users of an innovation can be divided into five categories, based on the timing of innovation diffusion (Rogers, 2003): (1) Innovators – these are a small group of imaginary and creative users who extensively invest their time, money, and energy on inventing new ideas or products; (2) Early adopters – once the applicability of innovations is tested, they are quickly adopted by the first group of users called early adopters; (3) Early majority – once an innovation has been accepted by respectable peers, early majority will open up to adopt it; (4) Late Majority – these are more conservative pragmatists that do not easily perceive innovation; and (5) Laggards – this group works hard looking for reasons not to adopt innovations. Poon et al. (2006) classified adoption level of a technology as follows: 0-5% by innovators, 5-15% by early adopters, 15-50% by early majority, 50-85% by late majority, and 85-100% as widespread adoption.

A few limitations of diffusion of innovations theory have been identified. First, the available information focuses on successful technologies, so the literature on bad technologies is relatively limited. The implication is that only effective or efficient technologies diffuse, and that may not be always the case (Soule, 1999; Bagchi, Solis, & Udo, 2005). Second, since innovation adoption is a dynamic and continuous process, determining the exact time a technology is adopted is often a difficult task. Third, the unintended negative impacts of diffusion of innovations, such as the rich getting richer and the poor getting poorer due to the diffusion of new technologies, are often overlooked in scholarly works (Rogers, 2003).

Despite its limitations, diffusion of innovations theory is widely applied in healthcare studies. Panzano and Roth (2006) studied diffusion of innovative mental health practices. They found that early adopters are willing to take specific risks because the risks are perceived as manageable. Wang et al. (2005) applied diffusion of innovations theory to build a predictive model of HIT adoption in hospitals. Their model consisted of three basic features: innovation determinants, organizational determinants, and contextual determinants. They found that HIT adoption was mainly influenced by organizational and financial factors of hospitals. Smythe (2002) built a model to understand physicians' innovation-adoption patterns. The finding was that if the innovation was found to have worth, then physicians would immediately adopt it because doing so would give them reputation advantages. More recently Kovach, Morgan, Noonan, and Brondino (2008) used an approach based on diffusion of innovations theory to bring change to the care provided to people with dementia. They concluded that diffusion of innovations is effective in bringing change in healthcare organizations.

3.3 A Comprehensive Conceptual Framework

For this study the structure-process-outcome model is applied to understand the various aspects of quality of healthcare provisions. The structure, process, and outcome measures of a hospital are all important indicators of specific features of the quality of care provided in hospitals. Each indicator independently measures quality of care to a certain degree, and each indicator has distinct strengths as well as weaknesses. As a result, Donabedian (2003) has suggested using them all in combination to benefit from the advantages of each and compensate for any downsides each may have. Miller et al. (2005) have also indicated that quality and safety are multidimensional constructs, highlighting the need for the utilization of more comprehensive structure, process, and outcome measures. In this study, therefore, all three measures will be applied, and the model includes structural, process, and outcome aspects of healthcare in a hospital setting.

Diffusion of innovation theory is next applied to understand the specific relationship between the various characteristics of hospitals and HIT adoption. Diffusion of innovations theory primarily seeks to find out the differences between early and late adopters of an innovation. The theory also aims to understand whether relative advantages and other attributes of an innovation will determine the rate at which adoption occurs. Thus, by applying diffusion on innovation theory, it is aimed to particularly identify structural aspects of hospitals that may affect the rate and level of adoption of HIT. The theory is also used to find out which specific HIT applications are likely to be selected for adoption by hospitals.

3.4 Development of Hypotheses and Selection of Variables

This study applies the structure-process-outcome model to understand which factors affect the quality of care delivered in hospitals (see Figure 2). As explained earlier, structure refers to how the healthcare provision is set up and is understood in terms of physical, financial, and human resources. The term *structure* is used to refer to organizational and contextual factors that determine the adoption of HIT in hospitals. Diffusion of innovations theory is next applied to identify the exact nature of the structure of hospitals that may determine the adoption of information technology. Diffusion of innovations theory argues that economic forces are important indicators of information technology adoption. Therefore, organizations with extra resources are more likely to adopt innovation (Ash, 1997). Typically these organizations have better access to information, financial position, and prestige and either innovate in house or adopt outside innovations before anybody else because their market position gives them the "legitimacy to differ" (Panzano & Roth, 2006; Roggenkamp, White, & Bazzoli, 2005; Sherer & Lee, 2002). Such organizations are capable of experimenting with new practices that can potentially give them further competitive advantages. Thus, they are perceived as "opinion leaders" and are able to influence other organizations' attitudes and behaviors by raising awareness and lending credibility to the innovation (Weiner et al., 2006).

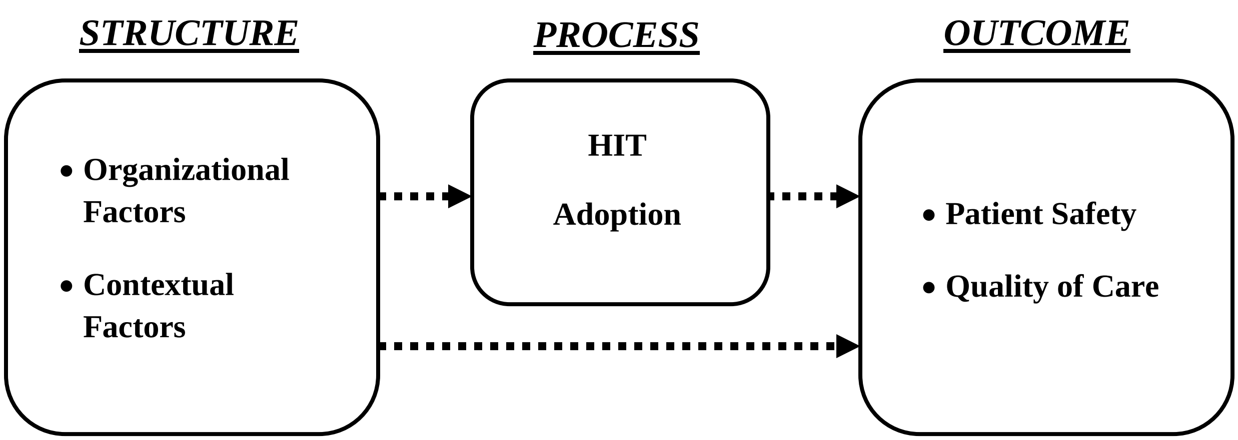


Figure 2: Conceptual Model Depicting a Relationship between Structure, Process, and Outcome Dimensions of Hospitals

The following structural characteristics of hospitals that may be associated with information and financial advantages as well as prestige are identified: hospital size, ownership, teaching status, HMO penetration, urban/rural location, regional location, market competition, and proportion of Medicare and Medicaid patients. The first four attributes (hospital size, ownership, teaching status, and HMO penetration) are referred to as organizational factors and are related to the financial, administrative, human resource, and other internal features of hospitals. The remaining four (urban/rural location, regional location, market competition, and proportion of Medicare and Medicaid patients) are referred to as contextual factors and are related to the geographical and market settings in which the hospitals exist.

As explained in the previous chapter, both the organizational and contextual factors are overlapping indicators of relative abundance or scarcity of resources in hospitals. Resources, according to diffusion of innovations theory, are critical in the adoption of innovations, as well as improving patient safety and quality of care. In addition, some of the attributes (large size, for-profit ownership, teaching status, and urban location) reveal the prestige of the hospitals, which is another factor identified by the diffusion of innovations theory as a determinant factor in the adoption of technologies. Thus, large size, for-profit ownership, teaching status, an HMO contract, urban location, regional location, higher market competition, and lower Medicare/Medicaid patient proportion are hypothesize to be positively associated with hospitals' adoption of HIT.

Hypothesis 1: Other factors being equal, organizational factors are associated with HIT adoption in acute care hospitals.

Hypothesis 1A: Other factors being equal, acute care hospitals of larger size will be more likely to adopt HIT.

Hypothesis 1B: Other factors being equal, acute care hospitals with for-profit ownership will be more likely to adopt HIT.

Hypothesis 1C: Other factors being equal, acute care hospitals with teaching status will be more likely to adopt HIT.

Hypothesis 1D: Other factors being equal, acute care hospitals with HMO penetration will be more likely to adopt HIT.

Hypothesis 2: Other factors being equal, contextual factors are associated with HIT adoption in acute care hospitals.

Hypothesis 2A: Other factors being equal, acute care hospitals located in urban areas will be more likely to adopt HIT.

Hypothesis 2B: Other factors being equal, acute care hospitals located throughout the four geographic regions will not have the same likelihood of adopting HIT.

Hypothesis 2C: Other factors being equal, acute care hospitals that face higher market competition will be more likely to adopt HIT.

Hypothesis 2D: Other factors being equal, acute care hospitals with lower proportion of Medicare and Medicaid patients will be more likely to adopt HIT.

Hypothesis 3: Other factors being equal, HIT adoption is associated with better patient safety in acute care hospitals.

Hypothesis 4: Other factors being equal, HIT adoption is associated with higher quality of care in acute care hospitals.

Process refers to the manner in which healthcare is provided. Donabedian (2003) indicated that the process components are more powerful indicators of the quality of care provided in the hospitals. Thus, the adoption and use of information technology systems was seen in this study as a process that affects patient outcomes. Several HIT applications exist in the market, and diffusion of innovations theory was used to identify which ones to include in this research.

Rogers (2003) identified five characteristics of innovations that determine their rate of adoption: *relative advantage, compatibility, complexity, trialability*, and *observability*. Fifty-two HIT applications that exhibit such characteristics are included in this study under three clusters: clinical, administrative, and strategic decision-making IT.

As explained in the previous chapter, empirical evidence indicates that using various ones of these applications has a *relative advantage* over not using them in terms of patient outcome, convenience, cost effectiveness, and prestige. Adoption of these technologies is also *compatible* with the values and practices of healthcare providers, which is providing the highest possible quality of care. These technologies are easy to comprehend (*not too complex*) by those who use them. They can be tested on a small scale or in a few departments before mass implementation (*trialability*). The effects of these technologies on the quality of care and health outcome of patients can easily be observed and measured by the providers, consumers, and policy makers through administrative data (*observability*).

Furthermore, Ash (1997) argued that selection criteria based on diffusion of innovations theory should focus on technologies that have hospital-wide application, are important, have strong presence now and potentially in the future, and are different from what is available. In line with that, the selected technologies have exhibited relatively higher diffusion rates in recent years in hospitals, are advancements from the old way of healthcare provision, and are highly associated with patient safety and quality of care in the hospitals. Another important aspect of diffusion of innovations theory is the enhanced communication or information sharing among users, which is at the center of these technologies. The hypothesized relationship between the organizational and contextual factors and adoption of technology is illustrated in Figure 3.

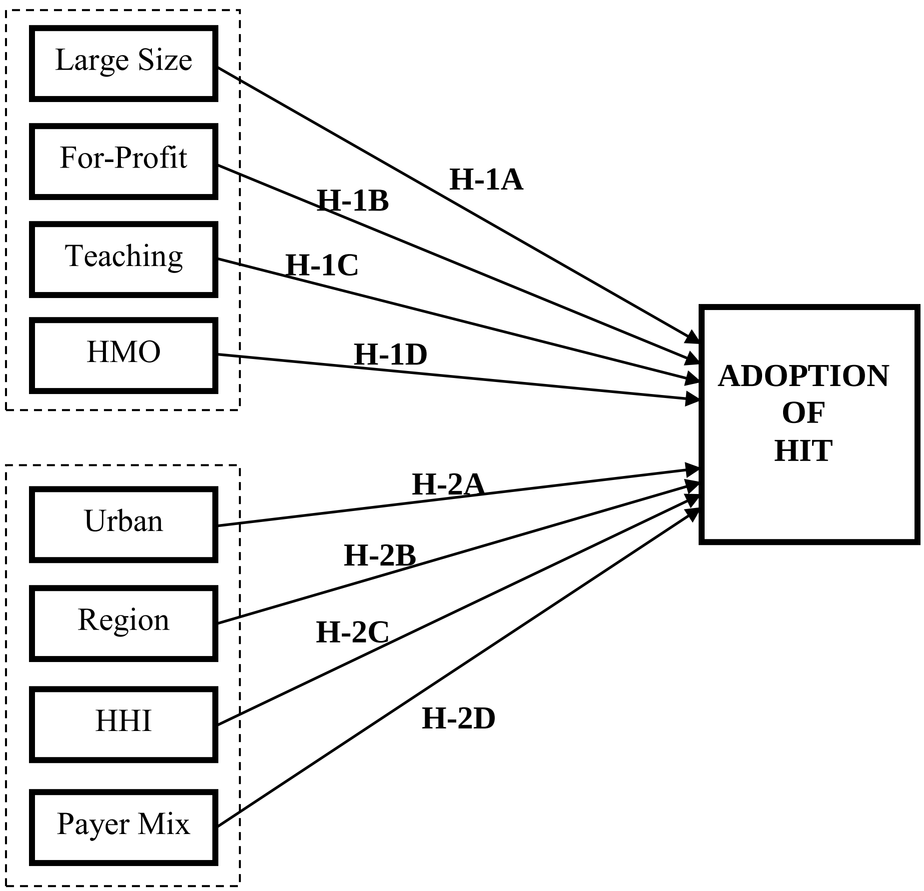


Figure 3: Analytical Model Depicting the Relationship between the Organizational and Contextual Factors and HIT Adoption

Outcome as applied in this study refers to factors that measure the effects of the care provided in hospitals as related to the application of HIT. In other words, outcome dimension of the model reveals not only what kinds of services are provided in hospitals but also the appropriateness of the services. When selecting outcome indicators, Donabedian (2003) advised that they be related to the objectives of care, be the results of appropriate healthcare provision, have information available about them, and have measurable magnitude. Thus, the adoption of HIT systems in hospitals is hypothesized to improve healthcare outcomes. Healthcare outcomes in this study are measured by patient safety and quality of care indicators. These terms are explained further in the next chapter. The hypothesized relationship between adoption of technology and the healthcare outcomes is illustrated in Figure 4 below.

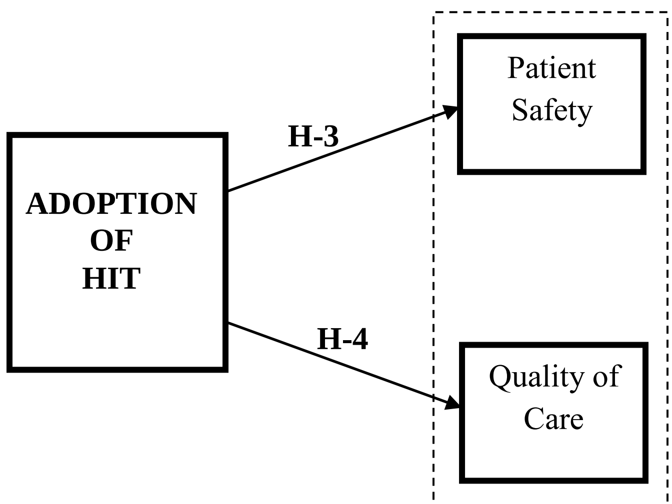


Figure 4: Analytical Model Depicting the Relationship between HIT Adoption and Patient Safety and Quality of Care

3.5 Summary

Structure-process-outcome and diffusion of innovations theories provided a guideline for this study. A conceptual model was developed that analyzed the quality of healthcare provision from the structure, process, and outcome dimensions. Diffusion of innovations theory was next applied to understand the flow of information on new ideas from early to late adopters. Innovators and early adopters were identified as financially successful, well connected, and respected by their peers. Specific contextual and organizational characteristics of innovators and early adopters were identified and applied to acute care hospitals. Hypotheses were developed and variables were selected based on the theoretical model. The next chapter will discuss the methodology of this study.

CHAPTER 4: METHODOLOGY

The previous chapter discussed the theories applied to develop the conceptual framework and the hypotheses. The structure-process-outcome model and diffusion of innovations theory were used to generate four major hypotheses. This chapter provides a description of the methodology, the rationale for choosing the methodology, and the operational definitions of variables used in this paper. It also describes the data sources, the nature of the data, the merging and cleaning rules followed, and the major differences between the included and excluded hospitals.

4.1 Design of the Study

The unit of analysis in this study is the individual acute care hospital. The initial plan was to conduct a longitudinal analysis by applying parallel process growth curve model approach with structural equation modeling (SEM) on five years of data (2002 to 2006). This was assumed to enable testing of the stability of the data over time and identification of the structural relationships between the exogenous and endogenous variables as well as between the endogenous variables. However, the use of longitudinal models and SEM proved not to be possible. One of the data sources, the HCUP Nationwide Inpatient Sample (NIS) data set, contains a representative sample of only 20% of U.S. hospitals. Each year the hospitals are selected randomly into the data set, which means the chances of having the same hospitals being selected year after year was very small. As a result, the longitudinal approach was abandoned in favor of a cross-sectional approach. The purpose of a cross-sectional study is to test whether two or more variables are related at one point in time. Cross-sectional designs are more convenient in the sense that they can be easily administered on data that the researcher has little control over, which is the case in this study.

Since the data are basically count and rate data, Poisson regression and negative binomial regression were explored as two possible options for the analysis. In the first stage of the analysis, the data did not meet the assumptions of Poisson regression (high dispersion) and thus, negative binomial regression was used. Similarly the data did not meet the assumptions of both Poisson and negative binomial regression in the second stage of the analysis. Therefore, multiple linear regression models were used after assumption tests, as shown in the next chapter, revealed no violation.

The goal of the researcher is to examine the statistical significance of hypothesized relationships between the variables. If the hypothesized model is found to fit the data, the relationships between the variables could be examined. Thus, by applying negative binomial and multiple linear regression analyses using SAS 9.1 software, the research identifies the factors that affect the adoption of HIT as well as understand the effects of adoption of HIT on patient safety and quality of care in U.S. acute care hospitals.

4.2 Data Sources, Sample, Merging, and Cleaning Rules

This study uses publicly available secondary data from 2006. The year 2006 was selected because it was the latest year with the most complete information available from all the three different data sources. Information on the type of technologies and the level of adoption is obtained from a retrospective administrative discharge data set submitted by hospitals from around the nation to the Healthcare Information and Management Systems Society (HIMSS) analytics annual survey. The HIMSS data set is collected from medical records and patient discharge data and contains vast information on the type of technology adopted by ambulatory, chronic care, and acute care providers. This data set has been widely used by other researchers on studies related to HIT (Burke et al., 2002; Furukawa et al., 2008; Hillestad et al., 2005; Kazley & Ozcan, 2008; Parente & Van Horn, 2006; Yu et al., 2009). The 2006 HIMSS data set was used in this analysis to obtain the total number and type of technologies adopted in the acute care hospitals. Out of the eight different types of healthcare facilities on the HIMSS data set, only those with an entity type of "Hospital" were included in the analysis.

Hospital characteristics that are used for identifying organizational factors (size, ownership, and HMO penetration) and contextual factors (market competition, and payer mix) were obtained from American Hospital Association (AHA) annual survey. This data set has also been widely used in the literature on HIT (Burke et al., 2002; Furukawa et al., 2008; Hillestad et al., 2005; Kazley & Ozcan, 2008; McCue, 2000; Wang et al., 2005). The 2006 AHA data set is used in this analysis. According to the AHA 2006 Annual Survey Manual, hospitals need to keep at least 6 inpatient beds in order to be registered as a hospitals on the Survey.

The research also used the HCUP NIS data set. The HCUP data were sponsored by AHRQ and developed through federal, state and industry partnership with the aim of empirically measuring quality and safety (Miller et al., 2005). The HCUP data is based on administrative discharge data and has been used in several other studies (Isaac & Jha, 2008; Lee & Wan, 2002; Miller et al., 2005; Romano et al., 2003; Zhan & Miller, 2003). The Nationwide Inpatient Sample (NIS) data set is a stratified sample of about 20% of U.S. long term acute care hospitals from 38 states in the four geographic locations. This data set provided information on the quality of care and patient safety indicators as well as the three size categories, teaching status, urban/rural location, and region of the hospitals. The AHRQ Quality Indicators SAS Software Version 4.1 was used to generate risk-adjusted estimates for the patient safety and quality of care indicators.

Based on literature review, quality of care was measured in terms of three medical conditions (in-hospital mortalities due to heart failure (IQI 15), heart attack (IQI 16), and pneumonia (IQI 20)) while patient safety was measured in terms of four conditions (death in low mortality DRG (PSI 2), decubitus (pressure) ulcer (PSI 3), iatrogenic pneumothorax (PSI 6), and central line–associated blood stream infection (BSI) (PSI 7)).

The AHRQ Quality Indicators SAS Software Version 4.1 generated four different rates for each indicator: observed, expected, risk adjusted, and smoothed rates. Basically this study compared the hospitals based on their performance on the patient safety and quality of care indicators. Provider level explanatory variables (e. g. size, ownership, teaching status, etc.) were used to control for externalities. In situations like this, scores on a given quality or safety indicators could be significantly affected by the patient acuity of the individual hospitals. Thus, the *smoothed rate* estimates, which are the risk-adjusted estimates that refer to the "weighted averages of the population rate and the risk-adjusted rate, where the weight reflects the reliability of the provider's risk-adjusted rate" (AHRQ, 2007b, p. 37), were used in the analysis. The smoothed rates were calculated using algorithms provided in the AHRQ Quality Indicators SAS Software. Hospitals with fewer cases can perform better or worse than hospitals with a large number of cases. The smoothed rates are intended to reduce such noise and produce 'conservative' and 'more accurate' estimates (Miller et al., 2005; West et al., 2007)

The unit of analysis is at the hospital level. For the year 2006, there were 6,346 observations in the AHA data set; 5,082 observation with entity type "Hospital" in the HIMSS data set; and 1,045 observations in the HCUP NIS data set. The first two data sets were merged (HIMSS and AHA) through the common variable Medicare Identification Number after excluding those observations with missing or duplicate Identification Numbers. The remaining observations were next merged by using a combination of the variables Hospital Name and Hospital Address. Thus, after removing missing and duplicate hospital names and addresses, only those hospitals with common name and address were merged to form a new data set. The combination of Hospital Name and Zip Code were the next set of variables used to merge the remaining observations. Next, Hospital Address and Zip Code were used as a set of variables to merge the still remaining observations. Name of City and Zip Code were finally used in combination as a set of variables to merge the remaining observations. Hospitals with missing or duplicate values for any of the common variables were excluded from the analysis. The HCUP data set includes the AHA ID number as a variable, and thus it was easily merged with the final AHA-HIMSS data set through this common variable. Data sources are forbidden in some states (GA, IN, KS, MI, NE, OH, OK, SC, SD, TN, and TX) from releasing information that could identify the hospitals on the HCUP data set. Therefore, hospitals from these states were excluded from the analysis and 647 hospitals were left in the final data set.

