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Hospital Electronic Health Record Adoption and its Influence on Postoperative Sepsis

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Hospital Electronic Health Record
Adoption and its Influence on Postoperative Sepsis

A dissertation submitted in partial fulfillment of the requirements for the degree of Doctor of Philosophy at Virginia Commonwealth University.

by

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Abstract

HOSPITAL ELECTRONIC HEALTH RECORD ADOPTION AND ITS INFLUENCE ON POSTOPERATIVE SEPSIS

By Naleef Fareed, Ph.D., M.B.A.

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Electronic Health Record (EHR) systems could make healthcare delivery safer by providing benefits such as timely access to accurate and complete patient information, advances in diagnosis and coordination of care, and enhancements for monitoring patient vitals. This study explored the nature of EHR adoption in U.S. hospitals and their patient safety performance in relation to one hospital acquired condition: postoperative sepsis – a condition that complicates hospitalizations, increases lengths of stay, and leads to higher mortality rates.

Administrative data from several sources were utilized in order to obtain comprehensive information about the patient, organizational, and market characteristics of hospitals, their EHR adoption patterns, and the occurrence of postoperative sepsis among their patients. The study

sample consisted of 404 general, short-term, acute care, non-federal, and urban hospitals based in six states, which provided longitudinal data from 2005 to 2009. Hospital EHR and the EHR's sophistication level were measured by the presence of eight clinical applications. Econometric techniques were used to test six hypotheses that were derived from macro-organizational theories and frameworks.

After controlling for potential confounders, the study's key findings suggested that hospitals had a significant increase in the probability of having EHR as the percent of other hospitals having the most sophisticated EHR (i.e., EHRS3) in the market increased. Conversely, hospitals had a significant decrease in the probability of having EHR when the percent of Medicaid patients increased within a hospital or when the hospital belonged to centralized or moderately centralized systems. Also, the study findings suggested that EHR was associated with a higher rate of postoperative sepsis. Specifically, the intermediate EHR sophistication level (i.e., EHRS2) and the most sophisticated EHR level (i.e., EHRS3) were associated with a significantly higher rate of postoperative sepsis when compared to hospitals that did not have such EHR sophistication. The study results, however, did not support the hypotheses that higher degrees of fit between hospitals' EHR sophistication level and specific structural dimensions were associated with greater reductions in postoperative sepsis outcomes vis-à-vis hospitals that did not have these types of fit.

Chapter 1: Introduction

Specific Aims

Since the highly publicized Institute of Medicine report *To Err Is Human* (2000), recent assessments of patient safety have suggested that hospitals have made limited progress in improving their patient safety performance (Landrigan et al., 2010). Poor patient safety is an important issue due to the significant psychological and financial toll it inflicts onto patients, providers, the healthcare system, and society as a whole (Institute of Medicine, 2000). A variety of public and private organizations has engaged in initiatives to promote patient safety (Furukawa, Raghu, Spaulding, & Vinze, 2008), and the Patient Protection and Affordable Care Act (ACA) has provisions that specifically focus on the reduction of hospital acquired conditions (U.S. Congress, 2010; sections 2702 & 3008).

Preventable patient safety events are defined as medical mistakes and complications that should not have occurred at the time when patients were provided care (Encinosa & Bae, 2011). Nosocomial sepsis is a common and preventable patient safety event with an estimated 934,000 cases annually (Moore et al., 2010). From a quality perspective, sepsis complicates hospitalizations, increases lengths of stay, and leads to higher mortality rates (Pittet, Tarara & Wenzel, 1994; Zhan & Miller, 2003b). In terms of costs, Rentz, Halpern, and Bowden (1998) found that hospitals in 1997 incurred additional expenses of $33,268 per patient suffering from nosocomial sepsis. Zhan and Miller (2003b) found that hospitals in 2000 had an excess cost of approximately $58,000 per patient for postoperative sepsis. Postoperative sepsis complications account for approximately 30 percent of nosocomial sepsis, and reductions in their occurrence could reduce inpatient mortality and improve quality of life (Vaughan-Sarrazim, Bayman, & Cullen, 2011).

Disconcertingly, suboptimal treatment that might contribute to the occurrence of sepsis is prevalent in hospitals (Claessens & Dhainaut, 2007). These deficiencies in healthcare delivery include: the delayed use of or incorrect selection of antibiotics, irregular monitoring of patients' physiological parameters, and the inadequate use of evidence based protocols to support the treatment of patients who may display early symptoms of sepsis (Claessens & Dhainaut, 2007; Zubrow, et al., 2008).

Hospitals have undertaken a plethora of activities and programs to reduce the prevalence of adverse patient safety events such as postoperative sepsis, but with quite limited success (Encinosa & Hellinger, 2008). Recent developments in health information technology (HIT), however, provide a potential opportunity through which hospitals may be able to improve their patient safety records, along with their costs, efficiencies, and quality of care (Hillestad et al., 2005; Shojania, Duncan, McDonald, & Wachter, 2001). Bates and Gawande (2003) noted that HIT can help hospitals improve their poor patient safety records. Hospitals with HIT may achieve this by improving communication, making knowledge more readily accessible, requiring key pieces of information, assisting with calculations, performing checks in real time, assisting with monitoring, and providing decision support; with increasing HIT sophistication possibly further enhancing the capacity of these features (Bates & Gawande, 2003). Electronic health records (EHRs) are a promising form of HIT that may help in improving patient safety in hospitals (Furukawa, Raghu, & Shao, 2010a; Kazley & Ozcan, 2008). They generally consist of numerous possible combinations of HIT applications that may range from a grouping of basic functionalities to a more comprehensive or sophisticated set of functions.

Anecdotal and empirical evidence demonstrates that the use of EHR applications may help avert postoperative sepsis events. Applications such as clinical data repository, radiology, pharmacy, or laboratory information systems work in unison to help clinicians make timely predictions of risk factors (i.e., based on patients' clinical or physiological symptoms) related to sepsis (Fujit, Gait, Siracuse, & Christoggerson, 2011). Nursing documentation and electronic medication administration applications, which may be tightly coupled with EHR systems, could help aid assessments of subtle changes (e.g., with the help of alert systems programmed with the systemic inflammatory response syndrome criteria) in patients' clinical conditions and facilitate the proper administration of time critical anti-infective medications to mitigate possible sepsis events, respectively (Dennis, Sweeny, Macdonald, & Morse, 1993). Moreover, EHR applications such as clinical decision support and computerized provider order entry systems may use standardized guidelines and alerts, like those prescribed by the Sepsis Treatment Enhanced through Electronic Protocolization method or the Surgical Care Improvement Project, to provide customized directives to help preclude patients from contracting sepsis (Mathe et al., 2009).

The effectiveness of an EHR system may be enhanced by the integration of one or more of the applications noted above. Timely access to comprehensive information beyond what is maintained by a single EHR application has the potential to help clinicians to make optimal decisions in regard to a patient's condition (Fuji et al., 2011). Hence, the proposed study aims to explore the nature of EHR adoption in hospitals and the ability for EHR to reduce postoperative sepsis rates in hospitals.

Research Questions

This study will examine the following research questions in order to explore the nature of EHR adoption in hospitals and the association of EHR with hospital postoperative sepsis performance:

Q1: What organizational and environmental forces are associated with hospitals' having certain EHR applications?

Q2. Will hospitals that adopt EHRs have lower postoperative sepsis outcomes relative to those who do not adopt such applications?

Q3. Will hospitals that have a better fit between their organizational structures and technology contingency have lower postoperative sepsis outcomes relative to those who do not have this type of fit?

Conceptual Framework

The underlying conceptual framework for the study relies on organizational theories and frameworks that have been previously used by health services researchers to explain the nature of technology adoption and how it might affect hospital performance. Oliver's (1991) model on organizational responsiveness, derived from Institutional Theory (DiMaggio & Powell, 1983; Meyer & Rowan, 1977) and Resource Dependence Theory (Pfeffer & Salancik, 1978), will be used to address the first research question. Donabedian's (1980) Structure-Process-Outcome model and Structural Contingency Theory (Donaldson, 2001) will be used to examine the second and third research questions, respectively.

Using the Oliver (1991) model, this study will specifically test whether local institutional and resource motivators have an association with a hospital's decision to have EHR. With the help of the Structure-Process-Outcome framework this study will test whether hospital EHR and the level of sophistication of the EHR have associations with hospital postoperative sepsis performance. This study, additionally, incorporates the Structural Contingency Theory notion of fit between hospitals' structural features and their EHR technology to explore its association with hospital postoperative sepsis performance. In order to control for potential variables that may affect the relationship between the study's key explanatory and dependent variables, the study incorporates patient, hospital, and market control variables into the various empirical models as well. In summary, the study will derive eight hypotheses from the above described conceptual framework to address the study's research questions.

Scope and Approach

This study will primarily use a longitudinal data set, from Arizona, Florida, California, Maryland, New Jersey, and New York, between 2005 to 2009 to test the study's eight hypotheses. Study data will be drawn from several databases, which include: American Hospital Association (AHA) Annual Surveys of Hospitals, Healthcare Information and Management Systems Society (HIMSS) Analytics, and Healthcare Cost and Utilization Project (HCUP) State Inpatient Database. An ordered probit model is used to examine research question one. Fixed effects regression models with and without instrument variables are used to assess research question two. A fixed effects regression approach is also used for exploring research question three. Specific aspects of the study's methodologies, research design, and empirical approaches are described in Chapter 4.

Significance of the Study

Encinosa and Bae (2011) posited that EHR is increasingly becoming an essential part of the effort to improve patient safety in hospitals. Along with other researchers such as DesRoches et al. (2010), they cited a series of major policy initiatives, which were launched as early at 2004 and culminated in the enactment of the 2009 Health Information Technology for Economic and Clinical Health (HITECH) Act that had related provisions for EHR "meaningful use" in the 2010 ACA. However, the utility of such initiatives hinges on the successful adoption of potentially patient safety improving HIT, such as EHR. In order for this to occur, policy makers and healthcare administrators need to have an expanded understanding of EHR adoption and its relationship to patient safety performance. Using such knowledge, administrators may be able to better focus their HIT investments to improve patient care from these investments. Policymakers may also be better able to focus their HIT policies to particular types of HIT adoption rather than the current global or generic HIT policies they have in place.

Summary of Remaining Chapters

This chapter provided an overview of this study's aims and presented a summary of the conceptual framework, research questions assessed, and the analytical approach used in the study. The subsequent chapters will provide detailed information: Chapter 2 provides a review of the studies that present the basis for the study's primary variables and the fit and potential contribution of this study to the corpus of the existing literature related to the research questions explored; Chapter 3 defines a conceptual model based on various organizational theories, and provides the motivation for testable hypotheses; Chapter 4 discusses the research methodologies used in this study, which includes the research design, data sources, variable measurement, and empirical approaches; Chapter 5 presents the study findings, which includes the study's descriptive statistics, regression models, and sensitivity analyses; and Chapter 6 reflects on the findings based on the study's hypotheses and discusses the implications and limitations of the study.

Chapter 2: Literature Review

This chapter includes six major sections. The first section provides an overview regarding the background of EHR and its evolution in the U.S. healthcare system. The second section provides a review of the studies that present the basis for the study's primary variables. The third, fourth, and fifth sections discuss how studies have empirically examined the adoption of EHR, its performance in regard to patient safety, and the effect of fit on healthcare organization performance in the past, respectively. Based on the information gleaned from the five sections, section six presents the fit and potential contribution of this study to the corpus of existing literature that have explored similar research questions.

Electronic Health Record and Evolution

Since the advent of HIT in the 1960s, hospitals have utilized them in some form to support a diverse range of activities, and their purpose has increased in scale and scope (McCullough, 2008). HIT generally consists of technologies that help healthcare providers to administer care for patients through the use and exchange of secure health information (Department of Health and Human Services, 2012). EHR represents just one aspect of HIT, and other dimensions of HIT may include "the ability to exchange data electronically across organizations (known as health information exchange) or to collect electronic data for disease surveillance" (Jha et al., 2006; p.w498). An EHR is an electronic version of the hand written medical record, which traditionally was used to document important clinical and administrative-related information about patients and patient care. Systems designed around the fundamental characteristics of the EHR also present healthcare organizations the opportunity to integrate and automate many, diverse tasks and the ability to communicate between each other, with the overarching goal of improving the delivery of healthcare and patient outcomes.

Early efforts to apply the EHR concept began in a few academic medical centers and large businesses that recognized the value of this emerging HIT early on and attempted to develop their own systems (Amataykul, 2004). Initially known as clinical information systems, some well-known EHR products were developed by Massachusetts General Hospital and Lockheed. However, healthcare organizations, at the time, lacked source systems (e.g., laboratory information systems) that were needed to supply data for EHR systems (Amataykul, 2004). A growing consensus began to emerge that ancillary applications that documented provider's notes, presented laboratory information and radiology results, and allowed for electronic prescribing (i.e., Computerized provider order entry) were necessary to enhance the future value of EHR (Amataykul, 2004; Jha et al., 2006).

In the 1970s, the Department of Veterans Affairs began implementation of its EHR, known as the Veterans Health Information Systems and Technology Architecture (VistA) (Atherton, 2011). VistA is now widely used throughout the Veterans Health Administration system and can supply healthcare information on veterans across approximately 160 hospitals, 800 clinics, and 130 nursing homes throughout the U.S., using a single electronic healthcare information network (Veterans Health Administration, 2012).

The Institute of Medicine made a concerted effort to increase EHR use during the late 1980s and 1990s (Atherton, 2011). Two Institute of Medicine reports, published in 1991 and revised in 1997, made a strong case for EHR adoption. Aside from replacing the hand written patient record, the Institute of Medicine argued that EHR served as a broader vision for the conventional patient record (Atherton, 2011). The technology was to be a resource that could "provide accurate longitudinal account of care, in management of the healthcare system, and in extension of knowledge" (Institute of Medicine, 1991; p.3).

The Institute of Medicine published another set of reports which emphasized the potential relationship of HIT, such as EHR, to patient safety, medical costs, and quality (Institute of Medicine, 2000; 2001). As several actors in the healthcare arena started to take note of the relevance of EHR in a system that was overshadowed by criticisms of escalating costs and poor quality in the 2000s, President George Bush also made it an imperative for HIT, such as EHR, to become a mainstay in the U.S. healthcare system. With the promulgation of Executive Order 13335 in 2004, a new department, The Office of the National Coordinator for Health Information Technology, was created under the Department of Health and Human Services to promote and enable the implementation of EHR across the healthcare system (Atherton, 2011).

More recently, President Barack Obama incorporated EHR into the American Recovery and Reinvestment Act (ARRA) of 2009 as part of the HITECH Act and the ACA of 2010. The ARRA included $19 billion in funds to help promote the adoption and use of HIT, especially EHR (Kropf, 2011). The HITECH Act offered incentive payments for the meaningful use of a certified EHR for providers and hospitals that participated in the Medicare and Medicaid programs. The purpose of meaningful use generally includes "electronically capturing health information in a coded format, using that information to track key clinical conditions, communicating that information in order to help coordinate care, and initiating the reporting of clinical quality measures and public health information" (Blumenthal, 2010; p.383). The Centers for Medicare and Medicaid Services (CMS) listed 24 objectives for hospitals that must be pursued in order for them to work towards the first stage, of three increasingly stringent stages, of EHR meaningful use (Centers for Medicare and Medicaid Services, 2012). If Medicare eligible hospitals failed to achieve 19 of the 24 objectives by 2015, then the HITECH Act provisions for financial penalties against these providers would take effect (Kropf, 2011).