Both the predictor and response variables had observations with missing values excluded from the analysis. Furthermore, in order to clean the data for extreme outliers, the top and/or bottom 0.5%, 1%, or 1.5% of observations of the response variables were excluded depending on the distribution of the data. Eventually 582 hospitals were analyzed to identify factors that affect the adoption of HIT. Likewise, 571 hospitals were analyzed to grasp the effects of HIT adoption on death in low mortality DRG; 579 hospitals on decubitus ulcer; 570 hospitals on iatrogenic pneumothorax; 582 hospitals on central line–associated BSI; 439 hospitals on in-hospital mortality due to heart failure; 474 hospitals on heart attack; and 485 hospitals on pneumonia.

4.3 Analyses

As depicted in Figure 5, the analysis in this study is divided into two stages.

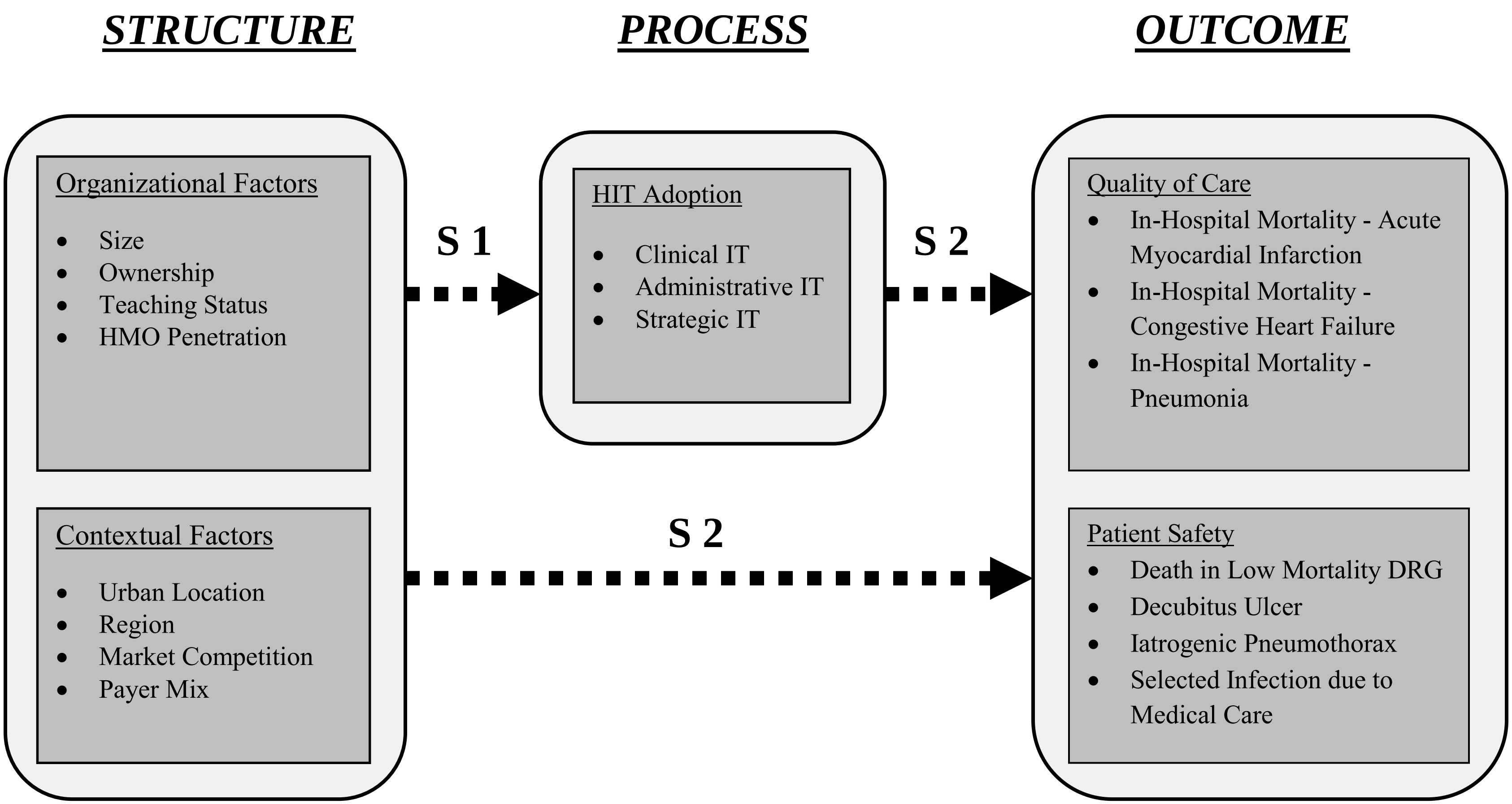


Figure 5: Conceptual Model Depicting the Two Stages of the Analysis

4.3.1 Stage One

In a regression model, the independent or predictor variables are the observed variables that affect the values of the dependent or response variable. The response variables on the hand are the dependent variables that are affected by the predictor variables. Inclusion of the predictor variables into the model is presumed to reveal changes in the values of the response variables. In the first stage of this study, HIT adoption was considered as the response variable while the predictor variables were grouped into two categories: organizational factors and contextual factors. Three regression models were developed to identify which factors affect the adoption of HIT (one for each of the clinical, administrative, and strategic IT clusters).

4.3.1.1 Organizational Factors

Organizational factors refer to financial, administrative, human resource, and other internal attributes of hospitals that may affect the adoption of HIT, patient safety, and quality of care. The following organizational factors are included in this study:

1. Hospital size – the number of set-up and staffed beds in the hospitals. The HCUP data set divides the hospitals into three size categories based on the number of beds, teaching status, and urban/rural location: small, medium, and large (HCUP, 2009a). These size categories are used for descriptive analysis purposes. See Table 3.

Table 3: Bed Size Categories

Location and Teaching Status	Hospital bed size		
	Small	Medium	Large
Northeast			
Rural	1–49	50-99	100+
Urban, nonteaching	1–124	125-199	200+
Urban, teaching	1–249	250-424	425+
Midwest			
Rural	1–29	30-49	50+
Urban, nonteaching	1–74	75-174	175+
Urban, teaching	1–249	250-374	375+
South			
Rural	1–39	40-74	75+
Urban, nonteaching	1–99	100-199	200+
Urban, teaching	1–249	250-449	450+
West			
Rural	1-24	25-44	45+
Urban, nonteaching	1-99	100-174	175+
Urban, teaching	1-199	200-324	325+

Source: HCUP (2009a).

2. Ownership – two types of ownership are analyzed in this study: for-profit and not-for-profit. In the 2006 AHA data set, hospitals owned by the government (federal and nonfederal), and other nongovernment hospitals (not-for-profit and church operated) are referred to as not-for-profit, while hospitals owned by investors (individuals, partnership, or corporation) are categorized as for-profit.
3. Teaching status – hospitals are categorized as either teaching or non-teaching. The HCUP data set documentation designates a hospital as a teaching hospital only if it meets either of the following criteria: “has an AMA approved residency program, is a

member of the Council of Teaching Hospitals (COTH); or has a ratio of full-time equivalent interns and residents to beds of .25 or higher" (HCUP, 2009a).

4. HMO penetration – refers to the presence or absence of an HMO contract in the hospitals.

4.3.1.2 Contextual Factors

Contextual factors refer to the physical and socio-economical settings of the hospitals. The following contextual factors are assumed in this study to affect HIT adoption, patient safety, and quality of care:

1. Urban/rural location – the HCUP data set designation based on hospitals' Core Based Statistical Area (CBSA).
2. Region – the four regions in which the hospitals are located: Northeast, Midwest, South, and West. Three dummy variables were created in order to compare the Northeast with the other three regions.
3. Market competition – the HHI index that measures the square of the ratio of the number of beds in the hospital to the total number of beds in the county. Thus, higher HHI indicates lower market competition while lower HHI index indicates higher market competition.
4. Payer Mix – the proportion of Medicare and Medicaid inpatient days to the total inpatient days.

4.3.1.3 <u>HIT Adoption</u>

There is evidence that over 80% of all hospitals have implemented at least basic IT applications in various departments, including radiology, laboratory, and pharmacy (Fonkych & Taylor, 2005). However, organizations may differ from each other based on the number, the timing, and the type of technologies they adopted. That is, some hospitals may have already installed several technologies while others may have focused only on a limited number of technologies; some hospitals may have a 100% installation of specific IT technologies while others may just have started implementing the technologies or have signed a contract to purchase them from vendors; and some technologies are adopted at an organizational level while others are adopted at a departmental or individual employee level. Therefore, the following points are taken into consideration:

1. The HIMSS data set shows seven status types of hospital technology: “Contracted/Not Yet Installed,” “Live and Operational,” “Installation in Process,” “Not Automated,” “Not Reported,” “Not Yet Contracted,” and “To be Replaced.” Only those hospitals that have actually implemented the technology (i.e., reported that they have “Live and Operational” technology) are considered to have adopted the technology. All other hospitals that reported any of the other six status types are considered not to have adopted the technology.
2. HIT adoption is analyzed both as a dependent variable (to identify factors affecting technology adoption) and as an independent variable (to determine the effects of technology adoption on patient safety and quality of care).

3. As a dependent variable (stage one of the analysis), HIT adoption could be affected by organizational and contextual environment of the hospitals, and it in turn may affect the patient safety and quality of care provided in the hospitals (stage two).
4. HIT adoption is analyzed at an organizational level.

Using the cluster of technology approach (Austin & Boxerman, 1998) the health information technologies were divided into three clusters: clinical IT, administrative IT, and strategic decision-support IT. The complete list of the technologies is depicted in Table 1. A technology adoption score that corresponds to the total number of technologies under each cluster was developed. Hospitals are given a score of 1 for each technology they adopted under the three categories. Therefore, a hospital can score in a range of 0 to 25 for the adoption of clinical IT. A score of 0 indicates that the hospital did not adopt any of the technologies under this cluster while a score of 25 indicates that the hospital has adopted all the 25 technologies. The scores range between 0 to 18 and 0 to 9 for administrative and strategic IT clusters, respectively. Similarly, a score of 0 indicates no adoption of the technologies while higher scores indicate the adoption of more technologies.

Ultimately, this study aimed to identify the organizational and contextual factors that predict the adoption of HIT (measured by the number of technologies adopted) in acute care hospitals. It also aimed to detect whether the adoption of technologies will affect patient safety and quality of care in the hospitals. Since these are purely count data, i. e., the dependent variable is the number of technologies adopted in each hospital, they cannot be accurately analyzed through traditional regression approaches. Instead, Poisson and negative binomial regression approaches were considered for the analysis. However, the test for goodness-of-fit revealed that the data are overdispersed (the ratio of the Pearson Chi-Square values to the degrees of freedom were significantly greater than 1, implying that the variance were greater than the mean). Therefore, negative binomial regression models were eventually used for the prediction of adoption of HIT. The following equations represent the models:

Adoption of Clinical IT = f (size, ownership, teaching status, HMO, urban location, region, market competition, payer mix)

Adoption of Administrative IT = f (size, ownership, teaching status, HMO, urban location, region, market competition, payer mix)

Adoption of Strategic IT = f (size, ownership, teaching status, HMO, urban location, region, market competition, payer mix)

4.3.2 Stage Two

In stage two, the response variables were the patient safety and quality of care indicators and the predictor variable was adoption of HIT, while the organizational and contextual factors were used as control variables. The effects of clinical, administrative, and strategic IT on patient safety and quality of care were analyzed separately. Multiple linear regression was used for this second stage of the analysis after assumption tests revealed no violation. Thus, three regression models were developed for each of the four patient safety indicators and three quality of care indicators. Eventually, 21 regression models were developed. The patient safety and quality of care indicators were multiplied by 10000 and log transformed in order to make the interpretation of the regression coefficients easier.

4.3.2.1 Patient Safety Indicators (PSIs)

Patient safety is measured in this model through patient safety indicators (PSIs). A team of researchers at the University of California San Francisco-Stanford's Evidence-Based Practice Center (EPC) sponsored by AHRQ developed PSIs with the aim of generating schemes that minimize patient risks associated with receiving healthcare services (Miller et al., 2001). The PSIs were primarily developed to analyze the quality of care provided in the hospitals by using publicly available data where the diagnoses and procedures in the data set are coded according to International Classification of Diseases, 9th Revision, Clinical Modification (ICD-9-CM) systems (Miller et al., 2005). The PSIs put emphasis on undesirable patient outcomes that are not the results of negligence, known procedural risks, or additional complications. Thus, they are limited in scope and are not an exhaustive list of all errors; they are rather a "conservative" small list of indicators based on administrative data (Miller et al., 2001). As a result, Miller and colleagues advised that PSIs should be used with caution.

Patient safety and quality of care are multidimensional measures (Miller et al., 2005; Romano & Mutter, 2004). This implies that at any given time an organization may not have the same level of performance in all the dimensions or in all measures of a single dimension; thus, drawing definitive conclusions based on analysis on a single quality or safety dimension would be incorrect. PSIs are generally considered to have low event rates (Miller et al., 2005). Although work remains to validate PSIs, they are widely used in studies related to patient safety (Isaac & Jha, 2008; Miller et al., 2005; Romano et al., 2003; Zhan & Miller, 2003). In this study, four

PSIs that are related to inpatient medical care and are obtained from administrative data are included to measure inpatient safety in hospitals (AHRQ, 2006b; Isaac & Jha):

1. Death in low mortality DRG (PSI 2) - "in-hospital deaths per 1,000 patients in DRGs with less than 0.5% mortality" (AHRQ, 2007b, p. 26);
2. Decubitus (pressure) ulcer (PSI 3) - "cases of decubitus ulcer per 1,000 discharges with a length of stay greater than 4 days " (AHRQ, 2007b, p. 28);
3. Iatrogenic pneumothorax (PSI 6) – "cases of iatrogenic pneumothorax per 1,000 discharges" (AHRQ, 2007b, p. 34); and
4. Selected infection due to medical care (PSI 7) - "cases of infections due to medical care, primarily those related to intravenous lines (IV) and catheters" (AHRQ, 2007b, p. 36).

A separate regression model is developed to understand the relationship between each of the three technology clusters and the patient safety indicators. The models are represented by the following equations (each equation represents a separate regression model for the four PSIs):

Patient Safety = f (size, ownership, teaching status, HMO, urban location, region, market competition, payer mix, Clinical IT)

Patient Safety = f (size, ownership, teaching status, HMO, urban location, region, market competition, payer mix, Administrative IT)

Patient Safety = f (size, ownership, teaching status, HMO, urban location, region, market competition, payer mix, Strategic IT)

4.3.2.2 Inpatient Quality Indicators (IQIs)

Quality of care is measured in this study in terms of inpatient quality indicators (IQIs). Similar to PSIs, IQIs were sponsored by AHRQ and developed by University of California San Francisco-Stanford's Evidence-Based Practice Center (EPC) based on discharge data from hospitals (Miller et al., 2005). The IQIs are also based on administrative data and are expected to serve as tools that will encourage institutions to look for means to improve the quality of their services. IQIs are generally focused on rates of mortality, utilization of procedures, and volumes of procedures for selected medical conditions. Information on IQIs for this study is obtained from the HCUP data set. Three measures of mortality rates for medical conditions that are widely endorsed and are responsive to clinical guidelines (Amarasingham et al., 2009; AHRQ, 2006a; Jha et al., 2005; Jha, Orav, Li, & Epstein, 2007; Kazley & Ozcan, 2008; Yu et al., 2009) are included as inpatient quality of care indicators. These indicators are also pointed out to have a significant financial impact on the Medicare program, as they are among the primary Medicare inpatient diagnoses (Centers for Medicare & Medicaid Services, 2010). The indicators are

1. Mortality due to acute myocardial infarction (IQI 15) – is defined as the "number of deaths per 100 discharges with a principal diagnosis code of AMI" (AHRQ, 2007a, p. 47);
2. Mortality due to congestive heart failure (IQI 16) – refers to the "number of deaths per 100 discharges with principal diagnosis code of CHF" (AHRQ, 2007a, p. 50); and
3. Mortality due to pneumonia (IQI 20) – refers to "mortality in discharges with principal diagnosis code of pneumonia" (AHRQ, 2007a, p. 58).

A separate model was developed to analyze the effects of each of the three technology clusters on the quality of care indicators. The equations for the models are given below (each equation represents a separate regression model for the three IQIs):

Quality of Care = f (size, ownership, teaching status, HMO, urban location, region, market competition, payer mix, Clinical IT)

Quality of Care = f (size, ownership, teaching status, HMO, urban location, region, market competition, payer mix, Administrative IT)

Quality of Care = f (size, ownership, teaching status, HMO, urban location, region, market competition, payer mix, Strategic IT)

4.4 Differences between Hospitals Included and not Included

The process of merging the HIMSS, AHA, and HCUP data sets involved tackling three major problems: (1) the data sets have a significant number of hospitals with missing and duplicate values for the variables used in this analysis; (2) hospitals in one data set may not be in the other data sets; and (3) no identifying information was available for hospitals in some states. In order to address these problems, therefore, the hospitals were carefully merged by using select common variables. Hospitals were excluded from the analysis if they do not match on the common variables, if they have duplicates, if they have missing values on the common variables, or if no information is available that will identify them. Thus, the final data set only contained a list of hospitals that exist in all the three data sets (HIMSS, AHA, and HCUP), that have some identifying variables, and that have non-missing common Medicare Identification Numbers, or

Hospital Address and Zip Code, or Hospital Name and Zip Code, or Hospital Address and Name, or Name of City and Zip Code.

4.5 Operational Definitions

Table 4 provides operational definitions of the variables used in the analysis.

Table 4: Operational Definitions of Response and Predictor Variables

Variable	Description	Attributes	Data source
Response variables			
HIT Adoption	The number of 'Live and Operational' technologies in the hospital; measured in terms of clinical, administrative, and strategic decision-support IT.	Numerical: • 0 to 25 for clinical IT • 0 to 18 for administrative IT • 0 to 9 for strategic IT	HIMSS
Patient Safety	Measured through four patient safety indicators (PSIs): death in low mortality DRG, decubitus ulcer, iatrogenic pneumothorax, and selected infection due to medical care.		
1. Death in Low Mortality DRG	Death per 1,000 patients in DRGs with less than 0.5% mortality.	Numerical	HCUP
2. Decubitus Ulcer	Cases that developed during hospitalization per 1,000 discharges with a length of stay of 5 or more days.	Numerical	HCUP
3. Iatrogenic Pneumothorax	Cases of iatrogenic pneumothorax per 1,000 discharges.	Numerical	HCUP
4. Selected Infection due to Medical Care	Cases of infection due to intravenous lines and catheters.	Numerical	HCUP
Quality of Care	Measured in terms of in terms of three inpatient quality indicators (IQIs): acute myocardial infarction, congestive heart failure, and Pneumonia.		
1. Mortality due to Acute Myocardial Infarction	Deaths per 100 discharges with a principal diagnosis code of AMI.	Numerical	HCUP
2. Mortality due to Congestive Heart Failure	Deaths per 100 discharges with principal diagnosis code of CHF.	Numerical	HCUP
3. Mortality due to Pneumonia	Deaths in discharges with principal diagnosis code of pneumonia.	Numerical	HCUP

Variable	Description	Attributes	Data source
Predictor Variables			
Organizational Factors			
Size	The number of staffed and setup beds in the hospital.	Continuous (regression analysis) Categorical (descriptive analysis): 1 = Small 2 = Medium 3 = Large	AHA HCUP
Ownership	Ownership status of hospitals.	Dichotomous: 0 = Not-for-profit 1 = For-profit	AHA
Teaching Status	Teaching status of hospitals.	Dichotomous: 0 = Non-teaching hospital 1 = Teaching hospital	AHA
HMO Penetration	The existence of a contract with an HMO.	Dichotomous: 0 = No HMO contract 1 = HMO contract	AHA
Contextual Factors			
Urban/Rural Location	Urban vs. rural location of hospitals.	Dichotomous: 0 = Rural location; and 1 = Urban location.	AHA

Variable	Description	Attributes	Data source
Region	Geographic locations of hospitals.	Categorical: 1 = Northeast (CT, MA, ME, NH, NJ, NY, PA, RI, and VT); 2 = Midwest (IA, IL, IN, KS, MI, MN, MO, ND, NE, OH, SD, and WI) 3 = South (AL, AR, DE, FL, GA, KY, LA, MD, MS, NC, OK, SC, TN, TX, VA, and WV) 4 = West (AZ, CA, CO, ID, MT, NM, NV, OR, UT, WA, and WY)	HCUP
Market Competition	Herfindahl-Hirschman Index (HHI) of market concentration, small HHI indicates more market competition.	Numerical	AHA
Payer Mix	The ratio of Medicare and Medicaid patients to total hospital patients.	Numerical	AHA

AHA = American Hospital Association Annual Survey; HIMSS = Healthcare Information and Management Systems Society Analytics Annual Survey; HCUP = Healthcare Cost and Utilization Project.