Efforts by the Bush and the Obama administration, in summary, represent the preliminary efforts to promote and standardize the use of HIT and EHR. But, the current pattern of HIT and EHR adoption and their use in the healthcare system is diverse and fragmented, mainly based on the needs, capabilities, and resources available to healthcare organizations.

Measurement of Key Study Variables

Measurement of electronic health record.

EHRs exist in great variety and, as a result, have led to varying interpretations and assumptions of what exactly an EHR is and how an EHR system should function in a healthcare facility. Often, the term electronic medical record (EMR) has been used interchangeably with EHR, but information about a patient is intended to be more comprehensive in an EHR since it should contain data collected from several healthcare providers and facilities (Office of the National Coordinator for Health Information Technology, 2012). Healthcare Information and Management Systems (HIMSS, 2012; "Electronic Health Records," para.1) define EHR as,

> 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. The EHR automates and streamlines the clinician's workflow. The EHR has the ability to generate a complete record of a clinical patient encounter - as well as supporting other care-related activities directly or indirectly via interface - including evidence-based decision support, quality management, and outcomes reporting.

The above definition lists several characteristics that an EHR may possess. Although various institutions and groups have developed definitions of EHR, there has been little consensus on what functionalities should constitute the essential features of an EHR system present in hospitals (Jha et al., 2009).

In prior research, studies have tended to overlook their selected application's functional relevance to an integrated and automated clinical environment (Cutler, Felmand, & Horowitz, 2005), and have instead focused more on just the adoption trends and their unique contributions to hospital performance. For example, Cutler et al. (2005) used a categorical variable to measure four different levels of CPOE implementation in a hospital, which were defined using standards provided by the Leapfrog Group. Furukawa et al. (2008) used binary variables for eight different EHR applications and a count variable based on the presence of any of these applications in a hospital. McCullough (2008) used binary variables for three EHR applications in his study. The result of measuring EHR in the previously noted examples has been the presence of inconsistent results of EHR adoption on performance, since the evaluation of different applications, with potentially varying levels of automation, may have led to very different empirical findings (Cutler et al., 2005).

In an attempt to remedy this shortcoming, Furukawa et al. (2010a; 2011) and Jha et al. (2009) presented two very similar models of EHR adoption in hospitals. Their classification of EHR applications were based on clinical functionality, which in turn provided a clearer picture of how different sets of complementary applications helped provide minimal (i.e., basic systems) or more sophisticated (i.e., comprehensive systems) support and automation to hospital clinical work processes.

The Jha et al. (2009) measure of EHR is based on a survey, administered by the AHA, asked survey respondents to report on the presence or absence of various clinical functionalities (e.g., clinical documentation of medication lists and nursing assessments). The survey's construction was driven by questions present in earlier HIT surveys. Based on the review of an expert panel, 24 functions, present in the survey, were noted as being essential to a comprehensive EHR system that should be present in all major clinical units of the hospital. Similarly, the expert panel indicated that the presence of eight functionalities, in at least one clinical unit, would represent the presence of a basic EHR system. Table 1 presents the EHR requirements that belong to the two groups of EHR sophistication identified by Jha and colleagues.

The Furukawa et al. (2010a) measure of EHR is also based on a survey, administered by the HIMSS, of healthcare providers that requires respondents to report on the presence or absence of several EHR applications and functionalities. The measure's construction is based on the HIMSS EMR Adoption Model (Garets & Davis, 2008), which classifies the cumulative capabilities of a hospital EHR system based on the adoption of certain applications. Furukawa et al. (2010a) classified hospitals into three groups based on levels of cumulative electronic health record sophistication: EHRS1, EHRS2, and EHRS3, with higher levels representing greater EHR sophistication. Eight major clinical applications were considered in the categorization of the hospitals' EHR groups. EHRS1 contains four applications; EHRS2 additionally includes two more applications; and EHRS3 further includes two more applications. Table 2 presents the EHR applications that belong to the three groups of EHR sophistication identified by Furukawa and colleagues.

Neither the Jha et al. (2009) nor the Furukawa et al. (2010) measures have been empirically validated for internal consistency, and are noted only for their face validity based on a consensus agreement among experts as to what applications should constitute different levels of EHR sophistication. Both measures also have a very similar notion of basic EHR

Table 1

Taxonomy of Electronic Health Record Applications Proposed by Jha and Colleagues[1]

Electronic Health Record Requirements	Comprehensive Electronic Health Record	Basic Electronic Health Record
Clinical documentation		
Demographic characteristics of patients	Yes	Yes
Physicians' notes	Yes	-
Nursing assessments	Yes	-
Problem lists	Yes	Yes
Medication lists	Yes	Yes
Discharge summaries	Yes	Yes
Advanced directives	Yes	-
Test and imaging results		
Laboratory reports	Yes	Yes
Radiologic reports	Yes	Yes
Radiologic images	Yes	-
Diagnostic-test results	Yes	Yes
Diagnostic-test images	Yes	-
Consultant reports	Yes	-
Computerized provider-order entry		
Laboratory tests	Yes	-
Radiologic tests	Yes	-
Medications	Yes	Yes
Consultation requests	Yes	-
Nursing orders	Yes	-
Decision support		
Clinical guidelines	Yes	-
Clinical reminders	Yes	-
Drug-allergy alerts	Yes	-
Drug–drug interaction alerts	Yes	-
Drug–laboratory interaction alerts	Yes	-
Drug-dose support	Yes	-

[1] Source: Jha et al., 2009; Table 3.

Table 2

Taxonomy of Electronic Health Record Applications Proposed by Furukawa and Colleagues[2]

EHR Applications	EHRS1	EHRS2	EHRS3
Pharmacy information system	Yes	Yes	Yes
Laboratory information system	Yes	Yes	Yes
Radiology information system	Yes	Yes	Yes
Clinical data repository	Yes	Yes	Yes
Nursing documentation	-	Yes	Yes
Electronic medication administration record	-	Yes	Yes
Clinical decision support	-	-	Yes
Computerized provider order entry	-	-	Yes

Note: EHR=electronic health record. EHRS=electronic health record sophistication. EHRS1, EHRS2, and EHRS3 indicate increasing levels of sophistication.

functionalities that emphasize on the presence of information from ancillary services such as laboratory results and radiology reports.

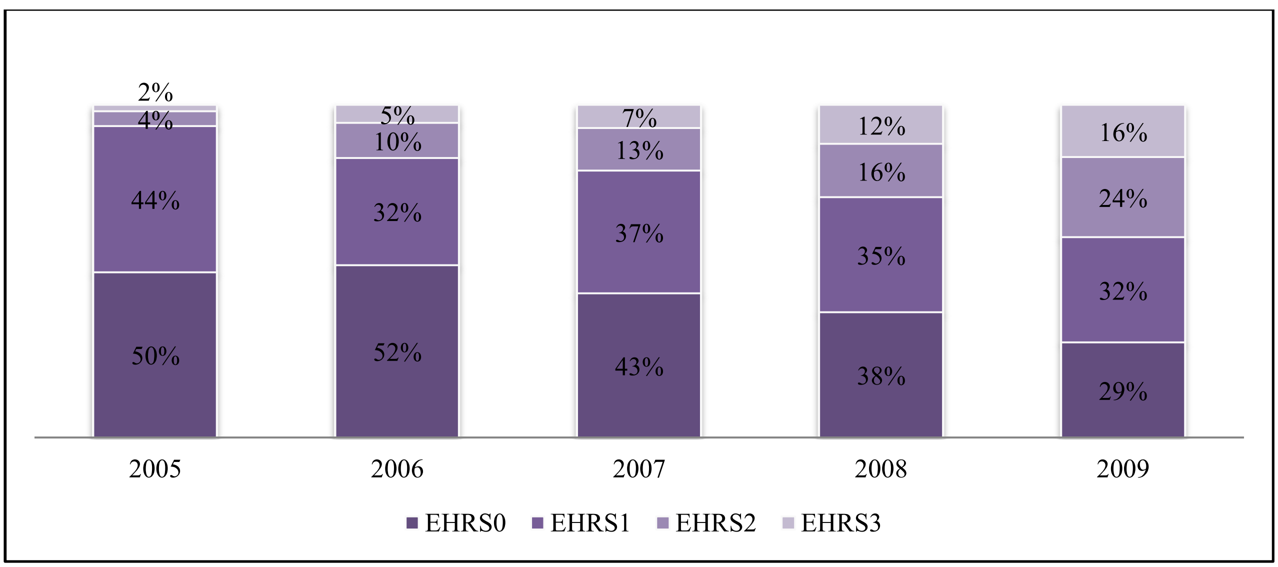
However, the Jha et al. (2009) measure specifically captures processes, within applications, that can address the requirements (e.g., presence of applications to perform drug-drug or drug-allergy checks) prescribed by the HITECH meaningful use provision. The Furukawa et al. (2010a) measure, conversely, focuses on the presence of certain applications that may allow providers to potentially perform many of the EHR functionalities as noted in the meaningful use requirements and the HIMSS definition of EHR. Appari, Johnson, and Anthony (2012), in particular, modeled their study of EHR performance based on the Furukawa et al. (2010a) definition of EHR. The authors noted that the meaningful use objectives required hospitals to undertake certain clinical and administrative activities, but that their measure was only able to show that hospitals were capable of performing such tasks rather than accomplishing them (Appari et al., 2012).

[2] Source: Furukawa et al., 2010a; Appendix Table 1.

The Furukawa et al. (2010a) definition of EHR will be used in this study since it relies on one of the primary datasets (i.e., HIMSS) available for this study's evaluation, which also has data for all the study years evaluated. The Jha et al. (2009) definition also requires hospitals to have adopted an exhaustive set of applications in order to be categorized as a sophisticated EHR adopter, which may consequentially eliminate several hospitals that do not belong to this category of leading adopters (McCullough, Casey, Moscovice, & Prasad, 2010). Also information based on the Jha et al. (2009) measurement was first made available only in 2007 through the AHA HIT survey. This survey contains fewer hospitals (approximately 3,000 in 2007) than the HIMSS survey, and does not have responses from hospitals for all the years used in this study.

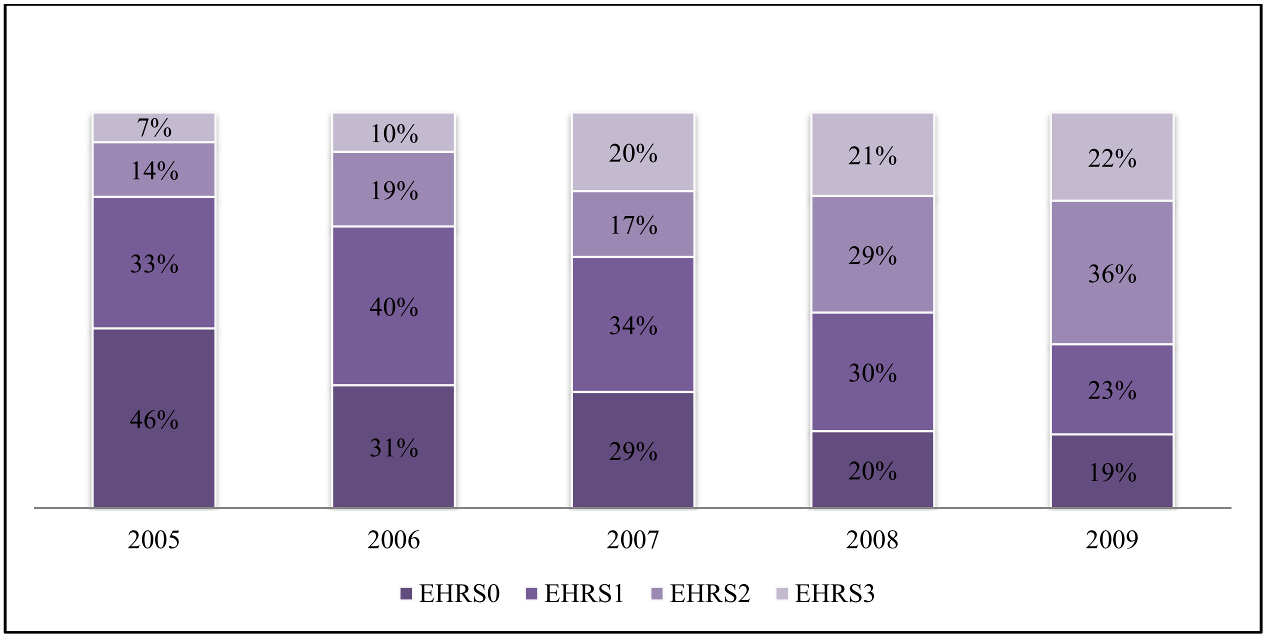
Figure 1 illustrates the general nature of EHR presence based on various levels of sophistication for non-federal, short-term, and acute care hospitals in the U.S. for the time period 2005-2009. Also, Figure 2 presents the diffusion of EHR across this study's sample hospitals.

Figure 1. Proportion of EHRS1, EHRS2, EHRS3, and EHRS0 (i.e., Not EHRS1, EHRS2, or EHRS3) in National Sample, 2005-2009



Note: EHRS=electronic health record sophistication.

Figure 2. Proportion of EHRS1, EHRS2, EHRS3, and EHRS0 (i.e., Not EHRS1, EHRS2, or EHRS3) in Study Sample, 2005-2009



Note: EHRS=electronic health record sophistication.

Hospitals that did not belong to any of the EHR sophistication groups (i.e., EHRS0) are also included in the above charts. In regard to Figure 1, the general trend over the study period indicates an increasing presence of EHR applications, with almost 70 percent of hospitals in the national sample having some level of EHR sophistication by 2009 versus the 50 percent level of presence in the base year. The chart also sheds light into another important dimension: hospitals increasingly switched to more sophisticated applications. The rates and levels of hospitals having applications related to the EHRS2 and EHRS3 groups rose over the study period. The year 2008 also experienced a marked increase in EHRS3 presence. The patterns present in Figure 2 illustrate similar trends among the study sample hospitals. Nonetheless, although the composition of EHR groups were quite similar for the study sample and national sample in 2005, the proportion of hospitals that had some level of EHR sophistication was greater for the study sample versus the national sample by 2009. The rates and levels of EHRS2 and EHRS3 adoptions were also typically higher among the study sample hospitals than the national sample over the five-year study period.

Measurement of postoperative sepsis.

Sepsis is generally described as a "medical condition in which the immune system goes into overdrive, releasing chemicals into the blood to combat infection (microbes in the blood, urine, lungs, skin, or other tissues) that trigger widespread inflammation (cellular injury in body tissues)" (Chang, Lynm, & Glass, 2010; p.1856). Postoperative sepsis is an example of patient safety events that result from medical mistakes and complications that should not have occurred at the time patients were provided care in a hospital (Encinosa & Bae, 2011).

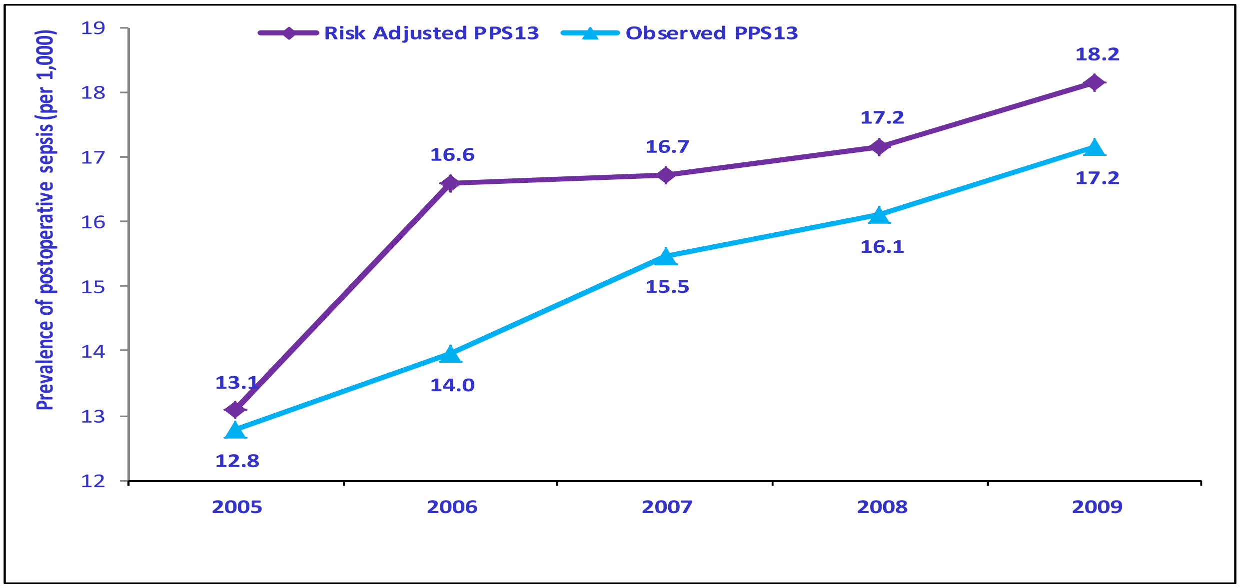
Medical records generally provide high quality and reliable clinical information for studies that investigate patient safety errors (Zhan & Miller, 2003a). But, information from these records may not be easy to extract and such records may not provide sufficient scope or statistical power (i.e., due to small study sample sizes) for researchers (Zhan & Miller, 2003a). Administrative data are a recognized source of patient safety data (Tsang, Palmer, Bottle, Majeed, & Aylin, 2012) that are "readily available, inexpensive, computer readable, typically continuous, and cover large populations" (Zhan & Miller, 2003a; p.58). Moreover, sepsis has been previously determined to be "reliably identified using administrative records; the specificity and positive predictive value of sepsis coding in administrative data are 99% and 89%" (Eber, Laximinaryan, Perencevich, & Malani, 2010; p.348).

Algorithms created by the Agency for Healthcare Research and Quality (AHRQ), known as the patient safety indicator (PSI), may be applied to administrative data to identify adverse events based on patient diagnoses codes (e.g., ICD-9 codes). Postoperative sepsis is one of 20 conditions that can be computed by executing AHRQ's PSI algorithm on administrative data such as state inpatient discharge data (Agency for Healthcare Research and Quality, 2011).

In their 2012 review of studies that used patient safety measures, Tsang and colleagues found many of their studies to have used measures associated with adverse surgical events, which were predominantly generated by AHRQ's PSI algorithms (Tsang et al., 2012). Postoperative sepsis represents one of the most common surgical PSI measures used by patient safety performance studies in the past. In terms of prevalence, the observed rate of postoperative sepsis cases rose continuously from 13 per 1000 cases in 2005 to approximately 17 per 1000 cases in 2009 among the hospitals present within the study's sample. Once risk-adjusted, the increase in rate per 1000 was slightly higher for all the years as presented in Figure 3. A similar trend may be noted among hospitals nationwide based on the trajectory of principal and secondary sepsis cases as presented in Figure 4.

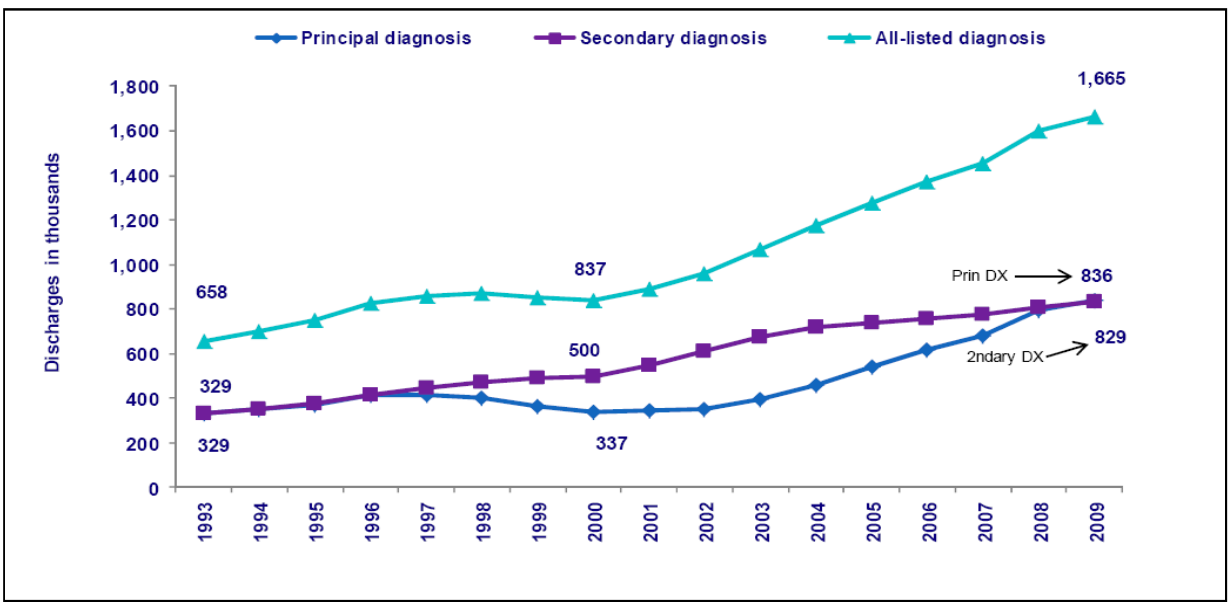
Health services research studies have incorporated the postoperative sepsis PSI at the patient and the hospital levels of evaluation. Also, a few studies have examined the occurrence of preventable postoperative sepsis specifically, whereas most studies have examined postoperative sepsis as one of many potential adverse events that could arise during a hospitalization. In particular, Zhan and Miller (2003b) examined the occurrence of preventable postoperative sepsis, along with the occurrence of several different other PSIs. Encinosa and Bernard (2005), on the other hand, used a surgical PSI composite that included not only preventable postoperative sepsis but eleven other PSIs. It is important to note that a problem with using a composite measure is that it may mask a negative effect on one PSI indicator when another PSI might be improving. This, as a result, may erroneously suggest that the performance of a specific

Figure 3. Prevalence of Postoperative Sepsis in Study Sample Hospitals, 2005-2009



Note: PPS13=postoperative sepsis rate.

Figure 4. Prevalence of Principal and Secondary Diagnosed Septicemia Discharges in Hospitals, 1993-2009[3]



patient safety measure may not be improving when, in reality, the performance change of that measure was offset by one or more other patient safety measures also present in the composite.

[3] Source: Elixhauser, Friedman, & Stranges, 2011; p.3; Figure 1.

Adoption of Electronic Health Record Applications

Studies investigating the adoption of EHR applications typically focused on their presence and the various environmental and organizational features that may be linked with their adoption. A summary of their findings is provided in Table 3.

Table 3

Summary of Electronic Health Record Application Adoption Studies

Study	**Hospital Sample/Study Year(s)**	**Main Explanatory Variable(s)**	**Main EHR Functionality Variable(s)**	**Significant Results**
Cutler et al. (2005)	751 hospitals for 2002/2003	Net income per admission, system affiliation, ownership status, & teaching.	Categorical variable that indicated four possible implementation levels of CPOE.	Teaching, public, & for-profit hospitals (+ve) level of CPOE implementation.
McCullough (2008)	1,965 hospitals for 1990 to 2000	Teaching status, ownership, system membership, case mix index, adjusted admissions, outpatient visits as a proportion of adjusted admissions, & payer mix, 1990 billing system adopter, HHI, market share, & proportion of hospitals within a market that previously adopted HIT.	Binary variables for three applications: laboratory, pharmacy, & radiology systems.	System affiliation & adjusted admissions (+ve) all three applications. Medicare (+ve) pharmacy. Case mix (+ve) laboratory. Medicaid (-ve) radiology & laboratory. Proportion of previous adoption (-ve) laboratory & pharmacy. Proportion of previous adoption interacted with time (-ve) pharmacy.
Furukawa et al. (2008)	4,561 hospitals for 2006	Bed size, teaching status, system affiliation, ownership status, payer mix, CBSA size, & JCAHO accreditation status.	Binary variables for eight applications: EMR, CDS, CPOE, BarD, ROBOT, ADM, eMAR, & BarA; a count variable of all eight applications.	Bed size (+ve) all applications & count. For-profit & public (-ve) EMR, CPOE, & count. Teaching status (+ve) ROBOT & count. System affiliation (+ve) all, except CPOE, ROBOT, & BarA. Medicare (-ve) CPOE, BarD, eMAR, count variable. Medicaid (-ve) eMAR. CBSA size (-ve) CPOE, ROBOT, & count. JCAHO status (+ve) all, except ROBOT.

Table 3 (continued)

Study	Hospital Sample/Study Year(s)	Main Explanatory Variable(s)	Main EHR Functionality Variable(s)	Significant Results
Jha et al. (2009)	2,952 hospitals for 2008	Bed size, region, ownership status, teaching status, system affiliation, urban location, & dedicated coronary care unit.	Binary variable of EHR based on presence of 24 electronic functionalities (comprehensive EHR) or presence of 10 functionalities (basic EHR).	Size, teaching status, system affiliation, urban location, & dedicated coronary artery unit (+ve) EHR.
Jha et al. (2010)	3,101 hospitals for 2009	Bed size, ownership status, teaching status, system affiliation, & urban location.	Binary variable of EHR based on presence of 24 electronic functionalities (comprehensive EHR) or presence of 10 functionalities (basic EHR).	Size, teaching status, & urban location (+ve) EHR. Public (-ve) EHR.

Note: ADM=automated dispensing machines. BarA=bar-coding at medication administration. BarD=bar-coding at medication dispensing. CBSA=core based statistical area. CDS=clinical decision support. CPOE=computerized provider order entry. EHR=electronic health record. eMAR=electronic medication administration records. EMR=electronic medical record. HHI= Herfindahl-Hirschman Index. HIT=health information technology. HMO=healthcare maintenance organization. JCAHO=joint commission on accreditation of healthcare organizations. MSA=metropolitan service area. PPO=preferred provider organization. ROBOT=robot for medication dispensing. +ve=positive relationship. -ve=negative relationship.

The empirical technique used to test study hypotheses primarily involved multivariate regression models. Whereas McCullough (2008) used a multi-year study, the majority of studies in this group used cross-sectional samples. Also, the primary datasets used in the studies included HIMSS Analytics (Furukawa et al., 2008; McCullough, 2008), AHA Annual Surveys (Jha et al., 2009; 2010), and Leapfrog Group's Hospital Patient Safety Survey (Cutler et al., 2005). Several of the studies listed in Table 3, found significant relationships between market or hospital characteristics and the adoption of specific EHR applications (e.g., CPOE, laboratory information system) or a group of applications that represent a comprehensive EHR system. Hospital size and teaching status were typically good predictors of EHR application adoption among the studies.

Relationship of Electronic Health Record and Patient Safety Outcomes

Previous studies provide evidence that various EHR applications may be associated with lower rates of adverse patient safety outcomes, especially those stemming from medication errors (Bates, et al., 2001; Chaudhry et al., 2006; King, Paice, Rangrej, Forestell, & Swartz, 2003; McCullough et al., 2010; Shamliyan, Duval, Du, & Kane, 2008). Many of the studies of this nature were discussed in Chaudhry et al. (2006), which was a systematic review of prior EHR research. Issues that he and his colleagues identified in this literature included: limited samples, a focus on academic institutions, and examination of a small number of geographical areas. Chaudhry et al. (2006) also noted that only a handful of studies examined the effects of EHR applications on a range of patient safety events.

Subsequent to the Chaudhry et al. (2006) review, however, there have been many new studies, using both cross-sectional and longitudinal samples and examining a range of outcome measures specifically related to patient safety (Amarasingham, Plantinga, Diener-West, Gaskin, & Powe, 2009; Dowding, Turly, & Garrido, 2012; Culler, Hawley, Naylor, & Rask, 2007; Encinosa & Bae, 2011; Furukawa, 2011; Furukawa et al., 2010a; Menachemi, Saunders, Chukmaitov, Matthews, & Brooks, 2007; Parente and McCullough, 2009). A summary of their findings is provided in Table 4.

Table 4

Summary of Patient Safety Performance Studies

Study	Hospital Sample/Study Year(s)	Main EHR Functionality Variable(s)	Main Patient Safety Variable(s)	Significant Results
Amarasingham et al. (2009)	41 hospitals for 2006	Four variables measured by level of automation: test results, notes & records, order entry, & decision support.	Inpatient complications related to AMI, HF, CABG, & Pneumonia.	Decision support (-ve) complications for all patients & AMI patients. Notes & records (-ve) HF.

Table 4 (continued)

Study	Hospital Sample/Study Year(s)	Main EHR Functionality Variable(s)	Main Patient Safety Variable(s)	Significant Results
Dowding et al. (2005)	29 hospitals for 2003 to 2009	Binary variable: adoption of KP Health Connect (contains CPOE, CDS, communication & documentation of all inpatient & outpatient laboratory, pharmacy, & clinical care activities).	Fall rates & HAPU.	KP Health Connect (-ve) HAPU.
Culler et al. (2007)	66 hospitals for 2003/ 2004	Three variables: 1) summary index of 96 applications, 2) summary index of 56 functional applications, & 3) summary index of 21 technological devices.	AHRQ PSI: Complications of AC, DLMD; DU; FTR; FOREIGN; IP; INFX; PHF; PHH; PPMD; PRF; PPE/DVT; PSEP; PWOUND; PUNC/LAC.	All application index, functional index, & technological devices index (-ve) PHH. Functional index (-ve) FOREIGN.
Encinosa & Bae (2011)	2,619 hospitals for 2007	Binary variable of basic EHR based on presence of eight functionalities.	Composite measure based on all AHRQ PSIs.	No significance reported.
Furukawa (2011)	3,048 hospitals for 2004 to 2008	Binary variables for three levels of increasingly sophisticated EHR: EHRS1, EHRS2, & EHRS3.	Total falls, injurious falls, & HAPU.	One year post implementation: EHRS1 (+ve) falls EHRS2 (+ve) falls EHRS3 (+ve) falls & injurious falls Two years post implementation: EHRS1 (+ve) HAPU EHRS2 (+ve) HAPU.
Furukawa et al. (2010a)	326 hospitals for 1998 to 2007	Binary variables for three levels of increasingly sophisticated EHR: EHRS1, EHRS2, & EHRS3.	Composite measure of all AHRQ PSIs; DU; FTR; INFX.	Two years post implementation: EHRS1 (+ve) composite Three years post implementation: EHRS3 (+ve) composite.
Menachemi et al. (2007)	98 hospitals for 2003	Three variables: summary index of 25 clinical applications, 2) summary index of 21 administrative applications, & 3)	All AHRQ PSI measures.	Clinical HIT (-ve) DLMD, DU, & PSEP. Administrative HIT (-ve) DU. Strategic HIT (-ve) INFX, PHF, PRF, PSEP, PWOUND, & PUN/LAC.