4.6 Summary

For this study a non-experimental design was applied on cross-sectional data in order to identify which factors affect the adoption of HIT in hospitals as well as understand the impacts of HIT adoption on patient safety and quality of care in U.S. acute care hospitals. A hospital-level unit of analysis was used and hospital information was gathered from HIMSS, AHA, and HCUP data sets. Data-cleaning rules were applied to account for extreme outliers, missing values, and duplicates. Two stage analyses were conducted. Stage one focused on the relationship between structure (organizational and contextual factors) and process (HIT adoption) while stage two focused on the association between process (HIT adoption) and outcome (patient safety and quality of care) after controlling for organizational and contextual factors. Since the study used the latest available real time data reported by the facilities themselves, the impact of threats to internal validity is expected to be minimal. Threats to external validity should not be an area of concern as well since the hospitals in the final data set are fair representatives of all hospitals in the nation.

CHAPTER 5: FINDINGS

The previous chapter provided a thorough explanation of the variables included in this study, the data sources and cleaning rules, the methodology used, and operational definitions of the variables. Information on organizational and contextual factors of hospitals was obtained from the AHA and HCUP data sets. The HCUP data set also provided information on the patient safety and quality of care indicators. Information on the HIT applications adopted by the hospitals was obtained from the HIMSS data set. The data from the three sources were cleaned and merged based on common identifying variables using SAS 9.1 software. Negative binomial and multiple linear regression models were then developed for the analysis. This chapter explains the findings of the analysis and compares them with previous studies.

5.1 Descriptive Statistics

Table 5 shows the results of the descriptive statistics for the final data set. The AHA Annual Survey Database Manual states that hospitals in the database should maintain at least six beds available for inpatients. Accordingly, the minimum number of set up and staffed beds in the data set was 6 while the maximum was 1,834, with mean and median values of 179.61 and 116.50 beds, respectively, indicating that the data set was highly skewed to the right. Market competition (HHI) varied among the hospitals from 1 (where the only hospital beds in the county exist in that specific hospital, indicating a complete absence of competition) to close to zero (indicating that a large number of hospitals compete within the same market area). The average HHI was 0.33 while the median was 0.06. Two hospitals in the data set reported zero payer mix (i.e., they did not treat any Medicare or Medicaid patients in that specific year), while the maximum, the mean, and median values were 0.99, 0.69, and 0.70, respectively.

Table 5: Descriptive Statistics of Acute care Hospitals

Variable	N	Mean (or %)	Median	SD
Patient Safety Indicators				
PSI 2	581	0.0003	0.0003	0.0000
PSI 3	583	0.0238	0.0210	0.0149
PSI 6	586	0.0005	0.0005	0.0001
PSI 7	586	0.0017	0.0015	0.0007
Quality of care Indicators				
IQI 15	452	0.0680	0.0682	0.0121
IQI 16	488	0.0318	0.0319	0.0065
IQI 20	489	0.0360	0.0358	0.0084
Health Information Technology				
Clinical IT	586	10.87	12.00	6.33
Administrative IT	586	10.44	12.00	5.22
Strategic Decision-Support IT	586	4.22	5.00	2.83
Organizational Factors				
Size	586	179.61	116.50	196.68
Small	242	41.3%	_	_
Medium	149	25.4%	_	_
Large	195	33.3%	_	_
Ownership				
Not-For-Profit	516	88.0%	_	_
For-Profit	70	12.0%	_	_
Teaching Status				
Non-Teaching Hospital	452	77.1%	_	_
Teaching Hospital	134	22.9%	_	_
HMO Penetration				
Without HMO Contract	168	28.6%	_	_
With HMO Contract	418	71.3%	_	_
Contextual Factors				
Urban/Rural Location				
Rural Hospitals	227	38.7%	_	_
Urban Hospitals	359	61.3%	_	_
Region				
Northeast	120	20.5%	_	_
Midwest	150	25.6%	_	_
South	152	25.9%	_	_
West	164	28.0%	_	_
HHI	586	0.33	0.06	0.42
Payer Mix	586	0.69	0.70	0.14

Out of the 586 hospitals included in the data set, 89 hospitals did not report having “Live and Operational” technologies under any of the clinical, administrative, or strategic categories. The maximum numbers reported were 23 out of 25 for clinical technologies, 16 out of 18 for administrative technologies, and 9 out of 9 for administrative technologies. The mean and the median values were 10.87 and 12 for clinical IT, 10.44 and 12 for administrative IT and 4.22 and 5 for strategic IT. In general, the findings indicate that hospitals adopt a large proportion of administrative information technology as compared to clinical and strategic IT.

With regard to patient safety and quality of care indicators, the maximum, minimum, mean, and median values reported were 0.0005, 0.0002, 0.0003, and 0.0003 for death in low mortality DRGs; 0.1268, 0.0022, 0.0238, and 0.0210 for pressure ulcer; 0.0011, 0.0002, 0.0005, and 0.0005 for iatrogenic pneumothorax; 0.0056, 0.0007, 0.0017, and 0.0015 for central line–associated BSI; 0.1392, 0.0356, 0.0680, and 0.0682 for in-hospital mortality due to acute myocardial infarction; 0.0626, 0.0129, 0.0318, and 0.0319 for in-hospital mortality due to congestive heart failure; and 0.0705, 0.0158, 0.0360, and 0.0358 for in-hospital mortality due to pneumonia.

Based on the number of beds, location, and teaching status, hospitals were divided into three groups: small, medium, and large. In the final data set, a large proportion of the hospitals (242 hospitals or 41.30%) were small, while only 149 hospitals (25.42%) were medium, and 195 hospitals (33.28%) were large in size. A significant proportion of the hospitals (516 hospitals or 88.05%) were not-for-profit while only 70 hospitals (11.95%) were for-profit. Similarly, a very large proportion of the hospitals (452 hospitals or 77.13%) were non-teaching while 134 hospitals (22.87%) were teaching. In terms of an HMO contract, 168 hospitals (28.67%) did not have a contract while 418 hospitals (71.33%) did have a contract. Provider location largely favored urban designations as 359 hospitals (61.26%) were located in urban areas while 227 hospitals (38.74%) were in rural areas. The hospitals were fairly equally distributed among the four regions: 120 hospitals (20.48%) were located in the Northeast, 150 hospitals (25.60%) were from the Midwest, 152 hospitals (25.93%) were from the South, and 164 hospitals (27.99%) were from the West.

The relationship between the hospitals' adoption of the three HIT groups and the predictor variables is depicted in Figure 6. The vertical bars represent the average number of the three technology groups adopted by the hospitals.

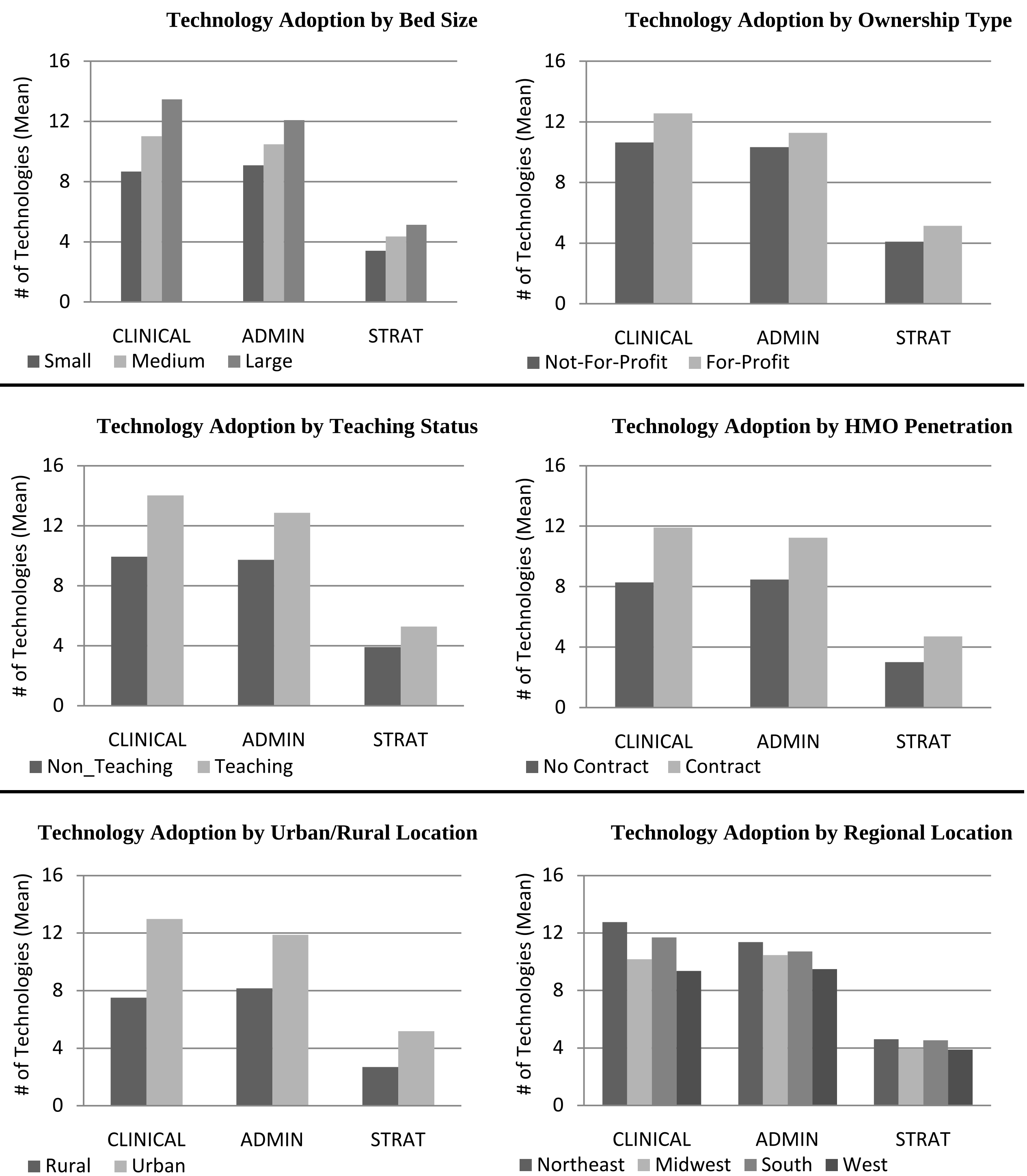


Figure 6: Clinical, Administrative, and Strategic IT Applications Adopted by the Hospitals (Mean)

- The mean values for each of the technological categories for large hospitals were consistently higher than that of the medium and small hospitals. On average, large hospitals adopted 13.47 clinical IT, 12.09 administrative IT, and 5.12 strategic IT compared to 11.02 clinical IT, 10.48 administrative IT, and 4.36 strategic IT for the medium and 8.67 clinical IT, 9.09 administrative IT, and 3.41 strategic IT for the small size hospitals.
- For-profit hospitals on average adopted more technologies than not-for-profit hospitals: for-profit hospitals adoption rates were 12.56 clinical IT, 11.27 administrative IT, and 5.14 strategic IT compared to not-for-profit adoption rates of 10.64 clinical IT, 10.33 administrative IT, and 4.10 strategic IT.
- Teaching hospitals adopted more technologies (14.02 clinical IT, 12.87 administrative IT, and 5.27 strategic IT) compared to non-teaching hospitals (9.93 clinical IT, 9.72 administrative IT, and 3.91 strategic IT).
- Hospitals with an HMO contract exhibited higher mean values for all of the technological categories (11.91 for clinical IT, 11.23 for administrative IT, and 4.71 for strategic IT) compared to hospitals without an HMO contract (8.27 for clinical IT, 8.46 for administrative IT, and 3.01 for strategic IT).
- Rural hospitals on average adopted a significantly smaller number of technologies (7.51 clinical IT, 8.16 administrative IT, and 2.70 strategic IT) compared to urban hospitals (12.99 clinical IT, 11.88 administrative IT, and 5.18 strategic IT).

- Finally, the Northeast consistently scored the highest mean information technology adoption rates compared to the other regions (12.76 clinical IT, 11.36 administrative IT, and 4.62 strategic IT) followed by the South (11.68 clinical IT, 10.72 administrative IT, and 4.54 strategic IT), the Midwest (10.17 clinical IT, 10.46 administrative IT, and 3.94 strategic IT), and finally the West (9.36 clinical IT, 9.49 administrative IT, and 3.89 strategic IT).

5.2 Correlation Analysis

Table 6 reveals the results of a Spearman correlation analysis among the explanatory variables.

Table 6: Correlation Matrix of Predictor Variables

	Spearman Correlation Coefficients, N = 586 Prob > |r| under H_0: Rho=0							
	1	2	3	4	5	6	7	8
1. Size	1.00							
2. For-profit	-0.04	1.00						
3. Teaching	0.52*	-0.10*	1.00					
4. HMO	0.33*	-0.02	0.20*	1.00				
5. Urban	0.56*	0.07	0.40*	0.29*	1.00			
6. Region	-0.09*	0.15*	-0.15*	-0.20*	-0.03	1.00		
7. HHI	-0.41*	-0.15*	-0.34*	-0.19*	-0.58*	-0.04	1.00	
8. Payer mix	-0.29*	-0.01	-0.23*	-0.14*	-0.33*	-0.06	0.22*	1.00

* $p < .05$

Higher correlations among variables imply multicollinearity, indicating that the variables are not independent of each other and they measure the same thing. The results here indicate that the variables are not strongly correlated with each other. At -0.58, the largest coefficient was that of the correlation between urban location and HHI, indicating the presence of higher market competition in urban areas. This was not a surprise; market competition could be higher in urban locations compared to rural locations given the fact that urban locations cover small geographic areas resulting in higher concentration of hospitals (the descriptive analysis also revealed that the average HHI for rural hospitals was 0.60 compared to 0.15 for urban hospitals). At 0.56, the second highest coefficient was for the correlation between urban location and size. Again this makes sense since 64% of urban hospitals were large in size compared to only 36% of rural hospitals. The only other relatively significant correlation was that of size and teaching status (0.52). This too is understandable given the fact that only 20% of small, 24% of medium, and 25% of large hospitals were designated as teaching hospitals.

5.3 Regression Analyses

5.3.1 HIT Adoption

Next, a negative binomial regression approach was used to identify the organizational and contextual factors that may affect the adoption of clinical, administrative, and strategic IT in acute care hospitals. The models are given as follows:

Adoption of Clinical IT = f (size, ownership, teaching status, HMO, urban location, region, market competition, payer mix)

Adoption of Administrative IT = f (size, ownership, teaching status, HMO, urban location, region, market competition, payer mix)

Adoption of Strategic IT = f (size, ownership, teaching status, HMO, urban location, region, market competition, payer mix)

5.3.1.1 Findings of Regression Analysis – HIT Adoption

Table 7 shows the results of the negative binomial regression analysis. The adoption of Clinical IT in acute care hospitals was positively affected by size ($p < .001$), urban location ($p < .001$), for-profit ownership type ($p < .01$), HMO penetration ($p < .05$), and negatively affected by payer mix (p < .05). In addition, compared to a Northeast location, being located in the West had had a negative effect on the adoption of clinical IT ($p < .001$), while the difference from the other two regions was not statistically significant. On the other hand, teaching status and market competition are shown not to have significantly associated with the adoption of clinical IT in the hospitals. Table 7 also reveals factors affecting adoption of administrative IT in the hospitals. Similar to clinical IT, the adoption of administrative IT was positively affected by size ($p < .001$), urban location ($p < .01$), and HMO penetration ($p < .05$), and negatively affected by payer mix ($p < .05$). The West had had a negative association with adoption of administrative IT compared to the Northeast. Ownership type, teaching status, and market competition did not appear to affect the adoption of administrative IT. Finally, Table 7 indicates that the adoption of strategic IT was positively affected significantly by size ($p < .001$), urban location ($p < .001$), ownership ($p < .01$), and HMO penetration ($p < .01$). Teaching status, regional location, HHI, and payer mix did not significantly affect the adoption of strategic IT.

Table 7: Multiple Regression Model for Adoption of HIT (N = 582)

	Clinical IT		Administrative IT		Strategic IT	
	β	95% CI	β	95% CI	β	95% CI
Intercept	2.2704***	1.9223, 2.6186	2.2943***	2.0057, 2.5829	1.0867***	0.6988, 1.4747
Size	0.0010***	0.0007, 0.0013	0.0005***	0.0003, 0.0007	0.0008***	0.0005, 0.0011
Ownership	0.1999**	0.0763, 0.3234	0.0987	-0.0277, 0.2252	0.2057**	0.0581, 0.3532
Teaching status	-0.0190	-0.1092, 0.0712	0.0425	-0.0238, 0.1089	-0.1032	-0.2108, 0.0044
HMO	0.1566*	0.0218, 0.2913	0.1414*	0.0200, 0.2627	0.2441**	0.0910, 0.3972
Urban location	0.2840***	0.1427, 0.4253	0.1812**	0.0562, 0.3062	0.4228***	0.2597, 0.5859
Midwest	-0.1039	-0.2409, 0.0331	0.0206	-0.0980, 0.1392	-0.0325	-0.1834, 0.1184
South	0.0179	-0.1144, 0.1501	0.0578	-0.0622, 0.1779	0.0897	-0.0594, 0.2389
West	-0.2677***	-0.4059, -0.1296	-0.1258*	-0.2512, -0.0004	-0.1292	-0.2843, 0.0260
HHI	-0.1281	-0.2887, 0.0325	-0.1304	-0.2792, 0.0184	-0.1345	-0.3064, 0.0373
Payer mix	-0.4014*	-0.7674, -0.0355	-0.3468*	-0.6506, -0.0430	-0.3189	-0.7262, 0.0884

* $p < .05$; ** $p < .01$; *** $p < .001$

5.3.2 Patient Safety

Patient safety was measured through four indicators: death in low mortality DRGs, pressure ulcer, iatrogenic pneumothorax, and central line–associated BSI. Multiple linear regression analysis was used to determine the relationship between each of these indicators and the three information technology groups after controlling for confounding factors. The following linear regression assumption tests were conducted on the final data set before running the HIT adoption models: tests for linearity, normality, multicollinearity, homoscedasticity, and independence of errors. In addition, a test for outliers was conducted to investigate the presence of extreme outliers that might influence the results. The results indicated no violations of the assumptions. The complete results of the assumption tests and regression analyses are included in the appendix at the end. The multiple linear regression models are given through the following equations:

Patient Safety = f (size, ownership, teaching status, HMO, urban location, region, market competition, payer mix, Clinical IT)

Patient Safety = f (size, ownership, teaching status, HMO, urban location, region, market competition, payer mix, Administrative IT)

Patient Safety = f (size, ownership, teaching status, HMO, urban location, region, market competition, payer mix, Strategic IT)

5.3.2.1 Findings of Regression Analysis – Patient Safety

Table 8 reveals the results of the regression analysis. None of the four patient safety indicators were found to be affected by the adoption of the technologies in a statistically significant way. Some of the unstandardized coefficients were found to be positive while the others were negative. Assumption tests revealed no violations.

Table 8: Multiple Regression Model for Patient Safety

Patient Safety Indicators (PSI)	Health information technology	β	95% CI
Death in low mortality DRGs (PSI 2), N = 571	Clinical IT	-0.0008	-0.0030, 0.0014
	Administrative IT	-0.0005	-0.0029, 0.0020
	Strategic IT	-0.0783	-0.2591, 0.1026
Pressure ulcer (PSI 3), N = 579	Clinical IT	-0.0008	-0.0110, 0.0093
	Administrative IT	0.0065	-0.0049, 0.0180
	Strategic IT	0.0000	-0.0221, 0.0221
Iatrogenic pneumothorax (PSI 6), N = 570	Clinical IT	-0.0026	-0.0058, 0.0006
	Administrative IT	-0.0023	-0.0058, 0.0013
	Strategic IT	-0.0045	-0.0115, 0.0024
Central line–associated BSI (PSI 7), N = 582	Clinical IT	0.0001	-0.0050, 0.0053
	Administrative IT	0.0015	-0.1403, 0.0224
	Strategic IT	-0.0043	-0.0530, 0.0443

Note: Each coefficient is from a separate linear regression model and is adjusted for size, ownership, teaching status, HMO, urban location, region, market competition, and payer mix.
* $p < .05$; ** $p < .01$

5.3.3 Quality of Care

Finally, multiple linear regression analyses were also used to determine the relationship between quality of care and the three technology groups after controlling for confounding factors (see Table 9). The complete results of assumption tests and regression analyses are included in the appendix. The multiple linear regression models are given through the following equations:

Quality of Care = f (size, ownership, teaching status, HMO, urban location, region, market competition, payer mix, Clinical IT)

Quality of Care = f (size, ownership, teaching status, HMO, urban location, region, market competition, payer mix, Administrative IT)

Quality of Care = f (size, ownership, teaching status, HMO, urban location, region, market competition, payer mix, Strategic IT)

5.3.3.1 Findings of Regression Analysis – Quality of Care

Table 9: Multiple Regression Model for Quality of Care

Inpatient Quality Indicators (IQI)	Health information technology	β	95% CI
Acute myocardial infarction (IQI 15), N = 439	Clinical IT	0.0005	-0.0019, 0.0029
	Administrative IT	0.0006	-0.0021, 0.0034
	Strategic IT	0.0033	-0.0020, 0.0087
Congestive heart failure (IQI 16), N = 474	Clinical IT	0.0003	-0.0028, 0.0034
	Administrative IT	0.0015	-0.0020, 0.0050
	Strategic IT	0.0015	-0.0054, 0.0084
Pneumonia (IQI 20), N = 485	Clinical IT	-0.0040*	-0.0078, -0.0001
	Administrative IT	-0.0037	-0.0080, 0.0006
	Strategic IT	-0.0060	-0.0145, 0.0025

Note: Each coefficient is from a separate linear regression model and is adjusted for size, ownership, teaching status, HMO, urban location, region, market competition, and payer mix.
* $p < .05$; ** $p < .01$

Table 9 shows that in-hospital mortality due to pneumonia was significantly negatively associated with the adoption of clinical IT ($p < .05$) but not with administrative and strategic IT (with p values of .09 and .16, respectively). In-hospital mortalities due to acute myocardial infarction and congestive heart failure were not found to be significantly associated with the adoption of any of the technology clusters. In addition, the unstandardized coefficients were positive for acute myocardial infarction and congestive heart failure and negative for pneumonia.