Table 4 (continued)

Study	Hospital Sample/Study Year(s)	Main EHR Functionality Variable(s)	Main Patient Safety Variable(s)	Significant Results
		summary index of 10 strategic applications.		
Parente & McCullough (2009)	2,707 for 1999 to 2002	EHR, nurse charts, & PACS.	Three AHRQ PSIs: INFX; PHH; PPE/DVT.	EHR (-ve) INFX.

Note: AC=complications of anesthesia. AHRQ=Agency for Healthcare Research and Quality. AMI=acute myocardial infarction. CABG=coronary artery bypass graft. CDS=clinical decision support. CPOE=computerized provider order entry. DLMD=death in low-mortality DRGs. DU=decubitus ulcer. EHR=electronic health record. EHRS=electronic health record sophistication. FOREIGN=foreign body left during procedure. FTR=failure to rescue. HAPU=hospital acquired pressure ulcer. HF=heart failure. HIT=health information technology. INFX=selected infections due to medical care. IP=iatrogenic pneumothorax. KP=Kaiser Permanente. PACS=picture archiving and communication system. PPE/DVT=postoperative pulmonary embolism or deep vein thrombosis. PHF=postoperative hip fracture. PHH=postoperative hemorrhage or hematoma. PPMD= postoperative physiologic and metabolic derangements. PRF=postoperative respiratory failure. PSEP=postoperative sepsis. PUNC/LAC=accidental puncture or laceration. PWOUND=postoperative wound dehiscence. +ve=positive relationship. -ve=negative relationship.

Among the above listed studies, Menachemi et al. (2007) found a significant relationship between clinical HIT (i.e., applications that provide information on diagnosis, treatment planning, and evaluation of medical outcomes) and reduced hospital acquired sepsis outcomes. Dowding et al.’s (2012) evaluation presented mixed findings, where an advanced EHR system was associated with a decreased rate of hospital acquired pressure ulcers, but the system did not have an effect with fall rates. Furukawa (2011) and Furukawa et al. (2010a) examined the differential effects of EHR, based on their length of adoption, and found a few significant associations between some groups of EHR applications and an increase in certain patient safety outcomes during the early stages of implementation. In general, studies similar to the ones just described did not account for endogeneity attributable to heterogeneity bias (unobserved, time-invariant hospital-specific factors) or simultaneity bias (EHR adoption is not strictly exogenous; the current or past values of the error term are correlated).

Encinosa and Bae (2011) accounted for endogeneity issues, related to simultaneity bias (e.g., between hospital quality and EHR), using instrument variables only to find that basic EHR did not significantly reduce the rate of postsurgical related and nursing related patient safety events. Their measure considered whether hospitals had eight basic EHR functionalities that included demographic characteristics of patients, problem lists, medication lists, discharge summaries, laboratory reports, radiologic reports, diagnostic test results, and CPOE. Unlike Furukawa et al. (2010a) the authors only examined a composite outcome measure (i.e., a summary score of several postoperative patient safety conditions) and thus, the potential relationships of EHR on specific clinical outcomes were not assessed.

Two recent systematic reviews of the EHR literature (Lau, Kuziemsky, Price, & Gardner, 2010; Buntin, Burke, Hoaglin, and Blumenthal, 2011) presented contradictory conclusions about EHRs influence on hospital performance. Lau et al. (2010) concluded from their review of 1994 to 2008 literature that EHR applications may be associated with some improved outcomes (e.g., medication errors), but a majority of the relationships for studies that used adverse patient safety outcomes were statistically insignificant. The Buntin et al. (2011) review of 2007 to 2010 studies, however, led them to conclude that a majority of the EHR studies presented results that suggested improved performance, a pattern that was also present in the subgroup of studies that investigated patient safety. Potential explanations for different conclusions between the initial and more recent review include the wider scope of hospitals evaluated (e.g. academic and non-academic hospitals) and the incorporation of meaningful use dimensions in the measurement of EHR (Buntin et al. 2011). Both reviews, regardless of their conclusions, also underscored the possibility of EHR applications being associated with observing higher rates of adverse events due to the resulting complexities that may arise between a technology's design and a clinician's workflow or due to the better documentation of patient conditions (Buntin et al., 2011; Lau et al., 2010).

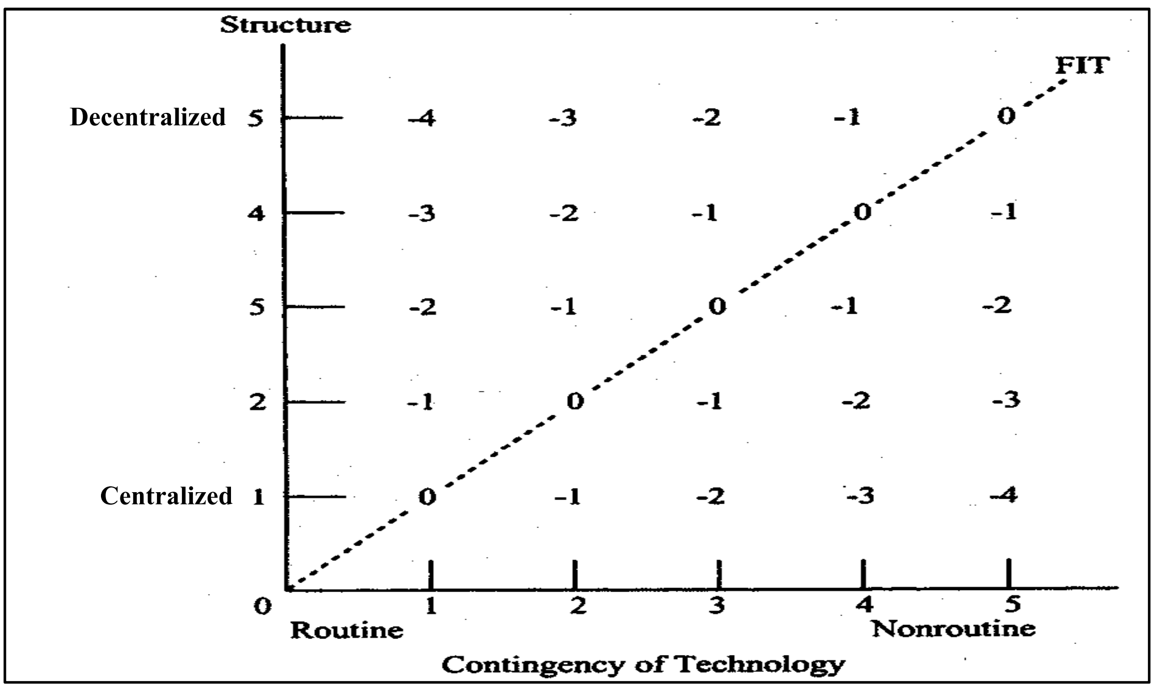
Hospital Fit and Performance

The studies in this group explored the relationships between technology and structure on performance (e.g., Alexander & Randolph, 1985; Dalton, Tudor, Spendolini, Fielding, & Porter, 1980; Miles, Snow, Meyer, & Coleman, 1978). The studies that utilized such a perspective also predominantly used Structural Contingency Theory (Donaldson, 2001; Leatt & Schneck, 1984), whose core tenet is that organizational outcomes are primarily determined by fit. Alexander and Randolph (1985) and Joyce, Slocum, and Von Glinow (1982) generally define fit as congruence which is based on an appropriate combination of the levels of certain contingencies, such as between technology and structure, that motivate higher performance in organizations. Fit exists when similar dimensions of the key independent variable pairs (i.e., technologies and structures) are matched either high or low; the resulting congruence of these variables may affect performance in different ways (Donaldson, 2001).

More specifically, theoretical and prior logic or empirical research is used to identify certain values of an organization's structure that fits best with different values of a technology. An organization, for example, with a high level of centralization in its structure may perform best with a technology that is routine (e.g., technology that is highly automated) – this forms one type of fit. Likewise, another organization with a high level of decentralization may perform best with a technology that is non-routine – this forms another type of fit. A similar logic may extend to other configurations (e.g., moderate centralization and moderate level of technology routines) as well. It is important to note, however, that fit relationships between technology and structure do not necessarily have to be linear, albeit organizations which do not have any of the ideal set of configurations are in misfit due to the misconfiguration of their structure and technology.

Figure 5 illustrates the previously described example: where, an organization in fit has constituent values that match each other (e.g., centralized structure and routine technology both have a value of 5), and the various, linear configurations of fit pass through the origin which has a 45 degrees slope. Whereas organizations in fit have a value of zero, those in misfit may have values that range from -4 to -1: dependent upon how far the technology level and structure are from each other (e.g., if centralized = 1 and nonroutine = 5, then fit = -4). In the case of a regression analysis, misfit is the residual or absolute residual from the regression of technology and structure (Pennings, 1987).

Figure 5. Organizational Performance Conceptualized by Fit/Misfit[4]



An apparent reality in the studies that have explored fit is the diversity of techniques used to construct the fit variable: along with the above described regression analysis, other means to construct the fit variable include subgroup analysis, correlations, count variables, and interaction terms (Donaldson, 2001). However, fit measures that are not derived from regression models

[4] Canvassed from Donaldson, 2001; p.211, Figure 7.2

may not effectively reflect the concept of fit as congruence or capture the notion of "iso-performance," in which the many different fit configurations may produce equally good performance outcomes (Donaldson, 2001). Also, an interacted fit measure may be "highly correlated with the terms that compose it, leading it to serious levels of multi-colinearity" (Dewar & Werbel, 1979; p.435), and the use of a categorical fit/misfit variable may eliminate a rich amount of variation present, which the fit measure from the regression analysis might retain.

Empirically, Alexander and Randolph (1985), Argote (1982) and Schoonhoven (1981) have successfully explored the fit between organizational structure and technology and its effect on performance in healthcare settings. A summary of their findings is provided in Table 5. These studies relied on surveys to measure the constituent variables that eventually formed the fit measures in the empirical analyses. However, the drawback of using survey measures is the inability for researchers to obtain responses from a large number of respondents (e.g., units or hospitals) – this may limit the level of variation present in the study sample and the measures and also be plagued by response bias. Early explorations of fit in healthcare organizations were based on cross-sectional samples and empirical models which contained few control variables to account for potential confounders in the relationship of fit and the dependent variables studied. Donaldson (2001) emphasized that researchers should avoid studies with cross-sectional samples and empirical models with few or no control variables since the fit results from these studies may be spurious or biased.

Hospital electronic health record performance and the concept of fit.

Karsch, Weingner, Abott, and Wears (2010) noted that there was inadequate contextual research to support effective HIT design and implementation. Furthermore, McCullough et al. (2010) echoed similar concerns by stating that "HIT value is truly context-driven" (p.652) and an

Table 5

Summary of Healthcare Specific Fit Studies

Study	Sample /Study Year(s)	Main FIT Variable(s)	Main Outcome Variable(s)	Significant Results
Alexandar & Randolph (1985)	27 nursing subunits (study years not available)	Three FIT measures: FIT1 = absolute difference between vertical participation & technology instability, FIT2 = absolute difference between horizontal participation & technology variability, & FIT3 = absolute difference between formalization & technology uncertainty. Fit constituent variables measured through a survey.	Quality of nursing care measured through a survey.	FIT2 (i.e., greater horizontal participation with greater technology variability) (+ve) quality of nursing care; FIT3 (i.e., greater formalization with greater technology uncertainty) (+ve) quality of nursing care.
Argote (1982)	30 ER units for 1979	Interaction of input uncertainty in ER unit & coordination methods (rules, scheduled meetings, authority, autonomy of the staff, policies of the unit, & mutual adjustment) used in ER unit, all measured through surveys. Also, subgroup analysis to assess relationships of coordination methods & quality during high input uncertainty & low input uncertainty.	Three surveyed measures of clinical efficiency in the ER:1) promptness of care, 2) quality of nursing care, & 3) quality of medical care.	For interaction & subgroup analyses: rules or authority coordination with low uncertainty (+ve) promptness of care. Autonomy of staff or policies of the unit with high uncertainty (+ve) promptness of care. Rules or authority with low uncertainty (+ve) quality of medical care. Autonomy of staff or policies of the unit with high uncertainty (+ve) quality of medical care.
Schoonhoven (1981)	17 operating rooms for 1974	Interaction terms of workflow uncertainty & structure (level of destandardization, decentralization, & professionalization), all measured through surveys.	Severe morbidity as measured by the risk-adjusted average rate for all surgical patients visiting the operating room.	High levels of decentralization or destandardization with low uncertainty (-ve) severe morbidity.

Note: ER=emergency rooms. +ve=positive relationship. -ve=negative relationship.

attempt to explore HIT value in hospitals “not only depend upon the installed technology but on the setting as well” (p.653). Although many of the empirical studies discussed in the previous section may have used control variables to adjust for confounding factors in the relationship between EHR applications and healthcare outcomes, these studies may not have completely accounted for the varying performance effects that might have resulted from the interaction of organizations' structures and their technology contingencies. As Galbraith (1973) noted, "there is no one best way to organize; however, any way of organizing is not equally effective" (1973; p.2).

HIT researchers have explored the concept of fit and its relevance to organizations' performance (Ammenweth, Iller, & Mahler, 2006; Berg, 2001; Heeks, 2006; Southon, Sauer, & Dampney, 1997; Lehoux, Sicotte, & Denis, 1999; Tsiknakis, & Kouroubali, 2009). A majority of these studies were qualitative in nature, where cases of fit or misfit between technology and organizations' structures were both common (Maryati, Stergioulass, & Zugic, 2007).

For example, in their study, Ammenweth, Iller, and Mahler (2006) noted that it was interesting to recognize that the same EHR system may be viewed as a success in one organizational setting, but as a failure or problem in another setting. Variations in settings, driven by differences in workflow, individuals, and patient characteristics, may be associated with different performance effects for a specific EHR (Ammenweth, Iller, and Mahler, 2006). Thus, the evaluation of an EHR application should not be isolated to just the quality of the EHR component, but should account for the interaction of different structural features present within a healthcare setting.

Furthermore, an organization's ability to achieve "optimal fit" may depend on its capacity to effectively match certain attributes of a technology with specific task features (e.g., work organization, task complexity, and task interdependencies). In Ammenweth, Iller, and Mahler's (2006) qualitative exploration of fit between task and technology in a single hospital setting, the authors initially discovered a poor fit between the nursing documentation system and nurse care plans. But, in light of an organizational restructuring intervention, the fit improved between the technology and task. The resulting enhancement in fit was also linked to higher perceived end-user (i.e., nurses) satisfaction.