5.4 Hypotheses Test

Hypothesis 1: Other factors being equal, organizational factors are associated with HIT adoption in acute care hospitals.

Adoption of information technology was significantly affected by three of the four organizational factors (hospital size, ownership, and HMO penetration), while only one organizational factor (teaching status of hospitals) did not have a significant effect. Thus, Hypothesis 1 is supported by the findings in this study.

Hypothesis 1A: Other factors being equal, acute care hospitals of larger size will be more likely to adopt HIT.

The findings in this study strongly support Hypothesis 1A. Size of hospitals, as measured by the number of staffed and set-up beds, was found to significantly affect the adoption of all three HIT clusters (clinical, administrative, and strategic IT) at p value of $< .001$. It was the only predictor variable that consistently affected all three HIT groups at such a small p value, indicating that the size of a hospital is perhaps the most important factor affecting the adoption of information technology in the hospital. The descriptive analysis also revealed that large hospitals' adoption rates were consistently higher than that of medium and small hospitals (see Figure 6). As will be discussed in the next chapter, this finding confirms the conclusions of several other studies.

Hypothesis 1B: Other factors being equal, acute care hospitals with for-profit ownership will be more likely to adopt HIT.

Hypothesis 1B is also supported by the findings in this study. For-profit ownership of hospitals was found to significantly affect the adoption of clinical and strategic decision-support IT ($p < .01$). The descriptive analysis also revealed that for-profit hospitals adopted all three information technology clusters at consistently higher rates compared to not-for-profit hospitals. However, with a p value of 0.13, for-profit ownership of hospitals was not found to significantly affect the adoption of administrative IT.

Hypothesis 1C: Other factors being equal, acute care hospitals with teaching status will be more likely to adopt HIT.

This study does not support Hypothesis 1C. The descriptive analysis showed that on average teaching hospitals adopted more technologies compared to non-teaching hospitals. However, with p values of 0.68 for clinical IT, 0.21 for administrative IT, and 0.06 for strategic IT, respectively, teaching status of hospitals was not found to significantly affect the adoption of any of the three technology clusters.

Hypothesis 1D: Other factors being equal, acute care hospitals with HMO penetration will be more likely to adopt HIT.

Hypothesis 1D is supported by the findings in this study. HMO penetration, measured by the presence of an HMO contract in the hospitals, is the second variable that consistently affected the adoption of information technology in the hospitals. The descriptive analysis confirmed that hospitals with an HMO contract exhibited higher mean values under all the technological categories compared to hospitals without an HMO contract. The differences were significant for clinical and administrative IT at $p < .05$ and strategic IT at $p <.01$.

Hypothesis 2: Other factors being equal, contextual factors are associated with HIT adoption in acute care hospitals.

Though the effects may not be at the same level, this study indicates that three of the four contextual factors (urban location, regional location, and payer mix) significantly affected the adoption of technologies in hospitals while the effect of one contextual factor, i. e. market competition, was not statistically significant. Based on these findings, therefore, Hypothesis 2 is supported.

Hypothesis 2A: Other factors being equal, acute care hospitals located in urban areas will be more likely to adopt HIT.

The findings in this study support Hypothesis 2A. Urban hospitals on average adopted considerably higher numbers of all three information technology types compared to rural hospitals (see Figure 6). The differences were significant for clinical and strategic IT at the $p < .001$ level and administrative IT at $p < .01$ level. This finding makes urban location the number two predictor in terms of significance of effect on hospitals' information technology adoption, second only to size.

Hypothesis 2B: Other factors being equal, acute care hospitals located throughout the four geographic regions will not have the same likelihood of adopting HIT.

Hypothesis 2B is supported by this study. The Northeast consistently scored the highest mean information technology adoption rates compared to the other three regions. The differences between the adoption levels of the Northeast and particularly the West were found to be significant ($p < .001$ for clinical IT and $p < .05$ for administrative IT), though the differences with the other two regions (Midwest and South) were not statistically significant.

Hypothesis 2C: Other factors being equal, acute care hospitals that face higher market competition will be more likely to adopt HIT.

Hypothesis 2C was not supported by this study. With p values of 0.12, 0.09, and 0.13 for clinical IT, administrative IT, and strategic IT, respectively, higher market competition was not found to significantly affect the adoption of the technologies. Thus, the findings in this study imply that hospitals' adoption of clinical and strategic IT is independent of the severity of the market competition they face.

Hypothesis 2D: Other factors being equal, acute care hospitals with a lower proportion of Medicare and Medicaid patients will be more likely to adopt HIT.

Hypothesis 2D was supported by the findings. Payer mix was significantly negatively associated with adoption of only clinical IT ($p < .05$) and administrative IT ($p < .05$), while the association with the adoption of strategic IT was not significant ($p = .12$). This finding implies that a higher proportion of Medicare and Medicaid patients in a hospital is associated with lower adoption rates of clinical and administrative IT and not with strategic IT. Figure 7 depicts the findings of this study on the associations between the organizational and contextual factors and HIT adoption.

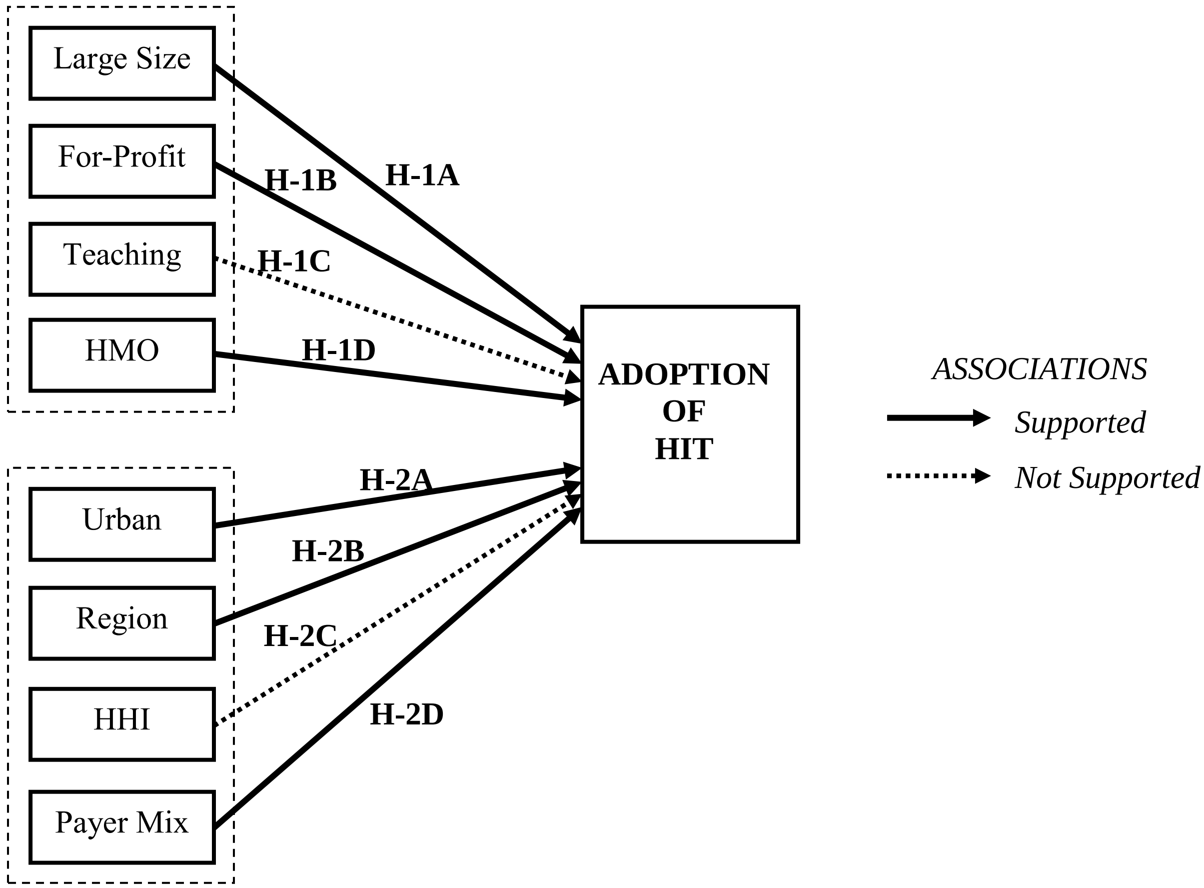


Figure 7: Analytical Model Depicting the Findings on the Associations between the Response and Predictor Variables – Stage 1

Figure 8 depicts the final analytic model of the first stage of the analysis.

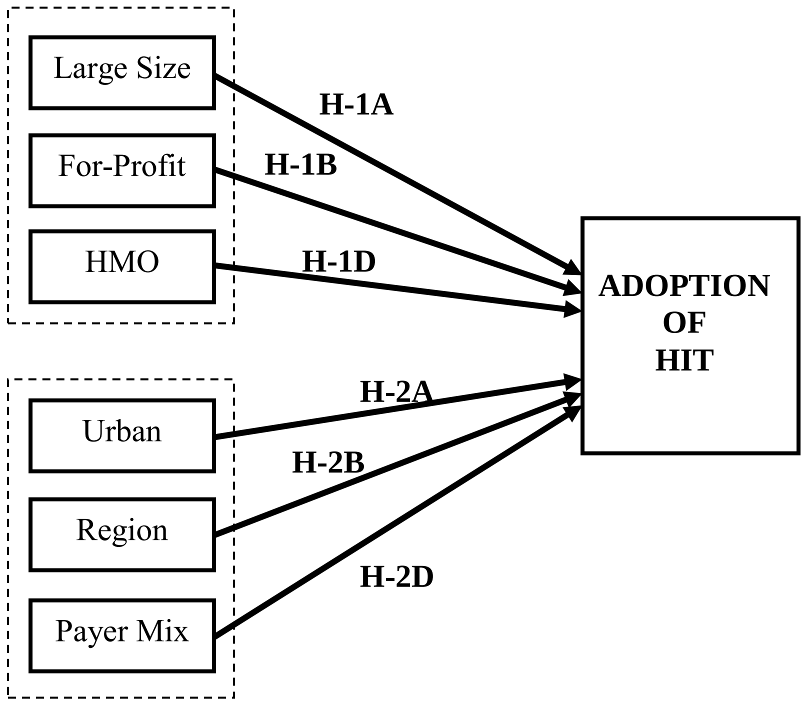


Figure 8: Final Analytical Model – Stage 1

Hypothesis 3: Other factors being equal, HIT adoption is associated with better patient safety in acute care hospitals.

Hypothesis 3 was not supported by the findings of this study. The adoption of the three technology clusters (clinical IT, administrative IT, and strategic IT) was not found to be associated with any of the four patient safety indicators in a statistically significant manner. In addition, the findings revealed both positive and negative coefficients for the indicators.

Hypothesis 4: Other factors being equal, HIT adoption is associated with higher quality of care in acute care hospitals.

The results only partially support Hypothesis 4. None of the technologies was found to affect in-hospital mortality due to acute myocardial infarction and congestive heart failure while only the adoption of clinical IT significantly affected in-hospital mortality due to pneumonia at $p < .05$. Figure 9 depicts the findings of this study on the associations between the HIT adoption and the healthcare outcomes.

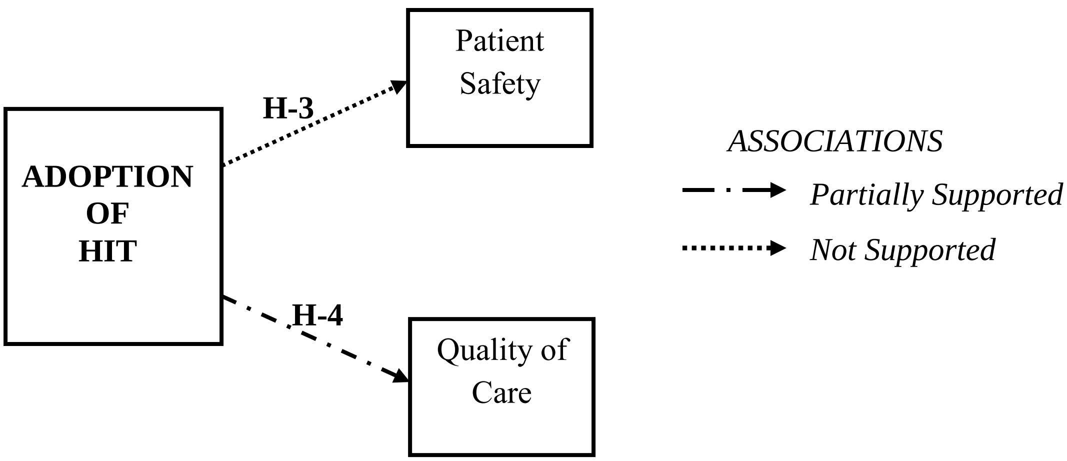


Figure 9: Analytical Model Depicting the Findings on the Associations between the Response and Predictor Variables – Stage 2

The standard estimate of the multiple linear regression analysis (not shown here) revealed that regional location and size of hospitals (with that order) were the most important factors that affected patient safety and quality of care in the acute care hospitals. The final analytical model of the second stage of the analysis is depicted in Figure 10.

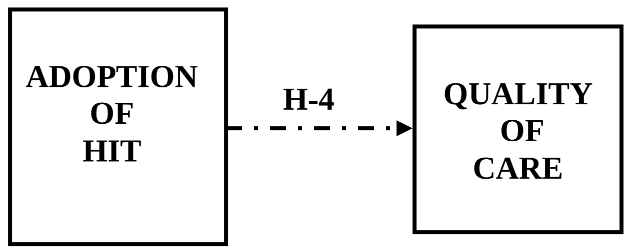


Figure 10: Final Analytical Model – Stage 2

5.5 Summary

Chapter 5 presented the findings of this study. The adoption of information technology was found to be affected by size of hospitals, ownership type, HMO penetration, urban/rural location, regional location, and the proportion of Medicare and Medicaid patients. Teaching status of the hospitals and market competition were not found to be significantly associated with the adoption of any of the technology types. The adoption of information technology in turn was found to partially affect quality of care outcomes in the acute care hospitals while the effects on patient safety were insignificant. The next chapter will provide discussion on the findings, the implications, the limitations of the study, and recommendations for future study.

CHAPTER 6: DISCUSSION AND RECOMMENDATIONS

Prior studies have identified advantages as well as disadvantages associated with the adoption of health information technology in hospitals. This study primarily focused on identifying organizational and contextual factors that affect the adoption of technologies in hospitals as well as the effects of the technologies on healthcare outcomes, particularly on patient safety and quality of care. The adoption of clinical, administrative, and strategic decision-making IT in acute care hospitals was analyzed from organizational and contextual perspectives. The previous chapter explained the findings of the analysis. Hospitals with attributes such as large size, for-profit ownership type, HMO contract, urban location, Northeast location, and lower proportion of Medicare and Medicaid patients adopted a higher number of technologies compared to their respective counterparts. In addition, the effects of the adoption of these technologies on patient safety and quality of care were analyzed. The findings revealed that the effect of the adoption of information technology on patient safety and quality of care were weak. See Table 10 for a summary of the hypothesis test results. This chapter will provide a discussion on the findings; the theoretical, methodological, and policy implications; recommendations for future study; and the limitations of the study.

Table 10: Hypothesis Test Summary

	Hypotheses	Test result
Hypothesis 1	Other factors being equal, organizational factors are associated with HIT adoption in acute care hospitals.	Supported
Hypothesis 1A	Other factors being equal, acute care hospitals of larger size will be more likely to adopt HIT.	Supported
Hypothesis 1B	Other factors being equal, acute care hospitals with for-profit ownership will be more likely to adopt HIT.	Supported
Hypothesis 1C	Other factors being equal, acute care hospitals with teaching status will be more likely to adopt HIT.	Not Supported
Hypothesis 1D	Other factors being equal, acute care hospitals with HMO penetration will be more likely to adopt HIT.	Supported
Hypothesis 2	Other factors being equal, contextual factors are associated with HIT adoption in acute care hospitals.	Supported
Hypothesis 2A	Other factors being equal, acute care hospitals located in urban areas will be more likely to adopt HIT.	Supported
Hypothesis 2B	Other factors being equal, acute care hospitals located throughout the four geographic regions will not have the same likelihood of adopting HIT.	Supported
Hypothesis 2C	Other factors being equal, acute care hospitals that face higher market competition will be more likely to adopt HIT.	Not Supported
Hypothesis 2D	Other factors being equal, acute care hospitals with lower proportion of Medicare and Medicaid patients will be more likely to adopt HIT.	Supported
Hypothesis 3	Other factors being equal, HIT adoption is associated with better patient safety in acute care hospitals.	Not Supported
Hypothesis 4	Other factors being equal, HIT adoption is associated with higher quality of care in acute care hospitals.	Partially Supported

6.1 Discussion

6.1.1 Adoption of HIT

The findings in this study support several prior findings. In terms of quality of care, the literature review shows that the adoption of one or more of the HIT applications may lead to improved quality of care by providing better surveillance, increasing adherence to guidelines, reducing inpatient days, increasing appropriateness of orders, enhancing integrated data review, and positively affecting medication and non-medication quality of care measures. In terms of patient safety, the adoption of HIT applications may lead to reduced error of omission, reduced numbers of adverse drug effects and serious medication errors, improved physician prescribing behavior, increased patient ID confirmation, and reduced number of fatal hospitalizations. Additional advantages of adoption of technologies include significant cost savings, increased physician time spent with patients, and increased nurse time spent on direct patient care.

Yet, even though clinical IT applications were more directly related to hospitals' primary goal of delivering higher quality of care, the evidence in this study shows that more emphasis is given to administrative and strategic technologies instead (on average hospitals have adopted 10.86 clinical IT out of 25 (43%) compared to 10.44 out of 18 (58%) for administrative and 4.22 out of 9 (47%) for strategic IT). This finding supports Poon et al. (2006), who found that technologies related to claims and eligibility checking of applications had large diffusion rates among healthcare providers compared to technologies with clinical application. Their conclusion was that the adoption of information technology is mainly motivated by financial functionality rather than improving the safety and quality of their services. Chaudry et al. (2006) also indicated that the healthcare industry has primarily focused on acquiring technological applications that are related to administration and financial transactions.

6.1.1.1 Organizational Factors

From an organizational perspective, the empirical analysis suggests that size of hospital was the most important predictor of the adoption of technologies. Large hospitals consistently adopted the largest number of clinical, administrative, and strategic IT applications compared to small- and medium-size hospitals. These results are similar to the findings of other authors. Burke et al. (2002) and Wang et al. (2005) also found positive associations between adoption of clinical, administrative, and strategic IT and hospital size. Furukawa et al. (2008) as well as Parente and Van Horn (2006) also detected significant relationships between large hospital size and adoption of some clinical IT applications. The logic behind this finding may be the fact that large hospitals generally have advantages of economies of scale compared to medium and small hospitals. This may result in relative abundance of resources, which, as explained by diffusion of innovations theory, is a very important factor that motivates and enables either in-house innovations or acquisition of outside technologies.

The study also shows that for-profit ownership type significantly affected adoption of clinical and strategic IT but not administrative IT. The positive effects of for-profit ownership on some clinical IT applications are also indicated by Taylor et al. (2005) and Furukawa et al. (2008). In addition, that for-profit ownership type affects adoption of strategic IT was supported by Burke et al. (2002) and Wang et al. (2005). Since for-profit hospitals have the obligation to make good returns on the investors' money, it would be logical for them to acquire technologies that help them effectively interact with the market and make strategic decisions.

Contrary to the findings by Furukawa et al. (2008), however, teaching status of a hospital was not found to be associated with any of the technologies, suggesting that there is no difference between teaching and non-teaching hospitals in terms of information technology adoption. Wang et al. (2005) also found no relationship between teaching status and adoption of technologies. However, unlike the study by Wang and colleagues (2005) that did not find a relationship between HMO penetration and the adoption of any of the three technology clusters, this study found a significant positive association between HMO penetration and all three technology clusters.

6.1.1.2 Contextual Factors

From a contextual perspective, this analysis suggests that urban location was the most important predictor of the adoption of all categories of HIT. This confirms the findings of other studies (Burke et al., 2002; Furukawa et al., 2008). As explained by diffusion of innovations theory, organizations with better access to information have higher likelihood of adopting technology. Compared to rural areas, urban areas are more diverse in terms of economic activities. Therefore, hospitals in urban areas have better opportunities to partner with various industries, government agencies, and higher learning and research institutes; thus, they may be able to secure external financial resources and acquire insider information about the technologies. This, in turn, may give them an advantage to effectively adopt better technologies both in terms of quality and quantity.

The findings indicate that being located in the West is negatively associated in terms of adoption of clinical IT ($p < .001$) and administrative IT ($p < .05$) compared to being located in the Northeast. This finding supports Furukawa et al. (2008), who found that hospitals on the east coast had higher IT adoption rates compared to hospitals on the west coast. There were no significant differences in terms of HIT adoption between the Northeast, the Midwest, and the South.

The analysis also shows that market competition was not associated with the adoption of any of the technology clusters. This finding implies that market pressure was not detrimental to the adoption of the technologies in the hospitals. This finding also supports Wang et al. (2005), since they did not find a relationship between market competition and the adoption of all three information technology types. Different from this, however, Burke et al. (2002) found a significant association between market competition and all three technology clusters.

The proportion of Medicare and Medicaid patients was found to be affected by the adoption of clinical and administrative IT but not by strategic IT. This also supports Furukawa et al. (2008), who found a negative association between proportion of Medicare patients and adoption of some clinical IT applications. The original hypothesis was that since Medicare and Medicaid reimbursement rates are lower than other sources, higher proportions of Medicare and Medicaid inpatients in the hospitals may lead to lower revenue levels. But this was not found to be the case in the adoption of strategic IT applications, because their adoption levels were found to be neutral to payer mix. On the other hand, the presence of a higher proportion of Medicare and Medicaid patients in hospitals also implies the need for more paperwork, more communications, and higher information processing. This need could be one reason for the significant association between payer mix and adoption of administrative IT. Since clinical IT applications are directly related to the treatment of patients, further investigation is needed to understand the relationship between the proportion of Medicare and Medicaid patients and, in particular, the adoption of clinical IT applications.