In another study, however, the implementation of an EHR system was seen as a misfit with an organization's structure. Lehoux et al. (1999) described how the EHR system, which was designed to integrate tasks through radical changes in workflow, adopted by a healthcare organization was in misfit with the entrenched clinical workflow structure. The misfit, the authors noted, led to the EHR system complicating clinical and administrative tasks (e.g., identifying the appropriate clinicians to transcribe prescriptions or defining the ideal place, time, and method to place orders for patients) (Lehoux et al., 1999).

Fit and Contribution of Study

This study will build on the strengths of prior work by drawing on a multidimensional measure of EHR sophistication, developing strong study designs, and applying rigorous modeling techniques. More specifically, the study uses a validated typology (Furukawa, 2010a) of EHR applications that may help improve patient safety in hospitals. Longitudinal data, from multiple sources, on hospitals and their environments will be used to evaluate EHR presence and performance. This study uses an individual AHRQ PSI measure for the evaluation of hospital performance (i.e., postoperative sepsis), which may overcome some of the masking effects that would arise in the study of composite measures. This study will also perform multiple sensitivity analyses to ensure that the results from the primary empirical evaluations are robust across potentially different scenarios. This study will also address potential endogeneity issues typically present in the evaluation of the relationship between HIT and hospital performance that may bias the study findings.

Lastly, this study uses Structural Contingency Theory and prior literature to explore the potential application of fit by matching different EHR applications to specific organizational structures. It further assesses whether the appropriate fit between specific EHR applications and their structures lead to improved hospital patient safety performance.

Summary

In summary, Chapter 2 reviewed the concept of EHR, how studies have measured the key variables that will be used in this study, and discussed the existing literature related to the effect of hospital and market factors on EHR adoption and the effect of EHR on patient safety performance. Throughout this review, this study identified the positive aspects and gaps present among current studies. In light of the findings, the proceeding chapters will reflect a plan that incorporates the successful components present among the prior studies and, concurrently, overcomes shortcomings which specifically need to be examined when attempting to assess this study's research questions.

Chapter 3: Conceptual Framework

The underlying conceptual framework for the study relies on organizational theories and frameworks that have been previously used by health services researchers to explain the nature of technology adoption and how it might affect hospital performance. Oliver's (1991) model on organizational responsiveness, derived from Institutional Theory (DiMaggio & Powell, 1983; Meyer & Rowan, 1977) and Resource Dependence Theory (Pfeffer & Salancik, 1978), will be used to address the first research question: what organizational and environmental forces are associated with hospitals' having certain EHR applications. Donabedian's (1980) Structure-Process-Outcome model and Structural Contingency Theory (Donaldson, 2001) will be used to examine the second and third research questions: will hospitals that adopt EHRs have lower postoperative sepsis outcomes relative to those who do not adopt such applications and will hospitals that have a better fit between their organizational structures and technology have lower postoperative sepsis outcomes relative to those who do not have this type of fit.

This chapter contains four major sections. It will begin with an overview of Oliver's (1991) model and then derive hypotheses from this theoretical perspective to explain EHR adoption in hospitals. Section two will provide a discussion of the Structure-Process-Outcome framework (Donabedian, 1980) and present related hypotheses that describe the link between hospital EHR and patient safety performance. Section three will provide a synopsis of Structural Contingency Theory (Donaldson, 2001) and present related hypotheses that explain the association between hospital EHR fit and patient safety performance. Finally, the fourth section provides an illustration of the conceptual framework, which will be used in this study to develop the research plan in Chapter 4.

Hospital Adoption of Electronic Health Record

To address research question one, four hypotheses are derived based on Oliver's (1991) model of organizational behavior. Over time, hospitals experienced growing pressures to incorporate EHR in order to improve patient safety (Encinosa & Bae, 2011). These pressures emanated from various institutional forces, which are defined here as a combination of "cultural-cognitive, normative, and regulative elements that, together with associated activities and resources, provide stability and meaning to social life" (Scott, 2001; p.48). Facing contemporary norms – as influenced by the aforementioned forces – Institutional Theory posits that organizations will conform to these expected and accepted beliefs in the organizational environment in order to receive support and legitimacy (Scott & Davis, 2007). Meyer (1977) contended that such behavior can also help an organization muster support and confidence even in scenarios where there is no proven technical advantage from the adoption of a potentially rationalized myth, such as EHR. More specifically, in light of claims of better efficiency and quality of healthcare due to the adoption of EHR and the fear of not being viewed as "appropriate, rational, modern" (Meyer & Rowan, 1977; p.307), hospitals may simply adopt the technology in order to maintain legitimacy.

On the other hand, Resource Dependence Theory explains organization behavior as dependent on interactions with other organizations and its environment (Scott & Davis, 2007). Organizations depend on exchange for subsistence and make necessary accommodations to guarantee exchange relationships with other organizations. Active changes in a focal organization's structure and behavior reflect accommodations to demands and pressures and are intended to ensure that the organization can secure stable flows of resources from its environment (Pfeffer & Salancik, 1978). In regard to EHR, hospitals may adopt such technology in order to appease the expectations of important stakeholders who believe in the utility of EHR and have control of the flow of essential resources (e.g., money, patients) that the hospital depends upon.

Oliver (1991) incorporated Institutional and Resource Dependence Theory, and argued that both theories were focused on the constraints presented by the external environment. She noted that although Institutional Theory focuses on the ability of powerful stakeholders to shape and enforce beliefs, Resource Dependence Theory presupposes that power resides in those who control scarce resources. Together, these two theories provide a range of strategic responses for organizations. The responses range from conformity to resistance and an organization's choice of strategy is based on the nature of the institutional pressure it faces, which involve five motivators: cause, control, constituents, content, and context (Oliver, 1991). For this study, cause and control are discussed in tandem since they contain organizational behavior perspectives that are related.

When evaluating the nature of an organization's response to an institutional pressure to engage in certain types of activities (e.g., adoption of EHR), it is essential to delineate its level of eventual compromise. Oliver (1991) noted that organizations may enact different forms of strategic behaviors in response to pressures, and these range from organizations' conformance to the defiance of an institutional pressure. In the middle of this continuum of actions is another potential type of response, namely the strategy of compromise. In this case, organizations partially accept some elements of the institutional pressure in an effort to balance, pacify, or artificially abide by the expectations of those imposing the pressure (Oliver, 1991). Scott (1983) observed such behavior across hospitals that tended to conform to at least the minimum standards of expectations forced onto them by powerful institutional agents, while still trying to retain some level of organizational autonomy. Meyer and Rowan (1977) even described such behavior as organizations potentially engaging in “window dressing,” ceremonial pretense, or symbolic acceptance of institutional norms.

Likewise, the extent of a hospital’s compliance to institutional pressures to adopt EHR may differ. Some hospitals may fully comply with institutional pressures and extensively adopt EHR as represented by the adoption of the more sophisticated EHRS2 or EHRS3 stages, while others may resist the pressure to adopt any EHR. Hospitals may also engage in more simple “adoptions” of basic applications (i.e., EHRS1) that may be only “skin deep” (D’Aunno, Vaughn, & McElroy, 1999). As noted by McCullough (2008), applications that belong to EHRS1 represent the initial shift from organizations’ historical focus on HIT for financial and administrative purposes to clinical processes. EHRS1 applications are typically mature technology and easily integrated with the more prevalent billing systems present in almost all hospitals (McCullough, 2008), and thus require less effort to adopt EHR than the two more sophisticated EHR categories.

Legal mandates or coercion, a potential source of institutional pressure, are an important factor that could result in organizational action but these were not influential during the period examined by this study (i.e., 2005 to 2009). Governmental action after the period examined by this study was largely precipitated by the haphazard adoptions of HIT by hospitals and other providers in a hope to rationalize acquisition decisions. Notions such as meaningful use and EHR certification standards were intended to establish norms that hospitals would consider when adopting and operating their EHRs (Halamka, 2010).

Cause and control are two related constructs in Oliver's (1991) model that explain the reason and the sources behind institutional pressures, respectively. With regard to the former, organizations' understanding and agreeability with potential gains in social legitimacy or economic prowess might determine their choice to conform. As noted by Oliver's (1991) notion of control, a means through which organizations may obtain such perceptions of benefits may be through an assessment of their surrounding environment, which might concurrently be the source of an institutional pressure. Over time, the independent actions of hospitals and health providers collectively drove EHR adoption in the healthcare system. Actions of competitors who are in close proximity and the growing visibility of their adoption of EHR may motivate a focal hospital to adopt EHR (i.e., mimetic isomorphism) in order to avoid being behind in industry norms, and thus, maintain a hospital's competitive advantage and ensure its control of important resources (DiMaggio & Powell, 1991). Thus,

Hypothesis 1.1: The degree of local diffusion of EHR adoption in a market will be positively related to the likelihood that an individual hospital adopts EHR.

Constituents, another construct in Oliver's (1991) model, involve the organization's ability to manage the various expectations of its stakeholders in the environment. These actors represent the collective normative order of the organization's environment. Pfeffer and Salancik (1978) described a scenario in which a single constituent may manifest a concentration of power by being the sole provider of essential resources to a focal organization. In such a case, the organizations will actively consider the expectations of the powerful stakeholder before electing to conform or resist an institutional pressure. A hospital that is highly dependent upon a single payer source is a prime example of the type of organization that may not resist the pressures of the key stakeholder in an effort to maintain operational stability. Managed care organizations and public payer groups (i.e., Medicare and Medicaid) are examples of important stakeholders to a hospital that may have control of the flow of patients, services rendered, and reimbursement levels of patients under their respective programs, and thus influence hospitals' strategic decisions.

Hospitals may adopt EHR as a strategy to address managed care's pressure to improve quality (e.g., patient safety) and contain costs of care (Wang et al., 2005). Many managed care organizations have adopted pay-for-performance plans for providers, which in some instances contain bonuses tied to a hospital's HIT development efforts (Baker & Carter, 2005). Medicare patients require more intensive treatment, and hospitals with a high proportion of these patients may adopt EHR in order to reduce the costs associated with providing such treatment (McCullough, 2008). Conversely, hospitals with a high proportion of Medicaid patients may not adopt EHR since the marginal benefits may be lower for such patients and because these hospitals may not have the capital to afford EHR (McCullough, 2008). Hence,

> **Hypothesis 1.2: Hospitals' dependence on managed care and Medicare will be positively related to EHR adoption, while dependence on Medicaid will be negatively related to EHR adoption.**

Content encompasses the nature of the pressure to which an organization is forced to conform. One dimension of pressure within this construct includes the consistency of the pressure with an organization's goals. Many teaching hospitals have missions and educational goals that emphasize innovation as a means to advance the delivery of high quality healthcare (Fareed & Mick, 2011). These hospitals typically care for sicker populations that have higher complication rates as well (Jha et al., 2009). Their need to coordinate a variety of different types of complex procedures (McCullough, 2008) along with their mission to improve care delivery can make EHRs a highly attractive investment. Several studies (e.g., Cutler et al., 2005; Fonkych

&Taylor, 2005; Wang et al., 2005) have found that academic hospitals are more likely to utilize EHR applications. Thus,

> **Hypothesis 1.3: Teaching hospitals will have a higher likelihood of adopting EHR than non-teaching hospitals.**

Interconnectedness, an aspect of context, refers to the "density of interorganizational relations among occupants of an organizational field" (Oliver, 1991; p.170). Highly interconnected environments have several formal and informal channels through which the diffusion of institutional norms can easily occur, and thus hospitals may have to conform to ubiquitous norms that have been collectively agreed upon by all actors in a network (DiMaggio & Powell, 1983; Oliver, 1991). The degree of centralization in hospital systems is a method of building relational density, through an elaboration of collective myths and values (Meyer & Rowan, 1977), which in turn provides a medium through which the diffusion of expectations and practices may take place (Proenca, Rosko, & Zinn, 2000).Therefore,

> **Hypothesis 1.4: The degree of centralization in a hospital's system will be positively associated with EHR adoption.**

Performance Effects of Electronic Health Record

To address research questions two, two hypotheses are derived based on Donabedian's (1980) model. Donabedian's (1980) model of Structure-Process-Outcome provides a meaningful framework for explaining hospital efforts to improve surgical patient safety (Birkmeyer, Dimick, & Birkmeyer, 2004). Structure may be defined as "the relatively stable characteristics of the providers of care, of the tools and resources they have at their disposal, and of the physical and organizational settings in which they work" (Donabedian, 1980; p.81). Process refers to the specific manner in which care is delivered (Donabedian, 1980). It may refer to the interpersonal aspects of a clinician's interaction with patients, the correct diagnoses, prescription, and delivery of care vis-à-vis a patient's specific condition. Outcomes refer to a "patient's current and future health status that can be attributed to antecedent healthcare" (Doanbedian, 1980; p.82), and encompass the patient's overall health status and perceived satisfaction with the care he or she received.

The study reasons that EHR, as a structural component of a hospital, might contribute to the enhancement of care processes that may decrease postoperative sepsis events. EHR applications could help transform the processes of healthcare delivery to be more standardized and automated, which in turn might make the ability to predict, detect, and prevent postoperative sepsis more effective and efficient (Miller & Sim, 2004; Shortliffe, 1999). The timely access to accurate and comprehensive information (e.g., lab reports of patient's white blood cell counts), assessments of changes in the nature of care provided or patients' vitals (e.g., the use of an algorithm to detect potential systemic inflammatory response syndromes in a patient), and clinicians following evidence-based guidelines (e.g., the use of prophylactics, broad-spectrum antibiotics, or hand-washing) may all help with the prediction, detection, and prevention of the early symptoms of postoperative sepsis. Hence,

Hypothesis 2.1a: Adoption of EHR is associated with lower postoperative sepsis outcomes.

Concomitantly, hospitals' progress towards a more comprehensive EHR functionality, brought about by their adoption of increasingly sophisticated EHR applications, may represent enhancements to its structures and synergistic improvements in clinical processes as well (Jha et al., 2009; Furukawa et al., 2011). Hospitals, more specifically, may first experience improvements in coordination of patient information and ancillary clinical functions through the adoption of EHRS1 applications (Furukawa et al., 2011). EHRS2 might contribute to improvements in nursing related work processes and the administration of medication, while

EHRS3 adoption might subsequently help the processes related to clinical decision making and patient management (Staggers, Weir, & Phansalkar, 2008). The decision to adopt more sophisticated EHR applications may generally provide hospitals with a greater ability to predict, detect, and prevent postoperative sepsis. Hence,

> **Hypothesis 2.1b: The degree of EHR sophistication is associated with greater reductions in postoperative sepsis outcomes.**

Hospital Fit and Electronic Health Record Performance

To examine research questions three, two hypotheses are derived based on Donaldson's (2001) rendition of Structural Contingency Theory. Structural Contingency Theory departs from Donabedian's (1980) model in the conceptualization of structure. The latter framework views structure as a "relatively immutable characteristic," while the former theory incorporates strategic dimensions to structure that reflect an "organization's choice of mechanisms for communication, coordination, and integration of effort (Zin & Mor, 1998; p.356)."

Hage and Aiken (1969) argued that task uncertainty is the most relevant contingency to consider when evaluating organizations. Alexander and Randolph (1985) defined task uncertainty as "the degree to which work to be performed is difficult to understand and complex" (p.848). Argote (1982) also noted that incomplete information was a core theme that was present across much of the work surrounding task uncertainty. She further elaborated by stating that "incomplete information makes it difficult to predict the future states of many factors associated with an organization's environment or tasks (Argote, 1982; p.420)." Kazandjan and Lipitz-Snyderman (2010) noted that task uncertainty may be considered a "defining feature of the medical field (p.1108)," and the authors argued that various EHR applications may help reduce the task uncertainty in care delivery and ultimately help reduce waste and improve the appropriateness of care.

Technology (e.g., adoption of EHRS1, EHRS2, or EHRS3) and organizational structure (e.g., centralized or decentralized) must conceptually fit together for performance to be effective (Alexander & Randolph, 1985; Dalton et al., 1980; Miles et al., 1978). By making choices regarding fit, Alexander and Randolph (1985) noted that managers define the environments within which their organizations operate, and thus characterize the levels of task uncertainty that must be managed through technologies and structures

Zin & Mor, (1998) noted that a primary means through which an organization may account for its structural elements is through the centralization of activities. Centralization is where an organization's decision making is concentrated (e.g., at the corporate headquarters of an organization) and work tasks are specialized and standardized through the use of formal rules and procedures (Donaldson, 2001). In contrast, a decentralized organization is one in which decision making is spread across the organization, and there is relatively lower specialization and formalization (Donaldson, 2001). Additionally, organizational researchers (e.g., Alexander & Randolph, 1985; Burns & Stalker, 1961; Donaldson, 2001; Hage & Aiken, 1969) have typically proposed that the structural response to low uncertainty is increased centralization, while the structural response to high uncertainty is increased decentralization.

In regard to this study, clinicians in hospitals with EHR applications that belong to the more sophisticated EHR category might be able to experience lower task uncertainty due to the increased automation of work tasks. When linked with a centralized structure, these appropriately fit organizations may yield higher performance when compared to organizations with high task uncertainty but centralized structures. Likewise, clinicians in hospitals with less sophisticated EHR could experience higher task uncertainty, since lower automation of work tasks and greater clinician autonomy are present. When linked with less centralized structures, these organizations may demonstrate a better fit that might concurrently yield optimal performance when compared to organizations with low task uncertainty but decentralized structures.

Additionally, the system's approach (Miller, 1981) to understanding organizational performance maintains that more than one notion of fit may be present through many different structural features that match with a technology (Khandwalla, 1973). This approach, which accounts for several alternative patterns of interdependencies in organizations, provides a more holistic understanding of performance versus the single dimensional view of one contingency (Drazin & Van de Ven, 1985). In regard to this study, hospital managers may also need to consider two other minor contingencies: task complexity and task interdependence, which involves the fit of a hospital's EHR with the differentiation and integration dimensions of a hospital's structure, respectively.

Scott and Davis (2007) defined task complexity as the "number of different items or elements that must be dealt with simultaneously by the performer" (p.126). The hospital's EHR sophistication level and its level of structural differentiation may need to conceptually fit together for performance to be effective. Lawrence and Lorsch (1967) defined structural differentiation as ''the state of segmentation of the organizational system into subsystems, each of which tends to develop particular attributes in relation to the requirements posed by its relevant external environment'' (p.4).

Hospitals that adopt more sophisticated EHR applications might be able to better manage high task complexity, since there is an automation of intricate work processes (Woodward, 1965). Furthermore, it has been previously argued that organizations with sophisticated technology will be in fit when they have greater structural differentiation (Scott & Davis, 2007;

Thompson, 1967), where various, complex tasks are managed through self-sufficient organizational clusters within their specialized domains (e.g., hospital development of services based on different clinical functions), and thus, perform better than those with low task complexity coupled with more sophisticated technology. Conversely, hospitals with less sophisticated EHR applications may have less task complexity, since the presence of intricate and diverse work processes may be limited. Moreover, such organizations might be in fit when they have lower structural differentiation, and hence, perform better than those with high task complexity and low structural differentiation.

Scott and Davis (2007) defined task interdependence as the “extent to which the items or elements upon which work is performed or work processes themselves are interrelated” (p.126). The hospital’s EHR sophistication level and structural integration may also need to fit together for performance to be effective. Integration, the other structural element that manager’s might need to consider, is defined as ‘‘the process of achieving unity of effort among the various subsystems in the accomplishment of the organization’s task’’ (Lawrence & Lorsch, 1967; p.4).

Hospitals with more interdependent work processes would benefit more from highly sophisticated EHR applications in order to maximize the functionality and interoperability features of the technologies. Hospitals with EHR applications of a lesser sophistication level may not have such a high level of interdependence since their HIT objectives might be primarily designed to address ancillary activities (e.g., laboratory orders, radiology tests). Scott and Davis (2007) and Thompson (1967) have both noted that the optimal structure for more interdependence is increased integration, where highly interdependent tasks are managed through the use of increasingly integrated coordination tools and mechanisms. Accordingly, hospitals that have more sophisticated EHR matched with higher levels of structural integration, may perform optimally when compared to organizations with lower task interdependence and more sophisticated EHR capabilities. In contrast, hospitals that have less sophisticated EHR matched with low levels of structural integration may perform optimally when compared to organizations with high task interdependence and low EHR sophistication.

The above discussion leads to two hypotheses, with the first focused on the main contingency noted above (i.e., task uncertainty) and the second allowing for the possibility that additional contingencies (i.e., task complexity and task interdependence) may be relevant for overall fit:

> **Hypothesis 3.1a: Higher degree of fit between a hospital's EHR sophistication and degree of centralization will be associated with greater reductions in postoperative sepsis outcomes.**

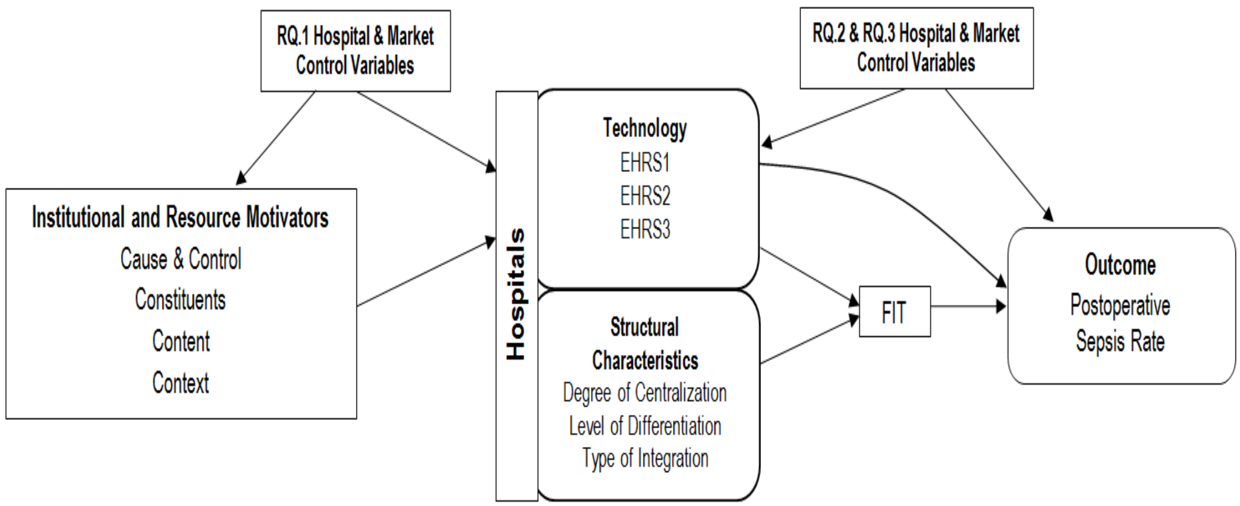
> **Hypothesis 3.1b: Overall degree of fit between a hospital's EHR sophistication and degree of centralization, level of hospital differentiation, and type of hospital integration will be associated with greater reductions in postoperative sepsis outcomes.**

The overall degree of fit measure, used in hypothesis 3.1b, signifies a more comprehensive measure of fit versus the one used in hypothesis 3.1a, and the measure could potentially encompass several interactions between the different structural variables used to construct the organization's fit value. The approach may also best capture the essence of Drazin and Van de Ven's (1985) argument for a more holistic fit measure in Structural Contingency Theory research.

Conceptual Framework

Figure 6 presents a graphical depiction of the conceptual framework drawn from the three organizational perspectives and literature discussed above. This study first examines what organizational and environmental forces are associated with hospital's having certain EHR applications. Using the Oliver (1991) model, this study will specifically test whether local

Figure 6. Conceptual Framework of Hospital Electronic Health Record Adoption and Performance



Note: EHRS=electronic health record sophistication. RQ=research question.

institutional and resource motivators – cause and control, content, constituents, and context – have an association with a hospitals' decision to adopt EHR. This study also explores the patient safety performance of hospitals that adopt EHR. With the help of the Structure-Process-Outcome framework this study will test whether hospital's adoption of EHR and the level of sophistication of the adopted EHR have an association with hospital postoperative sepsis performance. This study, additionally, incorporates the Structural Contingency Theory notion of fit between hospital's structural features and the EHR technology adoption to explore its association with hospital postoperative sepsis performance. In order to control for potential variables that may affect the relationship between the study's key explanatory and dependent variables, the study incorporates hospital and market control variables into the model, which will be discussed in more detail in Chapter 4.

Summary

This chapter developed and illustrated a conceptual framework based on three organizational perspectives: Oliver's (1991) integrated Institutional Theory and the Resource

Dependence model; Structure-Process-Outcome framework of Donabedian (1980); and Structural Contingency Theory of Donaldson (2001), which may explain the relationship between hospital EHR and performance. From the conceptual framework, eight hypotheses are derived. The next chapter will present a research plan for measuring and testing the hypotheses listed in this section.

Chapter 4: Methodology

The purpose of this chapter is to identify the research design, data sources and study sample, measurement of study variables, and the empirical methodology that will be used to address this study's three research questions. The details for each of these areas are provided in the first four sections of this chapter. Additionally, the fifth section of this chapter will present the potential sensitivity analyses that will be performed to test the robustness of the empirical results.

Research Design

General, short-term, acute care, non-federal, and urban hospitals in the U.S. are the unit of analysis in the study. Like Bazzoli, Chen, Zhao, and Lindrooth (2008), the study aggregates data to the hospital level rather than conducting a patient level analysis (i.e., specifically for research questions two and three). Aggregation to the hospital level is planned since most explanatory variables examined in the study are measured at the hospital level, and thus it is appropriate to define the dependent variable at the same level of analysis. Also, a patient level sample that contains discharges from several states would yield a large data set that would be potentially unmanageable given standard memory/capacity issues with existing statistical software.

To assess the eight hypotheses presented in the previous section, this study will use a multiple time-series design, which involves a five-year (2005-2009) longitudinal data set. A pooled cross-sectional design is used to address research question one, while a panel design is used to assess research questions two and three. The pooled design enhances the precision of estimates (versus a simple cross-sectional design) through an increase in number of degrees of freedom (Cameron & Trivedi, 2005). A panel design is able to control for unobserved time invariant hospital characteristics that may affect hospital performance and potentially lead to biased parameter estimates (Wooldridge, 2002). Although a panel design would be desirable for research question one instead of a pooled cross-section design, such a model could not be consistently estimated for the first research question's empirical model (i.e., there is no consistent estimator of a fixed effects ordered probit model). All the empirical models in this study will be estimated on a sample of hospitals that had continuously reported information across the five-year study period (i.e., a balanced panel).

A non-equivalent comparison group, which contains hospitals that did not belong to the EHRS1, EHRS2, or EHRS3 groups, will be used. The proposed study design is similar to the ones used by Furukawa et al. (2010a), Furukawa, Raghu, & Shao (2010b; 2011), and Parente and McCullough (2009). Specific to research questions two and three, the use of fixed effects models to test the hypotheses have advantages in terms of internal validity (e.g., overcoming the influence of time invariant omitted variables bias). Details of the study sample and the empirical models that will be used in this study follow.

Data Sources and Study Sample

Data from hospitals in six states: Arizona, Florida, California, Maryland, New Jersey, and New York, are used in this study to investigate the three research questions. The study states consistently provided the necessary hospital information over the study period that is required for this study's empirical evaluations. Hospitals within these states were also actively engaged in EHR adoption activities over the study time period. Although the study's findings may not be generalized to a national scale, the study sample from the aforementioned states contains approximately ten percent of community hospitals nationwide and spans four of the seven U.S. census divisions.

Administrative data obtained from several diverse sources are merged together in order to obtain comprehensive information about hospitals' characteristics, their EHR adoption patterns, and patient safety performance. In depth information about each dataset is provided in Table 6. Datasets such as the AHA Annual Surveys of Hospitals, HIMSS Analytics, and HCUP State Inpatient Database have been extensively used in prior literature to examine similar research questions.

Data from the AHA Annual Surveys of Hospitals, Medicare Hospital Cost Reports (HCRIS), and HIMSS Analytics database will be merged by hospital Medicare number. In regard to the Cost Reports, hospitals with a reporting period less than 360 days will be excluded. Since the HIMSS data sets contain information from the prior year, HIMSS data years will be appropriately lagged before being matched. The merged dataset is then linked with hospital-level measures that are constructed from state inpatient data by AHA identification number. Hospitals that have an at-risk patient population of less than 30 for the postoperative sepsis patient safety indicator will be excluded from the analyses because adverse events are rare and thus, random occurrences of these events for a hospital with a small number of relevant cases could yield a high frequency of negative outcomes (Agency for Healthcare Research and Quality, 2011). Lastly, market level information from the HealthLeaders-InterStudy, Area Resource Files, and Census Bureau Survey will be merged by the hospital's county federal information processing standard (FIPS) code.

Table 6

Description of Study Databases

Data Source	Description of Dataset
American Hospital Association Annual Surveys of Hospitals.	The survey collects hospital level data on almost 6,000 hospitals across the nation annually. Hospitals respond to almost 800 questions that range from demographics, organizational structure, facilities and services, utilization, community orientation, expenses, and staffing. The survey obtains a high response rate every year.
Healthcare Cost and Utilization Project (HCUP) State Inpatient Database for Arizona, California, Florida, Maryland, New Jersey, & New York.	HCUP state inpatient data, which is available through the Agency for Healthcare Research and Quality (AHRQ), provides uniform data on inpatient care, including patient diagnoses, procedures and services, length of stay, total hospital charges, expected primary and secondary payers, and patient demographics. AHRQ, which is the central distributor for the databases, has also developed indicators of patient quality of care using inpatient data that can be aggregated to the hospital-level. The hospital-level aggregated indicators are constructed based on computer programs that assess patterns of procedures, diagnoses, and outcome variables in the discharge data (Agency for Healthcare Research and Quality, 2011). Among these indicators is a set of measures for rates of adverse events known as patient safety indicators (PSIs). The PSIs were developed to capture potentially adverse events in acute care, such as complications from surgery, procedures, or medical care. Specific PSI rates for postoperative sepsis in hospitals will be examined in this study.
Healthcare Information and Management Systems Society (HIMSS) Analytics Database.	HIMSS Analytics annually surveys a sample of American nonfederal hospitals including independent hospitals and those affiliated with integrated healthcare delivery systems. The database includes information on over 5,000 hospital facilities and contains details on each hospital's adoption of specific electronic health record applications.
Medicare Hospital Cost Reports.	The Medicare Cost Report provides substantial financial data on the universe of hospitals receiving Medicare payments. The data are collected annually by the Centers for Medicare and Medicaid Services. These data provide an extensive array of income statement and balance sheet financial data with which to calculate annual financial performance.
HealthLeaders-InterStudy.	HealthLeaders-InterStudy contains information on managed care enrollment across various types of plans and providers at the county and core-based statistical area level.
Area Resource Files and Census Bureau Survey	These datasets contain data on socio-demographic characteristics, economic conditions, and other related factors in a hospital's community.