6.1.2 Patient Safety and Quality of Care

The relationships between adoption of HIT and selected patient safety and quality of care measures were also analyzed. None of the four patient safety indicators (death in low mortality DRGs, pressure ulcer, iatrogenic pneumothorax, and central line–associated BSI) were found to be affected by any of the three technology clusters. Similarly, two quality of care indicators (in-hospital mortalities due to acute myocardial infarction and congestive heart failure) were not found to be significantly associated with adoption of all the three technology clusters. In addition, while the link between mortality attributed to pneumonia and clinical IT was statistically significant, its association with the other two the information technology types (administrative and strategic IT) was insignificant.

This finding supports Menachemi et al. (2008), who used data from Florida hospitals to demonstrate that mortality due to congestive heart failure was not significantly associated with the adoption of any of the technology clusters. However, they also found that the adoption of clinical IT does have a negative association with mortality due to acute myocardial infarction but that no relationship exists between hospitals' adoption of information technology and mortality due to pneumonia, which is different from the findings in this study. In addition, the same authors also found a significant relationship between adoption of administrative and strategic IT and mortality due to acute myocardial infarction, which again is different from the present findings.

This finding also supports the studies conducted by Amarisingham et al. (2009) and McCullough et al. (2010), who found significant reduction in pneumonia-attributed mortality due to the adoption of HIT in hospitals. The similarities of the findings despite the fact that the aforementioned authors primarily focused on a limited number of technologies while this study observed the effects on quality of care and patient safety from 52 technologies categorized into three clusters provides credibility to the methodology applied in this study. On the other hand, however, the differences in the source, time, and size of the data could be one reason for the dissimilarities between the findings in this study and some of the other studies mentioned previously. An alternative explanation may be that the outcome indicators were affected by factors different from the ones included in this model, such as organizational efficiency, leadership, and technical qualifications of the healthcare providers.

The findings also indicated that teaching hospitals performed significantly better than non-teaching hospitals in terms of iatrogenic pneumothorax and central line–associated BSI while they performed worse in terms of acute myocardial infarction (Appendix F). In addition, compared to the Northeast, the other three regions were negatively associated with all three quality of care indicators (in-hospital mortalities due to acute myocardial infarction, congestive heart failure, and pneumonia) at a statistically significant level. Moreover, the West was negatively significantly associated with one patient safety indicator (death in low mortality DRGs) while the Midwest with another patient safety indicator (pressure ulcer) compared to the Northeast.

The descriptive analysis also supports this finding: the Northeast's mean scores were 0.0003, 0.0236, 0.0005, 0.0017, 0.0719, 0.0330, and 0.0385 on the four patient safety indicators (death in low mortality DRGs, pressure ulcer, iatrogenic pneumothorax, and central line associated BSI) and the three quality of care indicators (acute myocardial infarction, congestive heart failure, and pneumonia mortalities), respectively. In comparison, the mean scores for the same indicators were 0.0003, 0.0195, 0.0005, 0.0015, 0.0670, 0.0315, and 0.0343 in the Midwest; 0.0003, 0.0255, 0.0005, 0.0016, 0.0674, 0.0309, and 0.0368 in the South; and 0.0003, 0.0264, 0.0005, 0.0018, 0.0651, 0.0320, and 0.0343 in the West, respectively. This difference implies that quality of care and, to some extent, patient safety were better in hospitals in the Midwest, South, and West compared to hospitals in the Northeast despite the fact that the latter reported better adoption rates of technologies. The longer length of stay in East Coast hospitals compared to particularly West Coast hospitals (HCUP, 2009b), which is associated with adverse drug events (ADEs) (Classen, Pestonik, Evans, Lloyd, & Burke, 1997), could be one reason. Further study is warranted to identify region-specific characteristics of hospitals that may affect patient outcomes.

6.2 Implications

The U.S. healthcare system has several shortcomings. Widespread adoption of IT applications could be one very important step in addressing these problems, particularly with the recent rapid advances in science and technology. A very important point is that technology is no more than a tool; it is only as good as how skillfully it is used by humans. Final decisions on healthcare should always be made by a human practitioner, be it the physician, the nurse, or the pharmacist. Nevertheless, given the evidence, the urgent need for a widespread adoption of clinical IT in hospitals cannot be emphasized enough. The adoption of HIT applications in general and clinical IT in particular is believed to have a great potential to improve the way healthcare is provided in hospitals. However, the findings in this study were inconclusive with regard to the effect of the adoption of health information systems on the patient safety and quality of care provided in acute care hospitals. The implications of the findings are discussed below.

6.2.1 Theoretical Implications

The first theory applied in this study was Donabedian's structure-process-outcome model (1980, 2003). The structure-process-outcome model is one of the most widely cited theories in the healthcare literature (Birkmeyer et al., 2004; Ganz et al., 2007; Hoenig et al., 2002; Marathe et al., 2007; McGlynn, 2007; Romano & Mutter, 2004; Wan, 2002). Donabedian argued that structure affects process and process affects outcome. Accordingly, structure, which in this study refers to eight organizational and contextual characteristics of hospitals, was hypothesized to affect process, which refers to the adoption of HIT in the hospitals. Process (the adoption of HIT) was also hypothesized to affect outcome (patient safety and quality of care). In line with Donabedian and several previous studies that applied the theory, the findings in this study confirmed that structure (size, ownership, HMO penetration, urban location, region, and payer mix) affects process (the adoption of information technology), and the adoption of information technology in turn affects quality of care, though marginally. The fact that hospitals size, ownership type, teaching status, urban location and regional location of hospitals (structure) affected quality of care and patient safety (outcome) also confirms the validity of the modified structure-process-outcome model, which points out a direct association between structure and outcome.

The second theory used was the diffusion of innovations theory. Diffusion of innovations theory is also widely used in the healthcare literature that focuses on the process of how technologies diffuse among users (Ash et al., 2001; Kovach et al., 2008; Panzano & Roth, 2006; Roggenkamp et al., 2005; Smythe, 2002; Wang et al., 2005; Weiner et al., 2006). This theory was particularly used to identify hospital characteristics that are detrimental to the adoption of information technology. It was hypothesized that since the abundance of resources in a hospital was indicated by large size, for-profit ownership, teaching status, HMO penetration, urban location, Northeast location, and fewer Medicare and Medicaid patients, hospitals with these characteristics may adopt more technologies. In addition, higher market pressure may force hospitals either to innovate in house or acquire outside technologies. Except for teaching status and market competition, all the other hospital characteristics were found to affect the adoption of at least one of the technologies.

6.2.2 Methodological Implications

Publicly available secondary data obtained from three different sources (AHA, HIMSS, and HCUP) were used in this study. Using data from such independent sources entailed its own challenges. First, merging the data from all three sources was difficult due to the lack of a single common variable. It was necessary to use different combinations of several common variables, thus losing a significant number of observations in the process. In addition, the hospitals had to be present in all three data sets in order to be included in the analysis. Unfortunately, the three data sets contained different numbers of hospitals for the same fiscal year; i.e., hospitals that exist in one data may not exist in the others. The suggestion here is that these national-level data sources should consider making their data more standardized and compatible.

Second, as explained in Chapter 4, the original plan was to conduct a longitudinal analysis spanning five years. However, the HCUP NIS data set contained a sample of 20% of hospitals randomly selected from the total hospital population. Since it was highly unlikely that the same set of hospitals would be randomly selected in consecutive years, it was not possible to conduct a longitudinal analysis. Otherwise a longitudinal approach would have been more informative. In addition, hospitals from 11 states did not have identifying variables in the HCUP data set, and as a result, all hospitals from these states were dropped from the analysis. This data set is a rich source of important information, but it should also be created in such a way that more consistent information is provided and longitudinal analysis is possible.

Third, the regression analyses consistently produced negative coefficients for two patient safety indicators (death in low mortality DRGs and iatrogenic pneumothorax) and one quality of care indicator (pneumonia), implying that information technology adoption reduced the incidence of these indicators. However, the remaining two patient safety indicators (pressure ulcer and central line–associated BSI) had a mix of positive and negative coefficients while the two quality of care indicators (acute myocardial infarction and congested heart failure) consistently had positive coefficients. This gives a problematic message: the adoption of information technology reduces the incidence of some of the indicators but increases the incidence of the other indicators. An additional implication is that the indicators are not measuring the same thing. Even though these indicators are widely used in the literature with mixed results, the findings in this study point out the need for further validation.

Finally, along with patient safety and quality of care, technology attributed cost saving was one of the outcomes originally planned to be explored in this study. However, this was not possible due to a dearth of available financial information of hospitals. Only the AHA database provided information on hospitals' expenses and revenues, but even then, it was only for a very small number of hospitals. As explained in the literature review section, financial constraint is the main obstacles hindering hospitals from adopting technology. Financial data would enable researchers to conduct empirical analysis and prove (or disprove) the notion that the adoption of HIT is associated with cost saving. If adoption of HIT could be proved to be associated with cost savings, then hospitals will have one more reason to adopt technology. Therefore, the suggestion is that data sources should aim at providing more complete and clear financial information on the hospitals.

6.2.3 Policy Implications

For the most part, hospitals acquire commercially available information technologies that require substantial investment for installation, operation, and maintenance. Hospitals with better financial resources have a greater likelihood of adopting these costly technologies whereas smaller hospitals do not. Moreover, the current reimbursement reduction trends have forced hospitals to focus not only on providing high quality of care but also on cost containment. Previous studies demonstrated that investments in HIT applications are associated with eventual cost savings in hospitals (Hillestad et al., 2005; Taylor et al., 2005; Teich et al., 2000). This analysis, therefore, confirms that hospitals with fewer resources to invest in IT may be at a big disadvantage in terms of not only providing higher quality of care but also in the area of cost containment.

Over the years, other economic sectors have significantly benefited from the extensive utilization of IT. Technologies in these industries are characterized by standardization and maturity, whereas technologies the healthcare industry are generally fragmented and lack interoperability. After Taylor et al. (2005), the argument here is that in order to harvest similar levels of benefit from the adoption of IT in the healthcare industry and in order to improve coordination and efficiency among healthcare providers, there should be an emphasis on interconnectivity and interoperability of technologies. Moreover, it would be critical to enforce compliance with standards and focus on continuous improvement of quality and performance in order to gain the cost-saving benefits from the adoption of HIT.

This is a time of unprecedented change in the U.S. healthcare system. The new healthcare reform bills, the Patient Protection and Affordable Care Act (PPACA) of 2010 and the Health Care and Education Reconciliation Act of 2010, have been inked down into law by President Obama only a few months ago. In addition, the adoption of HIT is one of the major focus areas of the American Recovery and Reinvestment Act (ARRA) of 2009, which has allocated significant financial resources to encourage the widespread adoption of HIT among healthcare providers. Yet, the findings in this study and several previous studies warrant further aggressive policy interventions from the government that will particularly speed up the adoption of technologies with clinical applications.

6.3 Limitations

This study has some limitations. First, it is based on administrative data that may have questionable coding accuracy, variation, and timing of events (Miller et al., 2005). Second, since this study is not based on a randomly assigned design model, its generalizability may be limited. Third, the study did not take into consideration the effects of specific technologies as well as the capabilities and length of usage of the technologies. Fourth, the study focused on only four patient safety and three quality of care indicators due to the limitations of the available data. Other indicators could equally be helpful in understanding the effects of HIT on healthcare outcomes. And fifth, the study may not account for some other factors that affect the adoption of technologies, patient safety, and quality of care in hospitals. However, the impact of these limitations is expected to be minimal because: (1) the data sets have been repeatedly tested and used in the past; (2) the national sample of hospitals was a fair representative of all U.S. hospitals and was based on the most recent data that should be able to grasp the latest trend; (3) by including a large number of technologies in the analysis and by risk-adjusting the outcomes, the study captured more reliably the effects of information technology adoption on patient safety and quality of care; (4) the quality and safety indicators were developed by experts in the field and have been widely used in previous studies; and (5) the similarities of the findings to previous researches provide validity to the methodologies and the data in this study.

6.4 Recommendations for Future Study

Similar to previous studies, the findings indicate that better process is associated with better outcome. Put another way, improved performance in hospitals is associated with higher adoption rates of technologies. Since the current business trend requires more information exchange between the various actors in healthcare provision, these findings can have an implication for various stakeholders in the healthcare industry, including healthcare providers, patients, insurers, policy makers, and technology vendors. Thus, future studies should investigate the relationship between HIT adoption in hospitals and the efficiency of interactions among the various actors. In addition, the effect of the introduction of new technology applications in the work culture of the hospitals and the productivity of health professionals need further investigation. The effect of technical support and length of usage of HIT applications on healthcare outcomes is another area that needs further investigation. Since this is a provider level analysis, which has its own limitations, future researches should consider patient level analysis. Finally, the findings indicate that hospitals in different regions perform independently of their information technology adoption rates and other factors included in this study. Thus, the effect of region-specific characteristics such as state regulations on the adoption of technologies should be examined further.

6.5 Summary

In conclusion, though several previous studies demonstrated the value of adoption of technologies, many of them were based on single academic institutions, few information technology applications, or single healthcare outcomes. This study, on the other hand, aimed to fill the gap by including a very large number of technologies, nationally representative data, and two very important outcomes of healthcare in the analysis. The study used structure (organizational and contextual factors), process (adoption of information technology), and outcome (patient safety and quality of care) measures. This last chapter provided a discussion on the findings of the study, its theoretical, methodological, and policy implications, as well as its limitations. The conclusion was that more aggressive action is needed both from healthcare providers and policy makers in order to provide incentives for a far-reaching HIT adoption.

APPENDIX A: IRB APPROVAL LETTER

University of Central Florida Institutional Review Board
Office of Research & Commercialization
12201 Research Parkway, Suite 501
Orlando, Florida 32826-3246
Telephone: 407-823-2901, 407-882-2012 or 407-882-2276
www.research.ucf.edu/compliance/irb.html

NOT HUMAN RESEARCH DETERMINATION

From : **UCF Institutional Review Board #1**
FWA00000351, IRB00001138

To : Binyam K. Seblega

Date : February 17, 2010

Dear Researcher:

Thank you for sending the description of your proposed research to the IRB office. After reviewing this information and discussing your plans on the phone, the IRB determined that the following proposed activity is not human research as defined by DHHS regulations at 45 CFR 46 or FDA regulations at 21 CFR 50/56:

Type of Review:	Not Human Research Determination
Project Title:	"Effects of Health Information Technology Adoption on Quality of Care and Patient Safety in U.S. Acute Care Hospitals: A Parallel Process Growth Curve Model Approach"
Investigator:	Binyam K. Seblega
Research ID:	N/A

University of Central Florida IRB review and approval is not required. This determination applies only to the activities described in the IRB submission and does not apply should any changes be made. If changes are to be made and there are questions about whether these activities are research involving human subjects, please contact the IRB office to discuss the proposed changes.

On behalf of the IRB Chair, Joseph Bielitzki, DVM, this letter is signed by:

Joanne Muratori

IRB Coordinator

APPENDIX B: COPYRIGHT PERMISSION LETTERS

May 10, 2010

Darrell E. Burke, PhD
Associate Professor, Health Informatics Program
Department of Health Services Administration
University of Alabama at Birmingham
514 Webb Building
1530 3rd Avenue South
Birmingham, Alabama 35294-3361

Dear Dr. Burke:

I am completing a doctoral dissertation degree at the University of Central Florida entitled "Effects if Health Information Technology Adoption on Quality of Care and Patient Safety in US Acute Care Hospitals." I would like your permission to reprint in my dissertation excerpts from the following: Burke, D. E. & Menachemi, N. (2004). Opening the Black Box: Measuring Hospital Information Technology Capability. *Health Care Management Review, 29*(3), 207-217.

The excerpt to be reproduced is the list of the technology applications and capabilities in Appendix A, page 216.

The requested permission extends to any future revisions and editions of my dissertation, including non-exclusive world rights in all languages. These rights will in no way restrict republication of the material in any other form by you or by others authorized by you. Your signing of this letter will also confirm that you own the copyright to the above-described material.

If these arrangements meet with your approval, please sign this letter where indicated below and return it to me. Thank you for your attention in this matter.

Sincerely,
BinyamKS

Binyam K. Sèblega, MBA, MA
PhD Candidate and Research Assistant
University of Central Florida
PhD Program in Public Affairs
Orlando, Florida
Tel: 202-390-4315
Fax: 407-823-0744
Email: binyam@knights.ucf.edu

PERMISSION GRANTED FOR THE USE REQUESTED ABOVE:

By: ______________________
Darrell E. Burke, PhD

Date: 5/10/10

Subject: RE: [SPF] Permission Request
Date: Thu, 3 Jun 2010 14:41:59 -0500
From: hcup-us@thomsonreuters.com
To: binyam@knights.ucf.edu

Dear Binyam:

Thank you for your inquiry and interest in the HCUP databases. No special permissions are required to publish the information from our HCUP data documentation. We do, however, request that you source the information appropriately. There is a section of the HCUP-US Website that details different methods of citing HCUP data. This page is located at http://www.hcup-us.ahrq.gov/tech_assist/citations.jsp.

Sincerely,

HCUP User Support

APPENDIX C: GLOSSARY OF TERMS

- **Acute Myocardial Infarction (IQI 15)** – also known as heart attack, refers to the "number of deaths per 100 discharges with a principal diagnosis code of AMI" (AHRQ, 2007a, p. 47).

- **Administrative IT** – technologies used in the human resource department and include "financial information systems, payroll, purchasing, and inventory control, outpatient clinic scheduling, office automation, and many others" (Austin & Boxerman, 1998, p. 5).

- **Adverse Drug Event (ADE)** – "any unexpected or dangerous reaction to a drug" (http://www.medterms.com/script/main/art.asp?articlekey=26227).

- **Automated Dispensing Machine (ADM)** – "a medication dispensing cabinet that automates the storing, dispensing, and tracking of narcotics, floor stock and PRN (as needed [pro re nata]) medications in-patient care areas" (HIMSS Analytics, 2009, p. 4).

- **Bar-Coding at Medication Administration (BCMA)** – "barcode technology… used by nursing services to improve the efficiency of operations such as patient identification, nurse identification, medication identification, and closed loop medication administration process that improve patient safety" (HIMSS Analytics, 2009, p. 4).

- **Bar-Coding at Medication Dispensing (BCMD)** – "a code consisting of a group of printed and variously patterned bars and spaces and sometimes numerals that are designed to be scanned and read into computer memory as identification for the object it labels. Bar coding is used by the pharmacy department for inventory control of drugs" (HIMSS Analytics, 2009, p. 4).

- **Clinical Data Repository (CDR)** – "a centralized database that allows organizations to collect, store, access, and report on clinical, administrative, and financial information collected from various applications within or across the healthcare organization that provides healthcare organizations an open environment for accessing/viewing, managing, and reporting enterprise information" (HIMSS Analytics, 2009, p. 9).

- **Clinical Decision Support (CDS) Systems** – "an application that uses pre-established rules and guidelines, that can be created and edited by the healthcare organization, and integrates clinical data from several sources to generate alerts and treatment suggestions" (HIMSS Analytics, 2009, p. 9).

- **Clinical IT** – technologies that are directly associated with patient diagnosis, treatment, and evaluation of outcomes (Austin & Boxerman, 1998).

- **Computerized Practitioner Order Entry (CPOE)** – "an order entry application specifically designed to assist clinical practitioners in creating and managing medical orders for inpatient acute care services or medication" (HIMSS Analytics, 2009, p. 10).

- **Congestive Heart Failure (IQI 16)** – the "number of deaths per 100 discharges with principal diagnosis code of CHF" (AHRQ, 2007a, p. 50).

- **Death in Low Mortality DRGs (PSI 2)** – "in-hospital deaths per 1,000 patients in DRGs with less than 0.5% mortality" (AHRQ, 2007b, p. 26).

- **Decubitus (Pressure) Ulcer (PSI 3)** – "cases of decubitus ulcer per 1,000 discharges with a length of stay greater than 4 days" (AHRQ, 2007b, p. 28).

- **Electronic Health Record (EHR)** – "a longitudinal electronic record of patient health information generated by one or more encounters in any care delivery setting. Included in this information are patient demographics, progress notes, problems, medications, vital signs, past medical history, immunizations, laboratory data, and radiology reports" (http://www.himss.org/ASP/topics_ehr.asp).

- **Electronic Medical Administration Records (EMAR)** – "an electronic record keeping system that documents when medications are given to a patient during a hospital stay. This application supports the five rights of medication administration (right patient, right medication, right dose, right time, and right route of administration" (HIMSS Analytics, 2009, p. 14).

- **Electronic Medical Record (EMR)** – "a comprehensive database system used to store and access patients' healthcare information electronically. An application environment that is composed of the clinical data repository, clinical decision support, controlled medical vocabulary, order entry, computerized practitioner order entry, and clinical documentation applications" (Furukawa et al., 2008, p. _).

- **Health Information Technology (HIT)** – "the use of information and communication technology in health care. Health Information Technology can include electronic health records, personal health records, e-mail communication, clinical alerts and reminders, computerized decision support systems, hand-held devices, and other technologies that store, protect, retrieve and transfer clinical, administrative, and financial information electronically within health care settings" (http://www.hrsa.gov/healthit/).

- **Herfindahl-Hirschman Index (HHI)** – an index used to measure market competition; calculated as: H-H index = $\sum_{i=1}^{n}$ (number of beds in a hospital / total number of beds in a county)^2 (Phibbs & Robinson, 1993).

- **Inpatient Quality Indicators (IQIs)** – "a set of measures that provide a perspective on hospital quality of care using hospital administrative data" (http://www.qualityindicators.ahrq.gov/iqi_overview.htm).