Measurement of Study Variables

The key variables, which will be present in each of the empirical models used to address this study's research questions, are listed below. Discussions about the hospital and market control variables that will be included in each model are also presented in turn.

Research question one key variables.

Research question one explores what organizational and environmental forces are associated with hospitals' having certain EHR applications. Using Oliver's (1991) model, four hypotheses are derived that identify the degree of local EHR presence in a market, hospitals dependence on managed care, Medicare, and Medicaid, teaching status, and degree of centralization as potential predictors of whether a hospital adopts specific types of EHR applications. The table below presents the variables that will be constructed to reflect the constructs present in the aforementioned hypotheses.

Empirical evaluations in the prior literature have used similar variable measures, as listed in Table 7, for hospital EHR adoption (e.g., Furukawa, 2010a), presence of EHR in a hospital's market (e.g., McCullough, 2008), public payer mix and managed care penetration (e.g., Wang et al., 2005), teaching status (e.g., Cutler et al., 2005), and degree of centralization (e.g., Chukmaitov et al., 2009).

Research question one control variables.

Hospital adoption of EHR applications may be confounded by other factors present in the hospital's institutional environment. Proenca et al.'s (2000) application of Oliver's (1991) model to their research question of hospital adoption of community orientated programs investigated one such factor: hospital size, which may motivate an organization to conform to external social pressures. They argued that larger organizations attract greater attention from the state, the media, and various other groups (Meyer, 1979), and are thus more vulnerable to social pressures (Proenca et al., 2000). Large organizations may also have more slack to adopt programs that may largely serve ceremonial purposes rather than create true efficiency gains (Baron & Hannan, 1994). Hospital size is measured by the *number of staffed and set-up beds*, which will be

Table 7

Description of Research Question One Model (M1) Key Variables

	Variable	Database(s)	Construction Approach
Dependent Variable	*EHR* is measured by presence of EHRS1, EHRS2, EHRS3, and not having EHRS1, EHRS2, or EHRS3 (i.e., EHRS0).	2005-2009 Healthcare Information and Management Systems Society Analytics Database.	Categorical variables, 0= EHRS0, 1=EHRS1, 2=EHRS2, 3=EHRS3. Presence of the applications within the categories in a hospital should indicate an implementation status as being "fully automated."
Independent Variable	*Cause/Control* is measured by presence of EHR in a hospital's market.	2005-2009 Healthcare Information and Management Systems Society Analytics Database.	Measured by the percentage of other community hospitals with EHRS1, EHRS2, and EHRS3 in a market (county level).
Independent Variable	*Constituent* is measured by the share of patient days covered by public payers (Medicare and Medicaid) in a hospital and penetration of managed care (HMO and PPO) in a hospital's market.	2005-2009 HealthLeaders-InterStudy & State Inpatient Database for AZ, CA, FL, MD, NJ, & NY.	Medicare share is computed by Medicare inpatient days divided by total inpatient days, and Medicaid share is computed as Medicaid inpatient days divided by total inpatient days. Commercial managed care is computed by percent of commercially insured individuals in a hospital market (county level) covered by HMO or PPO.
Independent Variables	*Content* is measured by teaching status.	2005-2009 AHA Annual Surveys.	Binary variables for whether hospital is affiliated with Association of American Medical College's Council of Teaching Hospitals (COTH); minor teaching program (residency program, but not COTH); and not teaching (reference group).
Independent Variables	*Context* is measured by the degree of centralization of the system in which a hospital is a member.	2005-2009 AHA Annual Surveys.	Binary variables for centralized system; moderately centralized system; decentralized or independent hospital system; and not part of a system (reference group). Hospitals that belong to a hospital system but do not have a recorded system type measure in the AHA data (i.e., centralized, decentralized, etc.) were excluded from the analysis.

Note: AHA=American Hospital Association. AZ=Arizona. CA=California. COTH= Council of Teaching Hospitals. EHR=electronic health record. EHRS=electronic health record sophistication. FL=Florida. HMO=health maintenance organization. MD=Maryland. NJ=New Jersey. NY=New York. PPO=preferred provider organization.

obtained from the AHA Annual Surveys.

Another confounding factor encompasses an organization's potential to lose decision making discretion as a result of complying with a social norm. Oliver (1991) posited that an organization's desire to preserve its ability to control work processes and outputs will influence its willingness to conform to external institutional pressures that may appear as threats to the organization's current practices. Hospitals that have had prior experience with innovative technologies (Walston, Kimberly, & Burn, 2001) may already have work practices and routines that may facilitate the adoption of new technologies. The study measures a hospital's predisposition to adopt EHR applications by the level of *high-technology services* present in its facility. The measure represents a count of up to 33 services offered by the hospital as reported in the 2005-2009 AHA Annual Surveys, including services such as neonatal intensive care, trauma centers, open heart surgery, and transplant services (Bazzoli et al., 2008).

Also, *ownership type* and hospital *community orientation* are other organizational control related confounders that may influence the management's desire to comply with an institutional norm based on the agreeability of the pressures with management's own aspirations (e.g., as demonstrated in the work culture, goals, and mission). Binary measures, based on the information reported in the AHA Annual Surveys, are used to represent ownership types that include: for-profit, public, and not-for-profit (reference group). Also, an index variable is constructed to measure the community orientation of a hospital, based on the approach of Alexander, Young, Weiner, and Hearld (2009), using information present in the AHA Annual Surveys. In regard to community orientation, a sum of nine binary items present in the AHA Annual Surveys, which measure hospitals activities to address community health needs, is obtained (Alexander et al., 2009). The items present in the scale include: 1) hospital has mission statement focused on community benefit; 2) hospital has long-term plan for improving health of community; 3) hospital has resources for community benefit activities; 4) hospital works with other providers to conduct a health status assessment of the community; 5) hospital uses health status indicators to design new services or modify existing services; 6) hospital works with other local providers to develop written assessment of the appropriate capacity for health services in the community; 7) hospital uses the written assessment to identify unmet health needs, excess capacity, or duplicative services in the community; 8) hospital works with other providers to collect, track, and communicate clinical and health information across cooperating organizations; and 9) hospital disseminates reports to the community on the quality and costs of health care services (American Hospital Association, 2005).

Although the means through which the institutional pressure for adopting EHR applications may have been primarily driven by local hospital competitors, the unique political and legal climate in a hospital's environment could also influence cultural expectations (Oliver, 1991). For example, Furukawa et al. (2008) noted that some states had patient safety mandates that may have motivated hospitals to adopt innovations to mitigate the prevalence of adverse events in a hospital. The study accounts for this type of influence through the inclusion of *state indicators* present in the AHA Annual Surveys, with the state of California as the reference group.

Fareed and Mick (2011) noted that the severity of patients treated in a hospital may also influence the decision about technology adoption. Hospitals with a higher *all-patient diagnosis-related group (DRG) case mix* will face greater levels of task uncertainty due to the potential presence of increased complexity of care and need for coordination, and the adoption of EHR may help mitigate some of this uncertainty. Information from the State Inpatient Database for

Arizona, California, Florida, Maryland, New Jersey, and New York is used to construct an all patient case-mix measure (i.e., the average of patient DRG weights). Weights for individual DRGs used to construct this measure are based on the 2007 CMS DRG relative weights provided in the CMS Acute Inpatient files.[5]

In addition to task uncertainty, environmental uncertainty may influence organizational decisions through institutional pressures (Oliver, 1991). Pfeffer and Salancik (1978) defined environmental uncertainty as "the degree to which future states of the world cannot be anticipated and accurately predicted" (p.67). The study accounts for uncertainty through the use of several variables. The level of munificence in a hospital's environment could influence uncertainty (Pfeffer & Salancik, 1978) due to the varying availability of resources that may facilitate EHR adoption. The study will use *per capita income* in the hospital's county, *market size* (i.e., county's total resident population size), *hospital lagged total margin* (i.e., total margin in the prior year), and *rate of uninsured* (i.e., for individuals aged between 18 to 64) in the county. Higher levels of the first three variables may indicate more munificent environments that are associated with more EHR investments, whereas a higher rate of uninsured locally may mean that there are increased demands on the resources of a hospital and thereby fewer available internal resources to invest in EHR. Data to construct these variables are available through the ARF, CBS, and HCRIS.

Further, the level of *market competition* at the hospital county level might also influence a hospital's perception of uncertainty. Namely, hospitals may be more likely to adopt EHR in markets that are highly competitive in order to gain strategic and financial value by being different from their competitors and maintaining a strategic advantage in the market. Hospital

[5] Source: http://www.cms.gov/Medicare/Medicare-Fee-for-Service-Payment/AcuteInpatientPPS/Acute-Inpatient-Files-for-Download.html

competition, measured by the Herfindahl-Hirschman Index (HHI), is calculated by summing the squares of the market shares of admissions for all of the hospitals in the county. Market shares for hospitals within systems are collapsed to the system level within the county. The HHI measure takes a value between 0 and 1, with values of HHI approaching 1 indicating less competitive markets. Data to construct the HHIs is obtained from the AHA Annual Surveys.

Indicator variables for each specific *year* that capture time-specific effects that may influence the outcome variable across all the hospitals are also included in the model. Several of the variables used to address research question one have been previously used in the literature as well (c.f., Cutler et al., 2005; Furukawa et al., 2010a; 2010b; 2011; Jha et al., 2009; Kazley & Ozcan, 2008; Wang et al., 2005; Zinn, Weech, & Brannon, 1998).

Research question two key variables.

Research question two explores whether hospitals that adopt EHRs have lower postoperative sepsis outcomes relative to those who do not adopt such applications. Using Donabedian's (1980) framework, two hypotheses are derived that identify EHR and higher degrees of EHR sophistication as being associated with lower postoperative sepsis outcomes. Table 8 presents the variables that will be constructed to reflect the constructs present in the aforementioned hypotheses and also two candidate instrumental variables that will be used to examine the potential endogeneity of the adoption and degree of sophistication of a hospital's EHR.

Empirical evaluations in the prior literature have used similar variable measures, as listed in Table 8, for postoperative sepsis (e.g., Zhan & Miller, 2003b), presence of EHR (e.g., Furukawa et al., 2010a), presence of EHR in a hospital's market (e.g., McCullough, 2008), and community orientation (e.g., Alexander et al., 2009).

Table 8

Description of Research Question Two Model (M2) Key Variables

	Variable	Database(s)	Construction Approach
Dependent Variable	*Outcome* is measured as a hospital's PSI postoperative sepsis rate.	2005-2009 State inpatient databases for AZ, CA, FL, MD, NJ, & NY.	Estimated risk-adjusted probabilities were obtained for this PSI at the patient level and then aggregated to the hospital level. This measure was constructed only for hospitals with 30 or more patients at risk for the event associated with the indicator, as recommended by AHRQ (Agency for Healthcare Research and Quality, 2011; p.18).
Independent Variable	*Structure* is measured by presence of EHRS1, EHRS2, or EHRS3.	2005-2009 Healthcare Information and Management Systems Society Analytics Database.	For specification one, binary variable for a hospital having EHR (i.e., EHRS1, EHRS2, or EHRS3) or not (reference). For specification two, binary variables, for a hospital having EHRS1 (not EHRS1 reference), EHRS2 (not EHRS2 reference), EHRS3 (not EHRS3 reference). Presence of the applications within the categories in a hospital should indicate an implementation status as being "fully automated."
Potential Instrument Variable	Presence of EHR applications in a hospital's market.	2005-2009 Healthcare Information and Management Systems Society Analytics Database.	As previously described in M1 (Table 7).
Potential Instrument Variable	Community orientation.	2005-2009 AHA Annual Surveys.	Constructed as the sum of nine binary items that measure a hospital's investment of resources within its community (Alexander et al., 2009); higher values of this variable imply greater level of hospital community orientation.

Note: AHRQ=Agency for Healthcare Research and Quality. AHA=American Hospital Association. AZ=Arizona. CA=California. EHRS=electronic health record sophistication. FL=Florida. MD=Maryland. NJ=New Jersey. NY=New York. PSI=patient safety indicator.

The approach to constructing the hospital-level postoperative sepsis PSI relies on the algorithm present in the AHRQ PSI software – Version 4.3 (Agency for Healthcare Research and Quality, 2011; p.17). Based on ICD-9-CM codes, the algorithm flags patients who had postoperative sepsis and patients who were at risk for postoperative sepsis. In regard to the latter, several additional inclusion (e.g., only patients 18 and older) and exclusion (e.g., patients with a principal diagnosis of sepsis) criteria are incorporated into the algorithm's logic[6]. The total number of patients with postoperative sepsis is divided by the total population at risk (i.e., for hospitals with greater than 30 cases) for each hospital during a specific year to obtain a hospital's observed postoperative sepsis rate. To obtain risk-adjusted rates, a patient-level analysis is conducted to predict the likelihood of a patient experiencing postoperative sepsis (i.e., a 0/1 indicator) based on several patient characteristics (i.e., patient age category, gender, modified DRG category, co-morbidities, and interactions of age and gender) present within a group of randomly selected hospitals from a national database (Agency for Healthcare Research and Quality, 2011). The coefficients from the estimated model are then applied to a study's sample to obtain a prediction of postoperative sepsis for each discharge. The risk-adjusted rate represents the difference between the average observed rate and average predicted rate for a hospital in a specific time period.

For the potential instrument variables, it may be argued that other hospitals having EHR could not have an effect on a focal hospital's internal operations (e.g., patient safety performance), but it may influence the hospital's strategic decision making. Also, Encinosa and Bae (2011) argued that a focal hospital's engagement in community activities could suggest that they had less capital to invest in activities such as EHR adoption, while such investments had no effect on a hospital's patient safety performance.

Research question two control variables.

The ability of a hospital to provide high quality care may be confounded by several structural features present at the micro (i.e., hospital) and macro (i.e., market) levels. Such factors may complement the hospital's capacity to adopt better quality technologies and provide

[6] See Encinosa & Bernard (2005) for additional details on the inclusion and exclusion criteria.

better quality of care (Donabedian, 1980) due to the availability of resources (i.e., more or better structural and financial components) or because they reduce the strain on resources available to effectively operate a facility.