- **Iatrogenic Pneumothorax (PSI 6)** – "cases of iatrogenic pneumothorax per 1,000 discharges" (AHRQ, 2007b, p. 34).
- **Medication Errors** – "errors in drug ordering, transcribing, dispensing, administering, or monitoring" (Kaushal et al., 2001, p. 2115).
- **Patient Safety** – "freedom from accidental injury caused by medical care" (Miller et al., 2001, p. 112).
- **Patient Safety Indicators (PSIs)** – "a set of indicators providing information on potential inhospital complications and adverse events following surgeries, procedures, and childbirth" (http://www.qualityindicators.ahrq.gov/psi_overview.htm).
- **Pneumonia (IQI 20)** – "mortality in discharges with principal diagnosis code of pneumonia" (AHRQ, 2007a, p. 58).
- **Payer Mix** – the proportion of Medicare and Medicaid patients from the total patient population.
- **Quality of Care** – "the degree to which health services for individuals and populations increase the likelihood of desired health outcomes and are consistent with current professional knowledge" (IOM, 2001, P. 244).
- **Robot for Medication Dispensing (ROBOT)** – "robotic technology used by pharmacies to conduct dispensing and cart fill functions and to deliver medications to medication cabinets for restocking" (HIMSS Analytics, 2009, p. 33).
- **Selected Infection due to Medical Care (PSI 7)** – "cases of infections due to medical care, primarily those related to intravenous lines (IV) and catheters" (AHRQ, 2007, p. 36).
- **Strategic Decision-Support IT** – technologies used by the management team in the hospitals for "strategic planning, managerial control, performance monitoring, and outcomes assessment" (Austin & Boxerman, 1998, p. 5).

APPENDIX D: STATISTICAL NOTES

Multiple Linear Regression Analysis

First conceptualized by Sir Francis Galton and mathematically formalized by Karl Pearson in the nineteenth century (Azen & Budescu, 2009), multiple linear regression is used to understand the relationship between a single dependent variable *Y* and multiple independent variables X_n in either an exploratory or predictive way. The following equation represents the general form of multiple linear regression:

$$Yi = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \ldots + \beta_n X_n + \varepsilon$$

Where Y = the dependent variable;

β = the regression coefficient;

X = the independent variable; and

ε = a random error.

The independent variables (X_i) are also known as predictor variables or explanatory variables while the dependent variable *Y* is also known as the predicted or response variable (Azen & Budescu, 2009; Daniel, 2009). Also known as residuals, the error terms (ε) refer to the differences between the observed and predicted values of the dependent variables. Smaller error terms indicate more accurate prediction while larger error terms indicate less accurate predictions, and thus, the error terms reveal the accuracy of the predicted variation in the dependent variable (Hawkes & Marsh, 2005).

Assumptions in Multiple Linear Regression

Assumptions in multiple linear regression (Azen & Budescu, 2009; Daniel, 2009) include the following (the results of the tests for the assumptions are shown in Appendix E with the exception of test for linearity, which were excluded for brevity):

1. *Linearity* – a linear relationship is assumed to exist between the predictors and the response variables in a linear regression model. This assumption can be visually tested by looking at scatter plot of the observed versus the predicted variables. Linearity is assumed if the points in the plot are uniformly distributed around a diagonal line.
2. *Normality* – the error terms should be normally distributed. Visual test for normality is conducted by drawing residual versus predicted values histograms with normal curves and qq-plots. Normality is also tested numerically by checking the Skewness and Kurtosis values. Shapiro-Wilk W test could also be used for data with fewer than 2,000 observations. The rule of thumb is that points within ±3 standard deviation on the qq-plot and uniformly distributing along the diagonal line, Skewness and Kurtosis values between ±2, and a Shapiro-Wilk W test of close to 1 indicate normality.
3. *Constant Variance (Homoscedasticity)* – Another assumption in multiple linear regression is that residuals should not have a pattern (spreading out or conical) against the predicted values. In other words, the residuals should have constant or homogenous variance for the model to be acceptable. This is tested visually by looking at the scatter plot of the residual versus the predicted values. Increases in the value of residuals with increase in predicted values (i. e. spreading out of the residuals along the diagonal line with an increase in the predicted values) indicate lack of homoscedasticity.
4. *Multicollinearity* – Multicollinearity refers to linear combinations among the predictor variables in a model. Higher linear combination could result in inflated

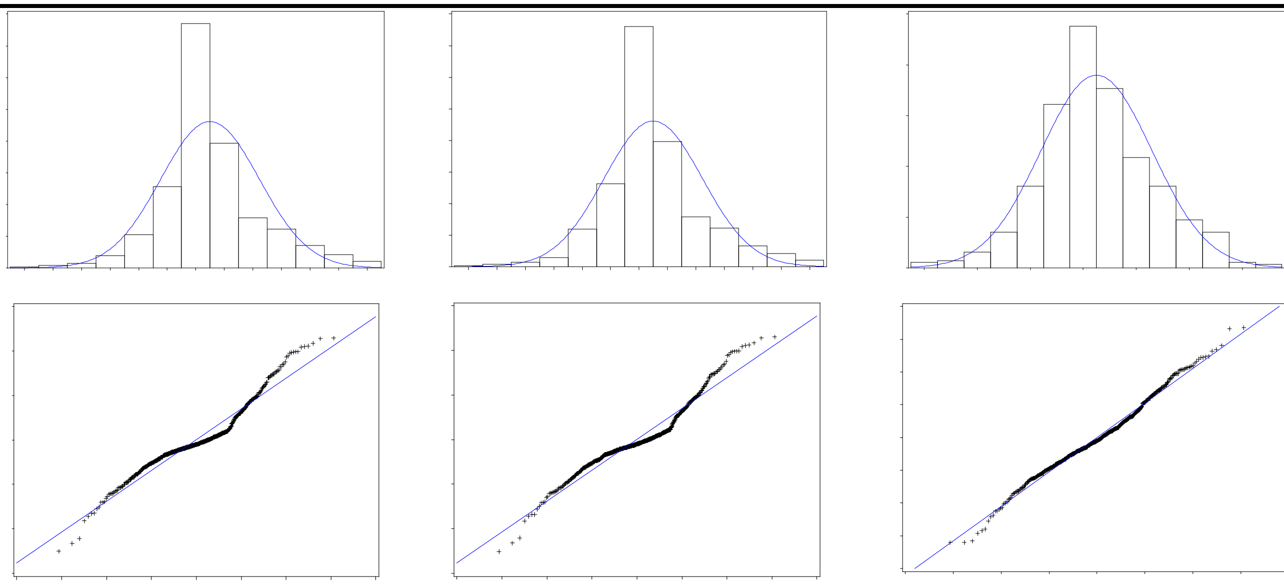
coefficients. The assumption of multicollinearity in the models is tested by using tolerance and variance inflation factors. Tolerance is explained as 1 / variance inflation. Variance inflation factor of 10 or above (and thus, a tolerance of .1 or less) may indicate the need for careful investigation.

5. *Independence of Error Terms* –Another assumption in multiple linear regression is that the error terms for each observation are independent of each other. This assumption is tested by using the Durbin-Watson test. The Durbin-Watson test has a range of 0 to 4. A value between 1.5 and 2.5 indicates the independence of the residuals and leads to the rejection of the assumption that the residuals are autocorrelated. A value close to 0 indicates strong positive correlation while a value close to 4 indicates negative correlation between the residuals.
6. *Test for Outliers* – A single extreme outlier can make significant differences and lead to erroneous conclusions. A test for outliers is visually conducted by generating scatter plots of the dependent variables versus the independent variables.

APPENDIX E: RESULTS OF ASSUMPTION TESTS

DEATH IN LOW MORTALITY DRG (PSI 2)

CLINICAL IT	ADMINISTRATIVE IT	STRATEGIC IT



Skewness = 0.570	Skewness = 0.570	Skewness = 0.173
Kurtosis = 1.657	Kurtosis = 1.668	Kurtosis = 0.440
Shapiro-Wilk = 0.942	Shapiro-Wilk = 0.942	Shapiro-Wilk = 0.999

Figure 11: Test for Normality – PSI2

CLINICAL IT	ADMINISTRATIVE IT	STRATEGIC IT

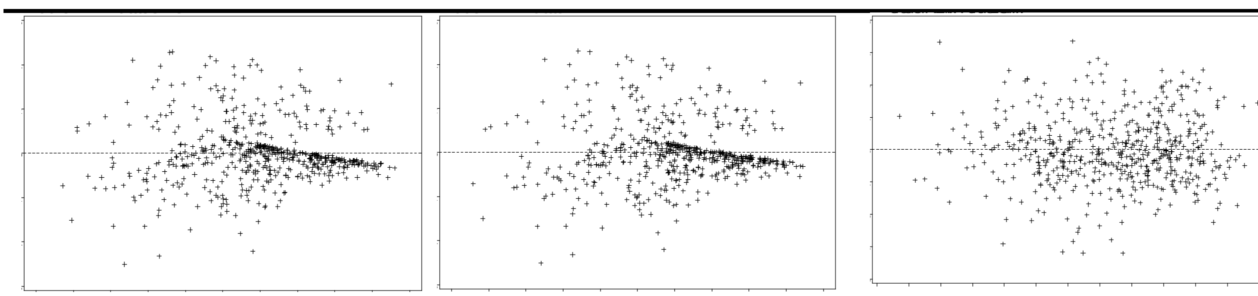


Figure 12: Test for Homoscedasticity – PSI2

Table 11: Test for Multicollinearity – PSI2

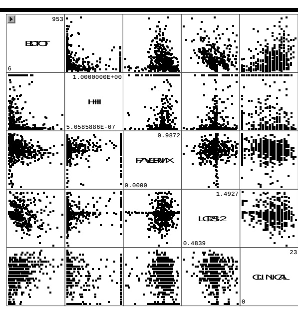
	Clinical IT		Administrative IT		Strategic IT	
	Tolerance	Variance inflation	Tolerance	Variance inflation	Tolerance	Variance inflation
Intercept	.	0	.	0	.	0
Size	0.54	1.84	0.57	1.77	0.56	1.79
Ownership	0.88	1.13	0.89	1.12	0.89	1.12
Teaching status	0.66	1.51	0.66	1.51	0.66	1.52
HMO	0.83	1.20	0.83	1.21	0.83	1.20
Urban location	0.57	1.77	0.58	1.73	0.55	1.80
Midwest	0.53	1.89	0.53	1.88	0.54	1.86
South	0.50	1.99	0.50	2.00	0.50	1.98
West	0.52	1.93	0.53	1.90	0.53	1.88
HHI	0.64	1.57	0.64	1.57	0.63	1.58
Payer mix	0.88	1.14	0.88	1.14	0.88	1.14
Clinical	0.69	1.44	-	-	-	-
Administrative	-	-	0.80	1.25	-	-
Strategic	-	-	-	-	0.73	1.37

Test for Independence of Error Terms – PSI2

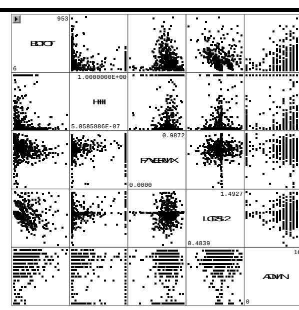
DW values:

Clinical IT = 1.92
Administrative IT = 1.92
Strategic IT = 1.92

CLINICAL IT



ADMINISTRATIVE IT



STRATEGIC IT

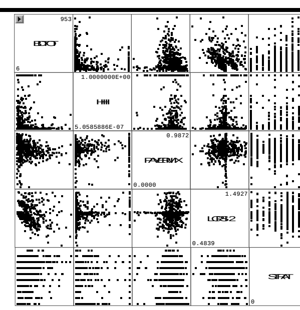
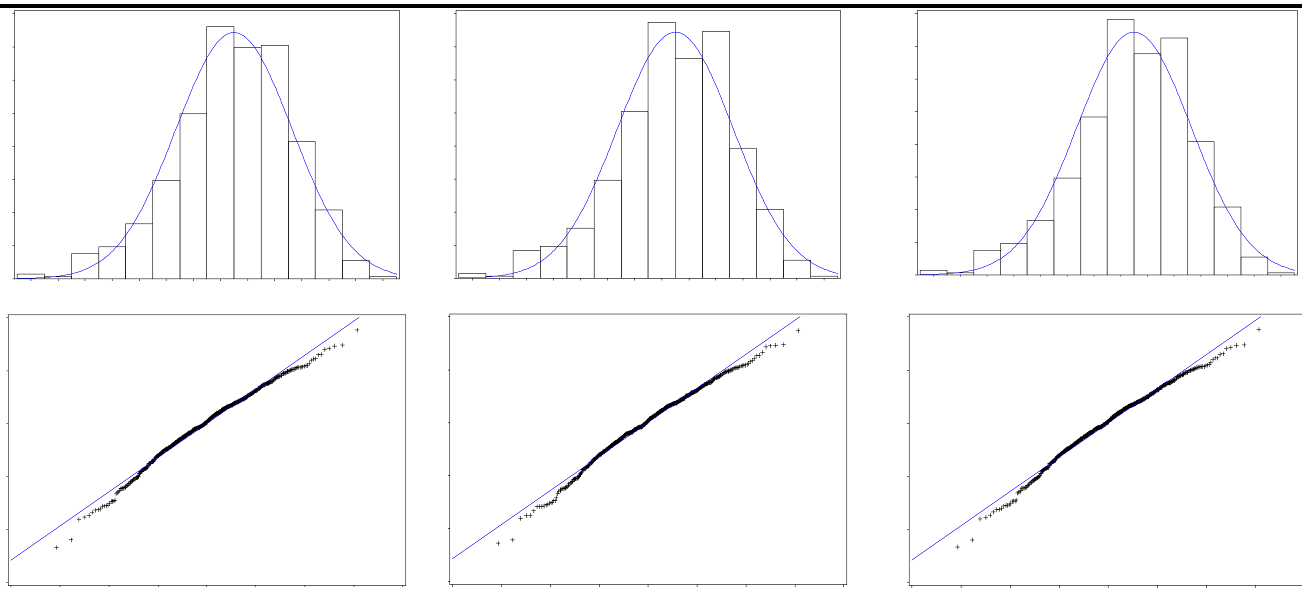


Figure 13: Test for Outliers – PSI2

<u>DECUBITUS ULCER (PSI 3)</u>

CLINICAL IT	ADMINISTRATIVE IT	STRATEGIC IT



Skewness = -0.453	Skewness -0.443	Skewness = -0.452
Kurtosis = 0.290	Kurtosis = 0.270	Kurtosis = 0.290
Shapiro-Wilk = 0.987	Shapiro-Wilk = 0.987	Shapiro-Wilk = 0.987

Figure 14: Test for Normality – PSI3

CLINICAL IT	ADMINISTRATIVE IT	STRATEGIC IT

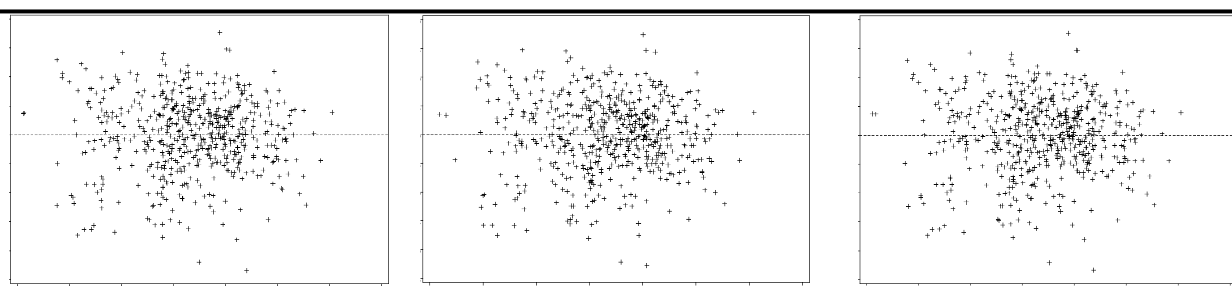


Figure 15: Test for Homoscedasticity – PSI3

Table 12: Test for Multicollinearity – PSI3

	Clinical IT		Administrative IT		Strategic IT	
	Tolerance	Variance inflation	Tolerance	Variance inflation	Tolerance	Variance inflation
Intercept	.	0	.	0	.	0
Size	0.54	1.84	0.57	1.76	0.56	1.80
Ownership	0.88	1.13	0.89	1.12	0.88	1.13
Teaching status	0.66	1.51	0.66	1.52	0.66	1.52
HMO	0.84	1.19	0.84	1.19	0.83	1.20
Urban location	0.57	1.76	0.58	1.73	0.56	1.79
Midwest	0.54	1.85	0.54	1.85	0.54	1.85
South	0.51	1.97	0.51	1.97	0.51	1.97
West	0.52	1.91	0.53	1.87	0.54	1.86
HHI	0.63	1.58	0.63	1.59	0.63	1.58
Payer mix	0.88	1.13	0.88	1.14	0.88	1.13
Clinical	0.69	1.45	-	-	-	-
Administrative	-	-	0.79	1.26	-	-
Strategic	-	-	-	-	0.72	1.39

Test for Independence of Error Terms – PSI3

DW values:

Clinical IT = 1.88

Administrative IT = 1.88

Strategic IT = 1.88

CLINICAL IT	ADMINISTRATIVE IT	STRATEGIC IT

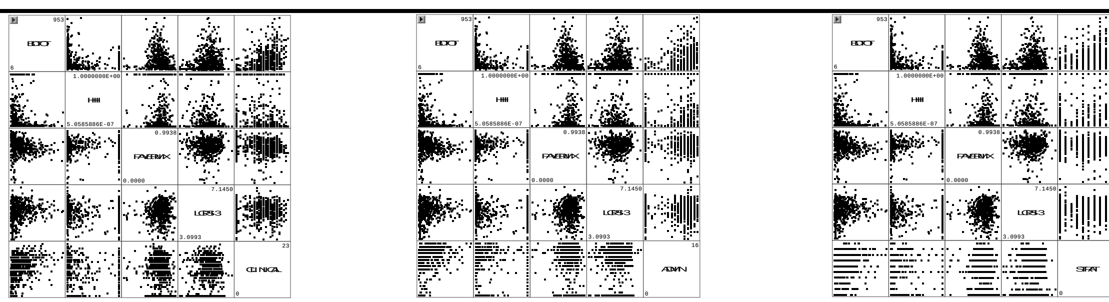
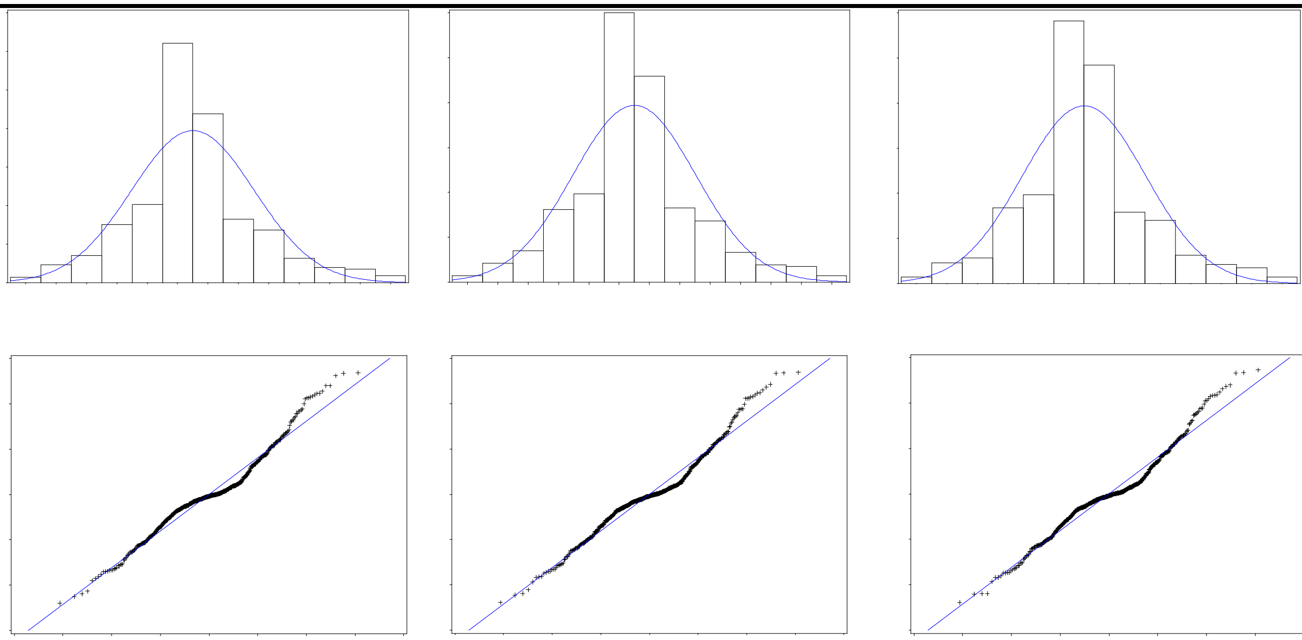


Figure 16: Test for Outliers – PSI3

IATROGENIC PNEUMOTHORAX (PSI 6)

CLINICAL IT	ADMINISTRATIVE IT	STRATEGIC IT



Skewness = 0.391	Skewness = 0.400	Skewness = 0.391
Kurtosis = 1.125	Kurtosis = 1.143	Kurtosis = 1.128
Shapiro-Wilk = 0.966	Shapiro-Wilk = 0.965	Shapiro-Wilk = 0.966

Figure 17: Test for Normality – PSI6

CLINICAL IT	ADMINISTRATIVE IT	STRATEGIC IT

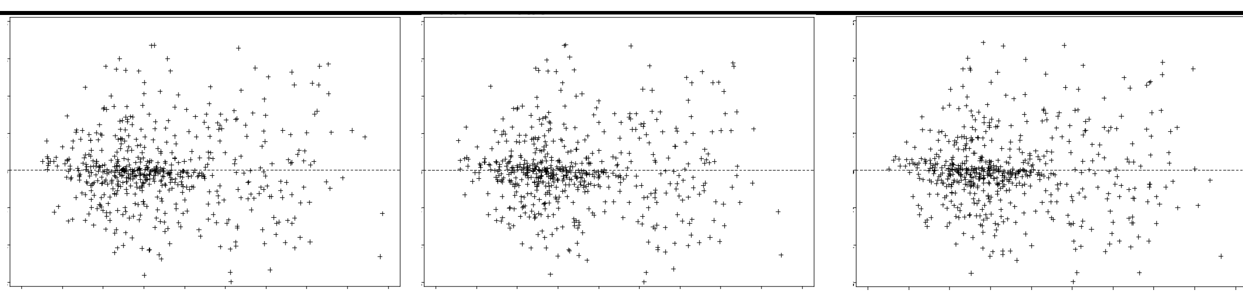


Figure 18: Test for Homoscedasticity – PSI6

Table 13: Test for Multicollinearity – PSI6

	Clinical IT		Administrative IT		Strategic IT	
	Tolerance	Variance inflation	Tolerance	Variance inflation	Tolerance	Variance inflation
Intercept	.	0	.	0	.	0
Size	0.55	1.81	0.58	1.73	0.56	1.77
Ownership	0.88	1.13	0.89	1.12	0.88	1.13
Teaching status	0.67	1.49	0.67	1.49	0.67	1.50
HMO	0.84	1.19	0.84	1.19	0.83	1.20
Urban location	0.57	1.76	0.58	1.73	0.56	1.79
Midwest	0.52	1.91	0.53	1.90	0.53	1.90
South	0.50	2.00	0.50	2.00	0.50	2.01
West	0.51	1.95	0.52	1.92	0.52	1.91
HHI	0.64	1.57	0.64	1.57	0.64	1.57
Payer mix	0.88	1.13	0.88	1.14	0.88	1.13
Clinical	0.69	1.44	-	-	-	-
Administrative	-	-	0.80	1.25	-	-
Strategic	-	-	-	-	0.73	1.38

Test for Independence of Error Terms – PSI6

DW values:

Clinical IT = 2.12
Administrative IT = 2.11
Strategic IT = 2.11

CLINICAL IT	ADMINISTRATIVE IT	STRATEGIC IT

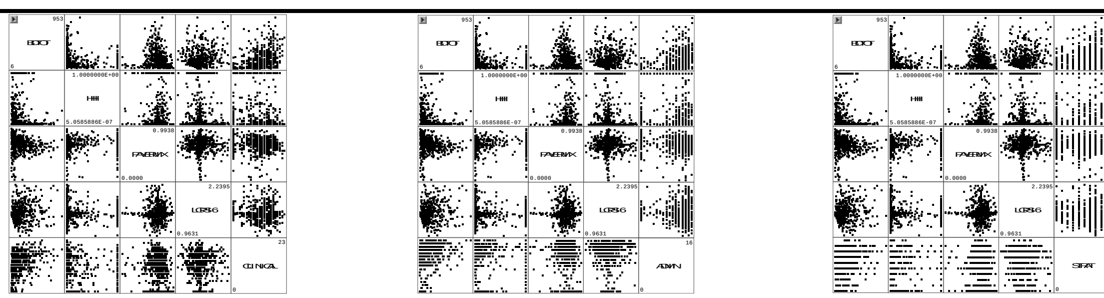
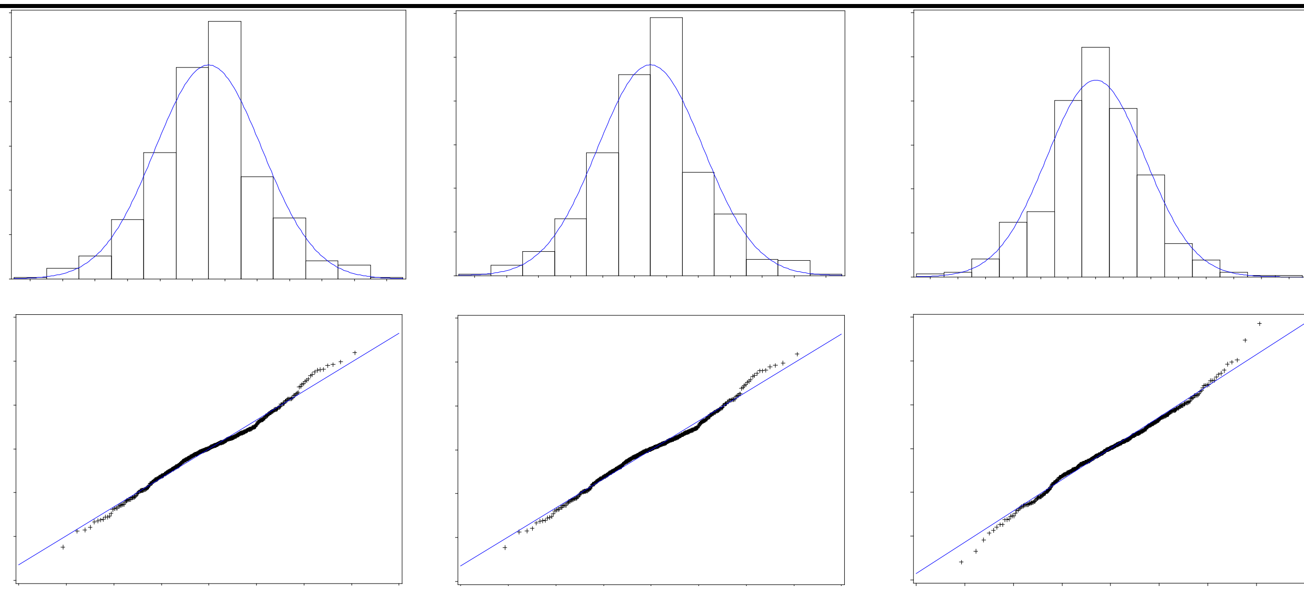


Figure 19: Test for Outliers – PSI6

SELECTED INFECTION DUE TO MEDICAL CARE (PSI 7)

CLINICAL IT	ADMINISTRATIVE IT	STRATEGIC IT



Skewness = 0.042	Skewness = 0.038	Skewness = -0.034
Kurtosis = 0.757	Kurtosis = 0.747	Kurtosis = 0.926
Shapiro-Wilk = 0.989	Shapiro-Wilk = 0.989	Shapiro-Wilk = 0.992

Figure 20: Test for Normality – PSI7

CLINICAL IT	ADMINISTRATIVE IT	STRATEGIC IT

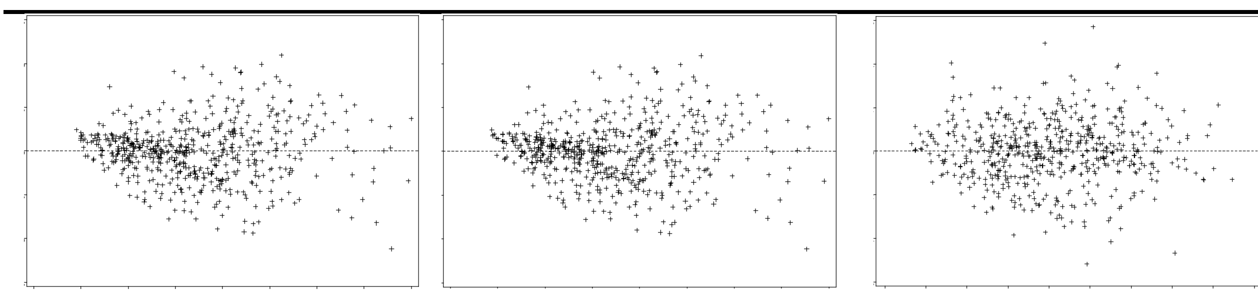


Figure 21: Test for Homoscedasticity – PSI7

Table 14: Test for Multicollinearity – PSI7

	Clinical IT		Administrative IT		Strategic IT	
	Tolerance	Variance inflation	Tolerance	Variance inflation	Tolerance	Variance inflation
Intercept	.	0	.	0	.	0
Size	0.54	1.84	0.57	1.76	0.56	1.80
Ownership	0.88	1.13	0.89	1.12	0.89	1.13
Teaching status	0.66	1.51	0.66	1.52	0.66	1.52
HMO	0.84	1.19	0.84	1.19	0.83	1.21
Urban location	0.57	1.76	0.58	1.73	0.56	1.79
Midwest	0.53	1.87	0.54	1.86	0.54	1.87
South	0.51	1.97	0.51	1.97	0.50	1.99
West	0.52	1.91	0.53	1.87	0.53	1.87
HHI	0.63	1.58	0.63	1.58	0.63	1.58
Payer mix	0.88	1.13	0.88	1.14	0.88	1.14
Clinical	0.69	1.45	-	-	-	-
Administrative	-	-	0.80	1.26	-	-
Strategic	-	-	-	-	0.73	1.38

Test for Independence of Error Terms – PSI7

DW values:

Clinical IT = 1.92
Administrative IT = 1.91
Strategic IT = 2.07

CLINICAL IT ADMINISTRATIVE IT STRATEGIC IT

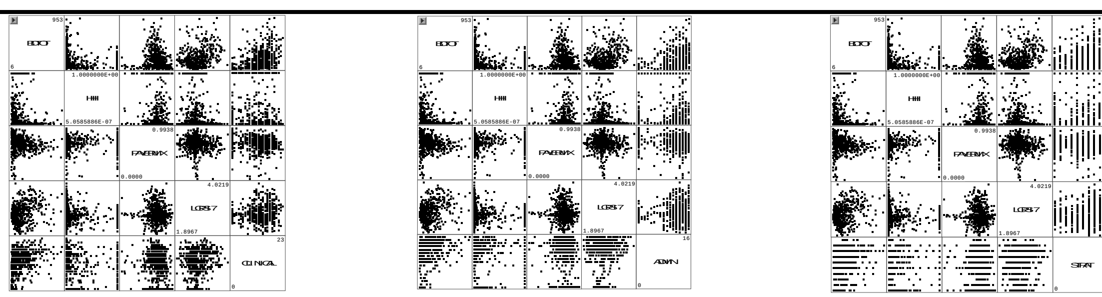
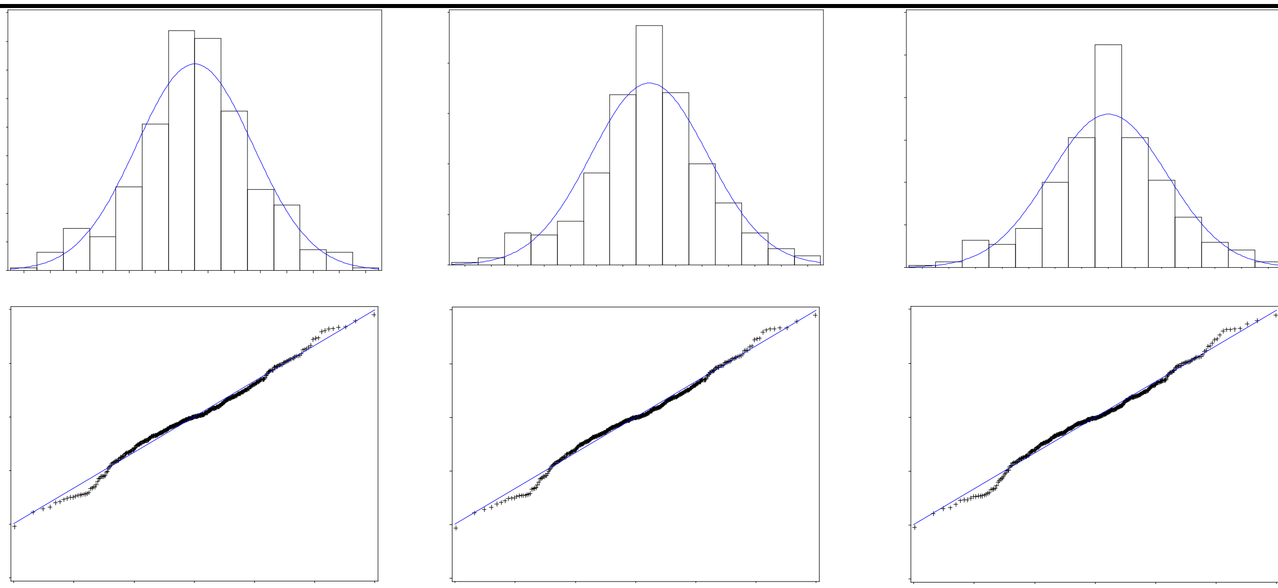


Figure 22: Test for Outliers – PSI7

<u>ACUTE MYOCARDIAL INFARCTION (IQI 15)</u>

CLINICAL IT	ADMINISTRATIVE IT	STRATEGIC IT



Skewness = -0.092	Skewness = -0.092	Skewness = -0.084
Kurtosis = 0.478	Kurtosis = 0.480	Kurtosis = 0.472
Shapiro-Wilk = 0.988	Shapiro-Wilk = 0.988	Shapiro-Wilk = 0.988

Figure 23: Test for Normality – IQI15

CLINICAL IT	ADMINISTRATIVE IT	STRATEGIC IT

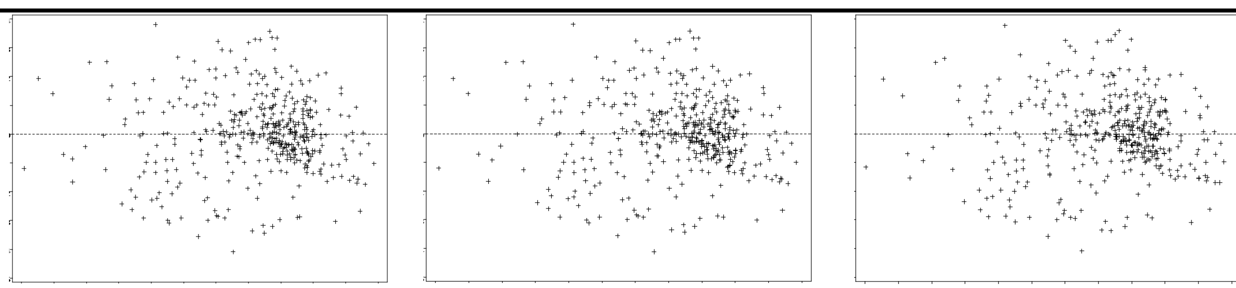


Figure 24: Test for Homoscedasticity – IQI15

Table 15: Test for Multicollinearity – IQI15

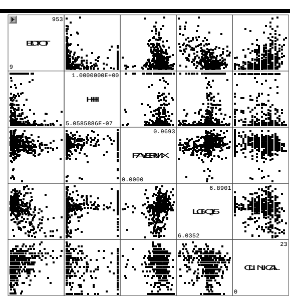
	Clinical IT		Administrative IT		Strategic IT	
	Tolerance	Variance inflation	Tolerance	Variance inflation	Tolerance	Variance inflation
Intercept	.	0	.	0	.	0
Size	0.53	1.87	0.55	1.81	0.55	1.83
Ownership	0.89	1.12	0.90	1.11	0.89	1.12
Teaching status	0.64	1.56	0.64	1.56	0.64	1.56
HMO	0.82	1.22	0.82	1.22	0.81	1.24
Urban location	0.57	1.76	0.58	1.73	0.56	1.80
Midwest	0.56	1.77	0.57	1.76	0.57	1.76
South	0.53	1.88	0.53	1.88	0.53	1.90
West	0.63	1.59	0.64	1.57	0.64	1.56
HHI	0.64	1.56	0.64	1.56	0.64	1.55
Payer mix	0.85	1.18	0.85	1.18	0.85	1.18
Clinical	0.68	1.47	-	-	-	-
Administrative	-	-	0.78	1.28	-	-
Strategic	-	-	-	-	0.69	1.45

Test for Independence of Error Terms – IQI15

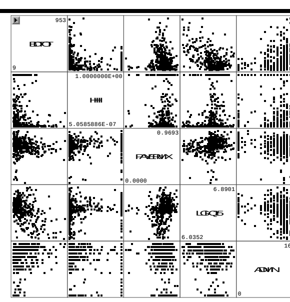
DW values:

Clinical IT = 2.07
Administrative IT = 2.07
Strategic IT = 2.08

CLINICAL IT



ADMINISTRATIVE IT



STRATEGIC IT

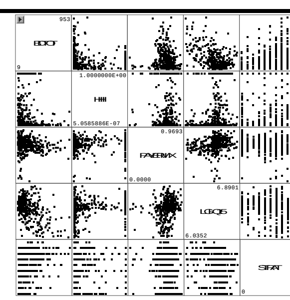
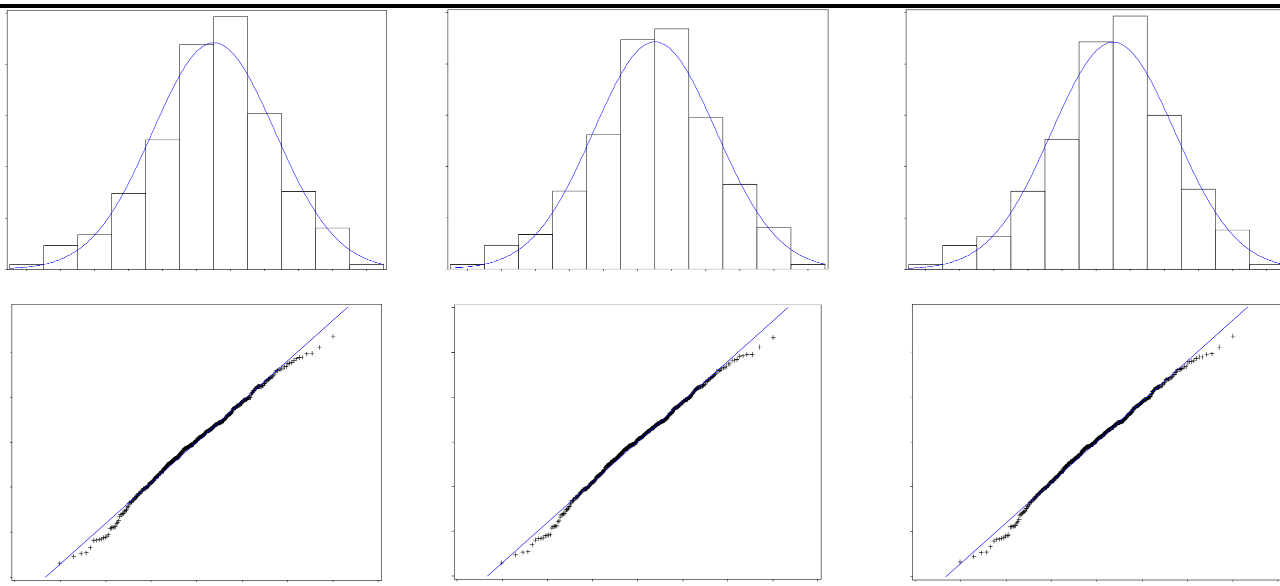


Figure 25: Test for Outliers – IQI15

CONGESTIVE HEART FAILURE (IQI 16)

CLINICAL IT	ADMINISTRATIVE IT	STRATEGIC IT



Skewness = -0.270	Skewness = -0.268	Skewness = -0.267
Kurtosis = 0.066	Kurtosis = 0.063	Kurtosis = 0.065
Shapiro-Wilk = 0.993	Shapiro-Wilk = 0.993	Shapiro-Wilk = 0.993

Figure 26: Test for Normality – IQI16

CLINICAL IT	ADMINISTRATIVE IT	STRATEGIC IT

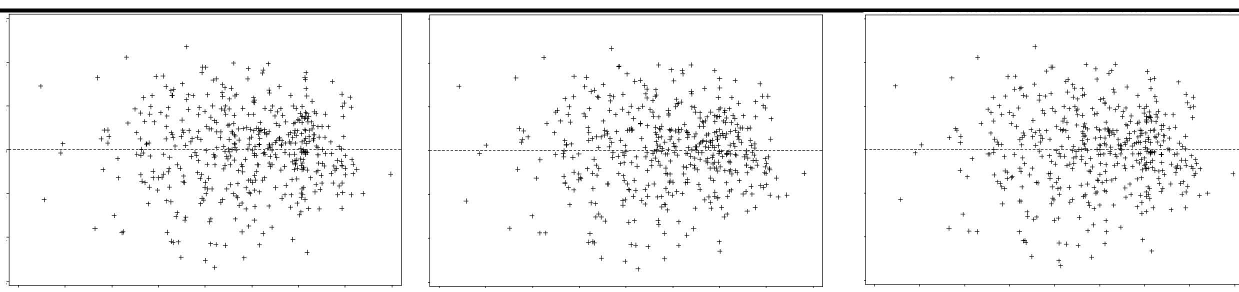


Figure 27: Test for Homoscedasticity – IQI16

Table 16: Test for Multicollinearity – IQI16

	Clinical IT		Administrative IT		Strategic IT	
	Tolerance	Variance inflation	Tolerance	Variance inflation	Tolerance	Variance inflation
Intercept	.	0	.	0	.	0
Size	0.52	1.92	0.54	1.86	0.53	1.87
Ownership	0.87	1.14	0.88	1.13	0.88	1.14
Teaching status	0.63	1.58	0.63	1.58	0.63	1.58
HMO	0.83	1.21	0.83	1.21	0.82	1.23
Urban location	0.58	1.73	0.59	1.69	0.57	1.75
Midwest	0.56	1.78	0.56	1.78	0.56	1.78
South	0.52	1.90	0.52	1.91	0.52	1.92
West	0.62	1.62	0.63	1.60	0.63	1.59
HHI	0.66	1.51	0.66	1.51	0.66	1.51
Payer mix	0.85	1.17	0.85	1.18	0.86	1.17
Clinical	0.66	1.51	-	-	-	-
Administrative	-	-	0.73	1.32	-	-
Strategic	-	-	-	-	0.69	1.44

Test for Independence of Error Terms – IQI16

DW values:

Clinical IT = 2.01
Administrative IT = 2.00
Strategic IT = 2.01

CLINICAL IT ADMINISTRATIVE IT STRATEGIC IT

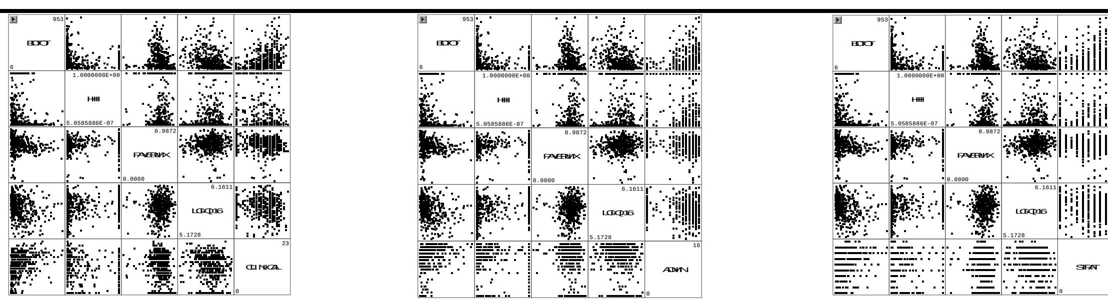
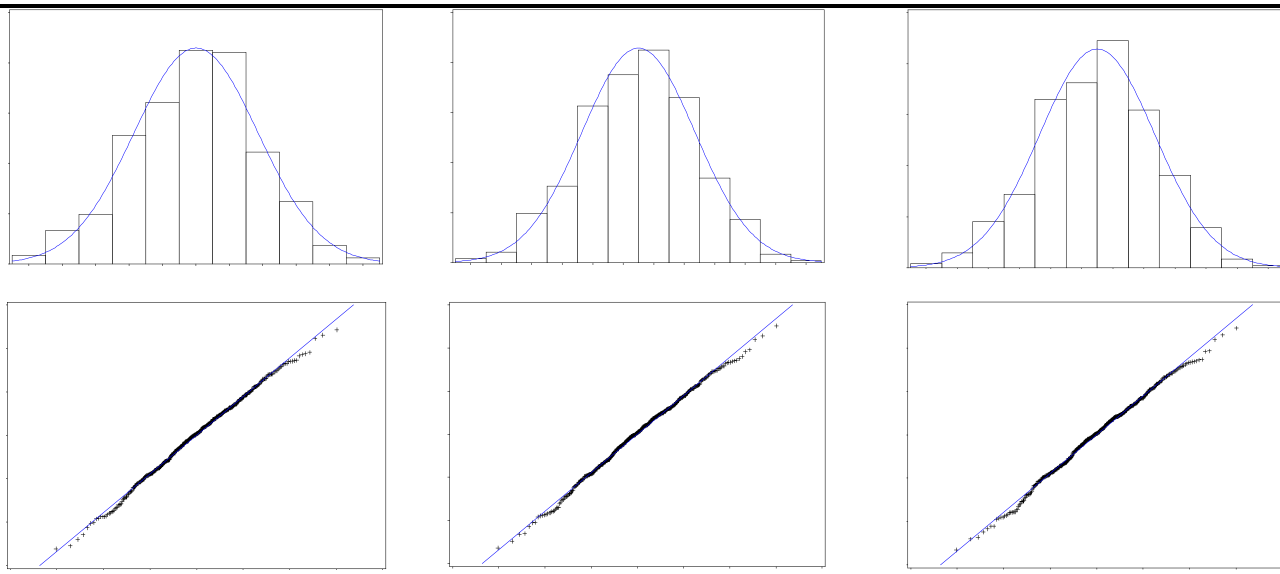


Figure 28: Test for Outliers – IQI16

PNEUMONIA (IQI20)

CLINICAL IT	ADMINISTRATIVE IT	STRATEGIC IT



Skewness = -0.164	Skewness = -0.172	Skewness = -0.179
Kurtosis = -0.119	Kurtosis = -0.139	Kurtosis = -0.136
Shapiro-Wilk = 0.997	Shapiro-Wilk = 0.996	Shapiro-Wilk = 0.996

Figure 29: Test for Normality – IQI20

CLINICAL IT	ADMINISTRATIVE IT	STRATEGIC IT

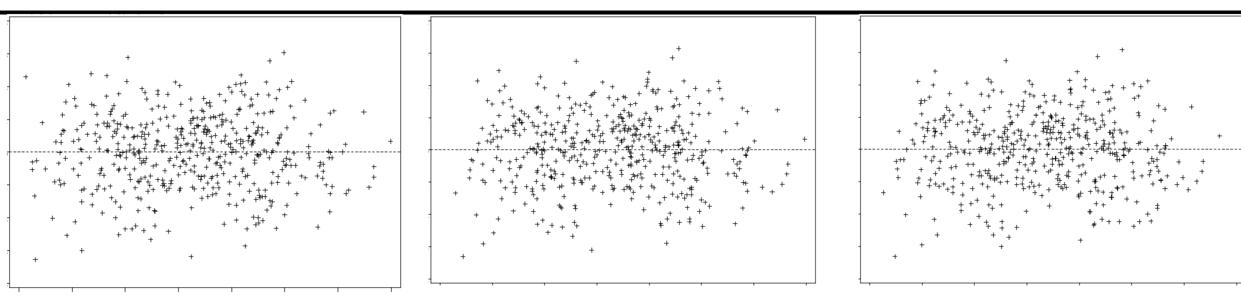


Figure 30: Test for Homoscedasticity – IQI20

Table 17: Test for Multicollinearity – IQI20

	Clinical IT		Administrative IT		Strategic IT	
	Tolerance	Variance inflation	Tolerance	Variance inflation	Tolerance	Variance inflation
Intercept	.	0	.	0	.	0
Size	0.53	1.90	0.54	1.84	0.54	1.85
Ownership	0.87	1.14	0.88	1.13	0.88	1.14
Teaching status	0.63	1.58	0.63	1.58	0.63	1.58
HMO	0.83	1.21	0.83	1.21	0.82	1.23
Urban location	0.57	1.75	0.58	1.72	0.56	1.78
Midwest	0.57	1.77	0.57	1.76	0.57	1.76
South	0.52	1.91	0.52	1.91	0.52	1.92
West	0.62	1.61	0.63	1.59	0.63	1.58
HHI	0.65	1.54	0.65	1.54	0.65	1.54
Payer mix	0.85	1.17	0.85	1.18	0.86	1.17
Clinical	0.67	1.49	-	-	-	-
Administrative	-	-	0.76	1.32	-	-
Strategic	-	-	-	-	0.69	1.44

Test for Independence of Error Terms – IQI20

DW values:

Clinical IT = 2.11
Administrative IT = 2.11
Strategic IT = 2.11

CLINICAL IT | ADMINISTRATIVE IT | STRATEGIC IT

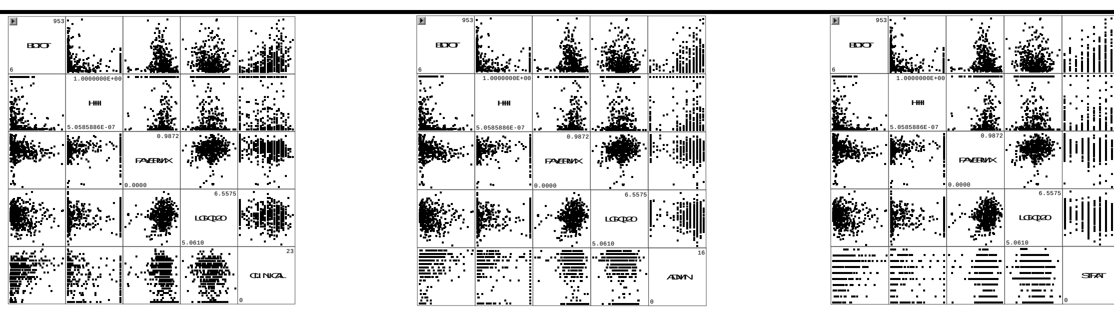


Figure 31: Test for Outliers – IQI20

APPENDIX F: REGRESSION ANALYSES

Table 18: Multiple Regression Model for Patient Safety – PSI2 (N = 571)

	Clinical IT		Administrative IT		Strategic IT	
	β	95% CI	β	95% CI	β	95% CI
Intercept	1.1211***	1.0407, 1.2016	1.1178***	1.0363, 1.1993	11.6632***	8.6630, 14.6633
Size	-0.0001**	-0.0002, -0.0000	-0.0001**	-0.0002, -0.0001	-0.0049**	-0.0084, -0.0015
Ownership	0.0396*	0.0019, 0.0773	0.0385*	0.0009, 0.0760	-0.3077	-1.7433, 1.1278
Teaching status	0.0032	-0.0307, 0.0371	0.0037	-0.0303, 0.0376	-0.3846	-1.6612, 0.8921
HMO	-0.0086	-0.0365, 0.0193	-0.0091	-0.0371, 0.0188	-0.0146	-1.0795, 1.0504
Urban location	-0.0204	-0.0516, 0.0109	-0.0219	-0.0528, 0.0091	0.4104	-0.7896, 1.6104
Midwest	0.0093	-0.0267, 0.0452	0.0102	-0.0257, 0.0461	-2.1448**	-3.5072, -0.7824
South	-0.0148	-0.0517, 0.0221	-0.0147	-0.0516, 0.0223	-1.0325	-2.4361, 0.3711
West	-0.0517**	-0.0873, -0.0162	-0.0501**	-0.0854, -0.0149	-4.5287***	-5.8537, -3.2037
HHI	0.0102	-0.0240, 0.0443	0.0106	-0.0236, 0.0448	0.0158	-1.2919, 1.3234
Payer mix	0.0173	-0.0685, 0.1030	0.0182	-0.0677, 0.1041	5.6373***	2.3828, 8.8917
Clinical IT	-0.0008	-0.0030, 0.0014	-	-	-	-
Admin IT	-	-	-0.0005	-0.0029, 0.0020	-	-
Strategic IT	-	-	-	-	-0.0783	-0.2591, 0.1026

* p < .05; ** p < .01; *** p < .001

Table 19: Multiple Regression Model for Patient Safety – PSI3 (N = 579)

	Clinical IT		Administrative IT		Strategic IT	
	β	95% CI	β	95% CI	β	95% CI
Intercept	4.7283***	4.3523, 5.1043	4.6512***	4.2708, 5.0316	4.7200***	4.3517, 5.0883
Size	0.0004	-0.0001, 0.0008	0.0003	-0.0001, 0.0007	0.0003	-0.0001, 0.0008
Ownership	0.2129*	0.0384, 0.3875	0.2051*	0.0316, 0.3786	0.2113*	0.0369, 0.3857
Teaching status	0.0435	-0.1127, 0.1997	0.0403	-0.1158, 0.1964	0.0437	-0.1128, 0.2002
HMO	0.0430	-0.0849, 0.1709	0.0343	-0.0935, 0.1621	0.0420	-0.0865, 0.1705
Urban location	0.1571*	0.0126, 0.3015	0.1436*	0.0006, 0.2865	0.1549*	0.0090, 0.3007
Midwest	-0.1888*	-0.3546, -0.0230	-0.1894*	-0.3547, -0.0241	-0.1879*	-0.3534, -0.0225
South	0.1086	-0.0614, 0.2785	0.1055	-0.0644, 0.2753	0.1085	-0.0617, 0.2788
West	0.1026	-0.0606, 0.2657	0.1130	-0.0484, 0.2744	0.1047	-0.0565, 0.2659
HHI	-0.0207	-0.1798, 0.1384	-0.0116	-0.1706, 0.1475	-0.0197	-0.1787, 0.1393
Payer mix	0.4713*	0.0719, 0.8707	0.4966*	0.0973, 0.8959	0.4742*	0.0753, 0.8731
Clinical IT	-0.0008	-0.0110, 0.0093	-	-	-	-
Admin IT	-	-	0.0066	-0.0049, 0.0180	-	-
Strategic IT	-	-	-	-	0.0000	-0.0221, 0.0221

* p < .05; ** p < .01; *** p < .001

Table 20: Multiple Regression Model for Patient Safety – PSI6 (N = 570)

	Clinical IT		Administrative IT		Strategic IT	
	β	95% CI	β	95% CI	β	95% CI
Intercept	1.5745***	1.4572, 1.6917	1.5717 ***	1.4531, 1.6904	1.5626***	1.4476, 1.6776
Size	0.0001	-0.0001, 0.0002	0.0001	-0.0001, 0.0002	0.0001	-0.0001, 0.0002
Ownership	-0.0085	-0.0630, 0.0459	-0.0115	-0.0658, 0.0428	-0.0096	-0.0641, 0.0450
Teaching status	0.0669**	0.0171, 0.1167	0.0687**	0.0188, 0.1186	0.0652*	0.0152, 0.1152
HMO	0.0094	-0.0310, 0.0498	0.0089	-0.0315, 0.0494	0.0098	-0.0308, 0.0504
Urban location	-0.0095	-0.0549, 0.0360	-0.0126	-0.0577, 0.0326	-0.0096	-0.0555, 0.0363
Midwest	-0.0006	-0.0535, 0.0523	0.0027	-0.0502, 0.0556	0.0018	-0.0511, 0.0546
South	0.0081	-0.0462, 0.0624	0.0091	-0.0453, 0.0635	0.0097	-0.0447, 0.0641
West	0.0225	-0.0294, 0.0744	0.0266	-0.0248, 0.0781	0.0273	-0.0241, 0.0786
HHI	-0.0262	-0.0762, 0.0237	-0.0259	-0.0760, 0.0242	-0.0256	-0.0756, 0.0244
Payer mix	-0.0559	-0.1800, 0.0682	-0.0548	-0.1791, 0.0695	-0.0526	-0.1767, 0.0714
Clinical IT	-0.0026	-0.0058, 0.0006	-	-	-	-
Admin IT	-	-	-0.0023	-0.0058, 0.0013	-	-
Strategic IT	-	-	-	-	-0.0045	-0.0115, 0.00243

* p < .05; ** p < .01; *** p < .001

Table 21: Multiple Regression Model for Patient Safety – PSI7 (N = 582)

	Clinical IT		Administrative IT		Strategic IT	
	β	95% CI	β	95% CI	β	95% CI
Intercept	2.6304***	2.4403, 2.8206	2.6168***	2.4244, 2.8092	27.3381***	26.5318, 28.1445
Size	0.0005***	0.0003, 0.0008	0.0005***	0.0003, 0.0007	0.0014**	0.0005, 0.0024
Ownership	0.1035*	0.0145, 0.1924	0.1025*	0.0140, 0.1910	-0.0381	-0.4283, 0.3520
Teaching status	0.0643	-0.0158, 0.1443	0.0634	-0.0166, 0.1435	0.4663**	0.1200, 0.8126
HMO	-0.0671*	-0.1326, -0.0017	-0.0687*	-0.1342, 0.0032	0.3250*	0.0384, 0.6117
Urban location	0.0506	-0.0233, 0.1245	0.0484	-0.0248, 0.1216	0.4409**	0.1184, 0.7635
Midwest	-0.0340	-0.1189, 0.0510	-0.0344	-0.1191, 0.0504	-0.9052***	-1.2721, -0.5384
South	0.0025	-0.0847, 0.0896	0.0017	-0.0854, 0.0889	0.0315	-0.3476, 0.4106
West	0.0702	-0.0133, 0.1536	0.0716	-0.0110, 0.1543	-0.2903	-0.6483, 0.0677
HHI	-0.0605	-0.1419, 0.0208	-0.0590	-0.1403, 0.0224	-0.2283	-0.5796, 0.1230
Payer mix	0.0223	-0.1791, 0.2237	0.0262	-0.1754, 0.2277	-0.4045	-1.2772, 0.4681
Clinical IT	0.0001	-0.0050, 0.0053	-	-	-	-
Admin IT	-	-	0.0015	-0.0043, 0.0073	-	-
Strategic IT	-	-	-	-	-0.0043	-0.0530, 0.04430

Table 22: Multiple Regression Model for Quality of Care – IQI15 (N = 439)

	Clinical IT		Administrative IT		Strategic IT	
	β	95% CI	β	95% CI	β	95% CI
Intercept	6.6223***	6.5288, 6.7159	6.6208 ***	6.5262, 6.7154	6.6153***	6.5242, 6.7065
Size	-0.0004***	-0.0005, -0.0003	-0.0004***	-0.0005, -0.0003	-0.0004***	-0.0005, -0.0003
Ownership	0.0024	-0.0417, 0.0466	0.0027	-0.0412, 0.0466	0.0003	-0.0436, 0.0443
Teaching status	-0.0511**	-0.0894, -0.0128	-0.0514**	-0.0897, -0.0131	-0.0508**	-0.0891, -0.0126
HMO	0.0005	-0.0312, 0.0322	0.0004	-0.0313, 0.0321	-0.0022	-0.0341, 0.0297
Urban location	-0.0390*	-0.0728, -0.0053	-0.0389*	-0.0724, -0.0053	-0.0428*	-0.0769, -0.0086
Midwest	-0.0995***	-0.13591, -0.0631	-0.1003***	-0.1366, -0.0641	-0.1005***	-0.1367, -0.0643
South	-0.0872***	-0.1255, -0.0490	-0.0877***	-0.1260, -0.0494	-0.0898***	-0.1282, -0.0514
West	-0.1271***	-0.1704, -0.0838	-0.1277***	-0.1706, -0.0848	-0.1284***	-0.1711, -0.0856
HHI	0.0203	-0.0164, 0.0569	0.0205	-0.0162, 0.0573	0.0215	-0.0150, 0.0581
Payer mix	0.0695	-0.0314, 0.1703	0.0699	-0.0310, 0.1708	0.0752	-0.0256, 0.1760
Clinical IT	0.0005	-0.0019, 0.0029	-	-	-	-
Admin IT	-	-	0.0006	-0.0021, 0.0034	-	-
Strategic IT	-	-	-	-	0.0033	-0.0020, 0.0087

* p < .05; ** p < .01; *** p < .001

Table 23: Multiple Regression Model for Quality of Care – IQI16 (N = 474)

	Clinical IT		Administrative IT		Strategic IT	
	β	95% CI	β	95% CI	β	95% CI
Intercept	5.8697***	5.7489, 5.9906	5.8551***	5.7324, 5.9779	5.8670***	5.7485, 5.9855
Size	-0.0002*	-0.0003, -0.0000	-0.0002*	-0.0003, -0.0000	-0.0002*	-0.0003, -0.0000
Ownership	0.0245	-0.0319, 0.0808	0.0230	-0.0331, 0.0790	0.0237	-0.0325, 0.0799
Teaching status	-0.0202	-0.0713, 0.0309	-0.0206	-0.0716, 0.0305	-0.0200	-0.0711, 0.0312
HMO	-0.0419*	-0.0826, -0.0013	-0.0438*	-0.0844, -0.0032	-0.0430*	-0.0839, -0.0022
Urban location	-0.0506*	-0.0941, -0.0070	-0.0525*	-0.0955, -0.0094	-0.0520*	-0.0959, -0.0082
Midwest	-0.0521*	-0.1001, -0.0041	-0.0527*	-0.1005, -0.0048	-0.0525*	-0.1004, -0.0046
South	-0.0898***	-0.1401, -0.0394	-0.0904***	-0.1408, -0.0401	-0.0907***	-0.1412, -0.0402
West	-0.0541	-0.1090, 0.0008	-0.0527	-0.1072, 0.0019	-0.0545*	-0.1088, -0.0001
HHI	0.0393	-0.0075, 0.0862	0.0411	-0.0058, 0.0880	0.0400	-0.0069, 0.0868
Payer mix	-0.0086	-0.1379, 0.1206	-0.0018	-0.1315, 0.1278	-0.0065	-0.1358, 0.1227
Clinical IT	0.0003	-0.0028, 0.0034	-	-	-	-
Admin IT	-	-	0.0015	-0.0020, 0.0050	-	-
Strategic IT	-	-	-	-	0.0015	-0.0054, 0.0084

* p < .05; ** p < .01; *** p < .001

Table 24: Multiple Regression Model for Quality of Care – IQI20 (N = 485)

	Clinical IT		Administrative IT		Strategic IT	
	β	95% CI	β	95% CI	β	95% CI
Intercept	5.9883***	5.8401, 6.1365	5.9874***	5.8365, 6.1383	5.9662***	5.8206, 6.1119
Size	-0.0001	-0.0002, 0.0001	-0.0001	-0.0003, 0.0001	-0.0001	-0.0003, 0.0001
Ownership	-0.0037	-0.0732, 0.0659	-0.0081	-0.0774, 0.0612	-0.0078	-0.0773, 0.0617
Teaching status	0.0324	-0.0290, 0.0938	0.0348	-0.0266, 0.0963	0.0330	-0.0285, 0.0946
HMO	-0.0344	-0.0838, 0.0151	-0.0354	-0.0850, 0.0141	-0.0348	-0.0847, 0.0152
Urban location	-0.0213	-0.0750, 0.0323	-0.0257	-0.0790, 0.0275	-0.0234	-0.0776, 0.0308
Midwest	-0.1374***	-0.1956, -0.0792	-0.1327***	-0.1909, -0.0746	-0.1332***	-0.1914, -0.0750
South	-0.0653*	-0.1270, -0.0036	-0.0635*	-0.1253, -0.0016	-0.0616	-0.1237, 0.0005
West	-0.1407***	-0.2082, -0.0732	-0.1357***	-0.2029, -0.0686	-0.1318***	-0.1988, -0.0649
HHI	0.0264	-0.0313, 0.0841	0.0268	-0.0310, 0.0847	0.0280	-0.0299, 0.0858
Payer mix	0.0492	-0.1095, 0.2078	0.0494	-0.1100, 0.2088	0.0562	-0.1027, 0.2151
Clinical IT	-0.0040*	-0.0078, -0.0001	-	-	-	-
Admin IT	-	-	-0.0037	-0.0080, 0.0001	-	-
Strategic IT	-	-	-	-	-0.0060	-0.0145, 0.0025

* p < .05; ** p < .01; *** p < .001

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