In regard to the micro factors, the study includes staffing variables such as the *proportion of hospital nurses who are registered nurses*, *ratio of registered nurses to patient discharges*, and the *ratio of full time equivalent employees per bed*. These variables can all be computed with the AHA Annual Surveys. Facility characteristics that will be controlled include the hospital's *share of inpatient days that are Medicare*, *share of inpatient days that are Medicaid*, *the number of staffed and set-up beds*, *degree of system centralization* based on the cluster type of the hospital's system, the provision of *high technology services*, *ratio of non-emergency room visits to total admissions*, *ratio of outpatient visits to total admissions,* and *total number of surgical operations*. Data to construct these variables are available through the AHA Annual Surveys and the State Inpatient Database for Arizona, California, Florida, Maryland, New Jersey, and New York. Effects of financial resources will be measured through *lagged total margin*, which will be constructed based on the information provided in the Medicare Hospital Cost Reports.

Although the analysis uses the AHRQ risk-adjustment process for calculating a hospital's post-operative sepsis rate, it also contains some additional patient clinical, demographic, and socio-economic variables to account for any residual confounding effects that may be present in M2. Additional variables include the *all-patient DRG case mix*, and *percent major or extreme severity of illness*[7] as provided by the AHRQ 3M APR-DRG software. Hospitals *average length of stay*, *proportion of patients who are female*, *proportion of patients who are non-Hispanic Black or Hispanic*, and *proportion of patients who are aged 19-64 (with those aged 65 and over*

[7] The 3M software generates scores ranging from 1 to 4, indicating whether a patient's severity of illness is minor, moderate, major, or extreme. At the hospital level, the study will measure the percent of a hospital's patients who were at major or extreme severity of illness.

as the reference group) will also be included in the model. An age variable for those below the age of 19 is not included because these patients are not typically affected by postoperative sepsis (Agency for Healthcare Research and Quality, 2011). These patient clinical, demographic, and socio-economic variables represent predisposing factors that may potentially contribute to a hospital experiencing higher rates of postoperative sepsis.

The potential macro confounders include *hospital market competition, managed care penetration, per-capita income* in the hospital's county, *rate of uninsured* (i.e., for individuals aged between 18 to 64) in the county, and *market size* (i.e., county's total resident population size), which are the same measures used in M1. Hospitals in more competitive environments may have to strive towards better quality outcomes in an effort to maintain their competitive edge in a marketplace due to the presence of alternative hospital providers (Fareed & Mick, 2011). Hospitals facing considerable managed care influence might have to meet certain quality expectations to retain contractual arrangements and also potentially to receive enhanced payments from managed care organizations, such as pay-for-performance bonuses (Fareed & Mick, 2011). Hospitals in areas with higher per-capita income may also have patients who can afford better care options that may, in turn, be linked to fewer adverse events. In areas that have a high rate of uninsured patients, hospitals may be forced to be very effective and efficient in their delivery of care in an effort to account for the increased needs of indigent care (Rosko, 1999). However, hospitals in larger markets could be linked with more adverse events since they are exposed to a greater diversity of patients, who may also have a wide spectrum of complicated medical conditions. Data to construct these variables are available through the ARF, AHA Annual Surveys, and CBS.

Finally, the empirical model will also include indicators for years for similar reasons as previously described. Several of the variables used to analyze research question two have been previously used in the literature (c.f., Bazzoli et al., 2008; Clement, Lindrooth, Chukmaitov, & Fen-Chen, 2007; Culler et al., 2007; Encinosa & Bae, 2011; Encinosa & Hellinger, 2008).

Research question three key variables.

Research question three explores if hospitals that have a better fit between their organizational structure and technology have lower postoperative sepsis outcomes relative to those who do not have this type of fit. Using Donaldson's (2001) Structural Contingency Theory perspective, two hypotheses are derived that identify fit and overall fit between a hospital's EHR sophistication and degree of centralization, differentiation, and integration as being associated with reductions in postoperative sepsis outcomes. Table 9 presents the variables that will be constructed to reflect the constructs present in the aforementioned hypotheses.

Table 9

Description of Research Question Three Model (M3) Key Variables

	Variable	Database(s)	Construction Approach
Dependent Variable	Hospital's PSI postoperative sepsis rate.	2005-2009 State inpatient databases for AZ, CA, FL, MD, NJ, & NY.	As previously described in M2 (Table 8).
Independent Variables	Hospital's degree of misfit is measured by obtaining absolute residual values from the regression of EHR sophistication on degree of centralization, level of differentiation, and type of integration (Donaldson, 2001).	2005-2009 AHA Annual Surveys & 2005-2009 Healthcare Information and Management Systems Society Analytics Database.	For specification one, the residual values from the regression in M1 is first obtained, which is then converted to absolute residual values to be used in M3. Hospitals that are in fit (in relation to the entire sample of hospitals) will have a zero value; higher values of this variable imply greater degrees of misfit. For specification two, the residual values from a regression in M1which will also include the two additional structural variables (i.e., level of differentiation and type of integration) are obtained which are then converted to absolute residual values to be used in M3. Hospitals that are in fit (in relation to the entire sample of hospitals) will have a zero

Table 9 (continued)

	Variable	Database(s)	Construction Approach
			value; higher values of this variable imply greater degrees of misfit.
Constituent Variables	Technology presence is measured by EHRS1, EHRS2, or EHRS3.	2005-2009 Healthcare Information and Management Systems Society Analytics Database.	As previously described in M2 (Table 8).
Constituent Variables	Degree of centralization a hospital system characterizes.	2005-2009 AHA Annual Surveys.	As previously described in M1 (Table 7).
Constituent Variable	Level of differentiation in a hospital.	2005-2009 State inpatient databases for AZ, CA, FL, MD, NJ, & NY.	Differentiation is measured by a hospital's Service Mix HHI (SPEC). SPEC is defined as the sum of the squares of the proportions of discharges for each of 25 major diagnostic categories where the proportions are measured relative to all discharges for the hospital (Zwanzinger, Melnick, & Simonson, 1996) and the score ranges between zero and one. A SPEC score of one represents a facility with highly undifferentiated services.
Constituent Variables	Type of integration in a hospital.	2005-2009 Healthcare Information and Management Systems Society Analytics Database.	Integration in a hospital is measured by a hospitals EHR enterprise application strategy (Fareed, Ozcan, & DeShazo, 2012; Ford, Menachemi, Huerta, & Yu, 2010). Self-Developed Technology (SDT); Single Vendor (SV), Best of Breed (BOB), and Best of Suite (BOS), and no strategy (NS) are the five different EHR enterprise application strategies that hospital administrators might implement. SDT provides the most integrated system solution for a hospital, whereas NS provides a hospital with the least integrated system. BOS is a hybrid strategy of BOB and SV. Binary indicators for each strategy (with SV as reference) are constructed.

Note: AHA=American Hospital Association. AZ=Arizona. CA=California. EHR=electronic health record. EHRS=electronic health record sophistication. FL=Florida. HHI= Herfindahl-Hirschman Index. MD=Maryland. NJ=New Jersey. NY=New York. PSI=patient safety indicator.

Empirical evaluations in the prior literature have used similar variable measures, as listed in the table above, for postoperative sepsis (e.g., Zhan & Miller, 2003b), degree of misfit (Dewar & Werbel, 1979), presence of EHR (e.g., Furukawa et al., 2010a), degree of centralization (e.g., Chukmaitov et al., 2009), level of differentiation in a hospital (e.g., Zwanzinger et al., 1996), and type of integration in a hospital (e.g., Ford, Huerta, Menachemi, Thompson, & Yu, 2012). Hospitals tend to rationalize the need for a specific level of differentiation by basing the types of services provided in relation to the number of patients served for each service line (Zwanzinger et al., 1996). Also, a hospital's EHR enterprise application strategy may reflect how managers enact tools and mechanisms that determine how work is performed in a hospital (Scott & Davis, 2007). The use of a Best of Suite strategy, for example, may represent a hospital's emphasis on pursuing a level of integration that is moderate (Fareed et al., 2012). More specifically, managers using this strategy may concurrently have a highly integrated coordination structure for administrative tasks and have a low integrated coordination structure for clinical tasks (Fareed et al., 2012). Since HIMSS did not report the EHR applications strategies for individual hospitals in 2010, the responses provided by hospitals in the 2009 survey were also used in 2010 for these measures.

Research question three control variables.

As noted by Donaldson (2001; p.241), the test of fit should include the constituent variables of fit, which include the technology (i.e., EHR) and organizational structural (i.e., degree of centralization) variables, in the analysis of fit and performance. Donaldson (2001) also emphasized the need to include potential confounders that may affect the relationship between fit and performance in an empirical analysis. Thus, the empirical model used to address research question three will include the constituent variables of fit and the hospital and market controls as identified for research question two.

Empirical Methodology

Before the primary analysis is performed, descriptive statistics will be examined to identify missing values and outliers. In terms of the former, missing value patterns will be identified in the data in order to decide whether an observation should be eliminated or if values require imputation. In the case of the latter, box plots and histograms will be used to identify any potential extreme values that need to be excluded from the analysis. Incorrectly reported values (e.g., millions of staffed beds instead of hundreds or thousands of beds) will be permanently removed or prior year values will be used. In general, study observations will be examined both cross-sectionally and longitudinally before they are excluded from the analysis. Variable distributions will also be assessed in case transformations (e.g., logs) need to be performed. The empirical models to test relevant hypotheses for each research question follow.

Research question one empirical model.

In order to test hypotheses 1.1 through 1.4, the study will estimate an ordered probit model, because the dependent variable *EHR* takes on ordered values (i.e., representing not having EHRS1, EHRS2, and EHRS3, having EHRS1, having EHRS2, or having EHRS3). Further, the ordered probit model assumes that correlations among alternatives exist, in contrast to the multinomial logit model which assumes independence between choices (Wooldridge, 2002). An ordered probit model with fixed effects is not estimated because the estimators from such a model may not be consistent.

The ordered probit model for *EHR* (conditional on the explanatory variables) can be derived from a latent variable (i.e., *EHR**) model, which is described in detail in Wooldridge (2002, p.505). The latent variable model for the study can be written as,

$$EHR^{*}{}_{it} = Cause/Control_{it}\beta_1 + Constituent_{it}\beta_2 + Content_{it}\beta_3 + Context_{it}\beta_4 + CNTRLS_{it}\beta_5 + Year_t\beta_6 + u_{it} \qquad (1)$$

Where $EHR_{it} = 0$ if $EHR^*_{it} \leq \alpha_1$, $EHR_{it} = 1$ if $\alpha_1 < EHR^*_{it} \leq \alpha_2$, $EHR_{it} = 2$ if $\alpha_2 < EHR^*_{it} \leq \alpha_3$, $EHR_{it} = 3$ if $EHR^*_{it} > \alpha_3$, with α denoting the unknown cut points that determine the observed values of *EHR* as a result of whether or not the latent variable crosses particular thresholds, *i* indexes a hospital and *t* indexes time. $Cause/Control_{it}$, $Constituent_{it}$, $Content_{it}$, and $Context_{it}$, represent vectors that contain the key variables described in Table 7. $CNTRLS_{it}$ represents a vector of control variables that are potential confounders in the study relationship. $Year_{it}$ is a vector for year dummy variables from 2006 to 2010 (2005 is the reference year).The β are vectors of parameters for their respective variables. u_{it} is an error term. Using (1), the probabilities that *EHR* will take a particular value are,

assuming $Z_{it} = Cause/Control_{it}\beta_1 + Constituent_{it}\beta_2 + Content_{it}\beta_3 + Context_{it}\beta_4 + CNTRLS_{it}\beta_5 + Year_t\beta_6 + u_{it}$,

$P\,(EHR=0) = \Phi(\alpha_1 - Z_{it})$

$P\,(EHR=1) = \Phi(\alpha_2 - Z_{it}) - \Phi(\alpha_1 - Z_{it})$

$P\,(EHR=2) = \Phi(\alpha_3 - Z_{it}) - \Phi(\alpha_2 - Z_{it})$

$P\,(EHR=3) = 1 - \Phi(\alpha_3 - Z_{it})$

The estimation of M1 does not include a constant (Wooldridge, 2002), and assumes that the relationship between each outcome group is the same (i.e., the proportional odds assumption). For example, the relationship between teaching and EHR is the same for EHRS1 or EHRS3. Also, cluster-robust standard errors will be computed to make standard errors robust to heteroskedasticity and serial correlation potentially present at the hospital level.

Research question two empirical model.

To test hypotheses 2.1a and 2.1b, the study will estimate a fixed effects model with two specifications. The fixed effect model is preferred over a pooled cross-sectional model, where the error structure is assumed not to have a hospital-specific component and where unobserved factors (such as hospital work culture) are assumed uncorrelated with the included explanatory variables. In other words, a pooled analysis is more likely to suffer from omitted variable bias if time-invariant characteristics of hospitals influence the outcome (Wooldridge, 2002). Assuming strict exogeneity, the fixed effects model for the study is,

$$PSI_{it} = \gamma_i + EHR_{it}\Omega_1 + Hospital_{it}\Omega_2 + Year_t\Omega_3 + e_{it} \tag{2}$$

Where PSI_{it} represents the outcome variable postoperative sepsis rate, with i indexing a hospital and t indexing time. γ_i denotes the hospital-specific fixed error component. EHR_{it} represents the binary indicator for a hospital having EHR (i.e., EHRS1, EHRS2, or EHRS3) in specification one and is a vector that contains indicators for whether a hospital had EHRS1 (not EHRS1 reference), EHRS2 (not EHRS2 reference), or EHRS3 (not EHRS3 the reference) for specification two. $Hospital_{it}$ represents a vector for micro and macro structural variables that may affect hospital performance. $Year_{it}$ is a vector for year dummy variables from 2006 to 2010 (2005 is the reference year).The terms Ω are vectors of parameters for their respective variables. e_{it} is an error term.

Prior EHR evaluation studies have suffered from endogeneity (Appari et al., 2012). Biases from endogeneity may arise from unobserved heterogeneity (e.g., hospital quality), simultaneity (e.g., decision to adopt EHR is concurrently influenced by current patient safety outcomes), or feedback effects (e.g., decision to adopt EHR is based on prior hospital performance).

In this study, although the fixed effects model may address unobserved time invariant aspects of heterogeneity, issues of simultaneity/feedback effects may still lead to biased estimates in the empirical model. The study will use an instrumental variables approach to assess the possible violation of the strict exogeneity assumption in the fixed effects model. The model will use the proportion of hospitals with EHRS1, EHRS2, and EHRS3 within a market (Diana & Zhivan, 2012; McCullough, 2008) and community orientation (i.e., an organizational decision making factor) as instrumental variables. For the instrument variable analysis, an F-test will be performed to test the joint significance of the instruments in the reduced form model and over-identification tests will be performed to ensure that all the instruments are properly excluded from the PSI model in (2). If the instruments are valid based on the results of the previously noted tests, a Hausman test will be used to test the endogeneity of the EHRS variables. The study will estimate two versions for each specification of the model (i.e., one that assumes the EHR (EHRS) variable(s) are exogeneous and one that assumes they are endogeneous) to assess the robustness of study findings. In both versions of the model, the study will calculate robust standard error estimates clustered at the hospital level.

Research question three empirical model.

Two specifications of M3 will be used to separately test hypothesis 3.1a and 3.1b. For the first specification, year specific-residuals are obtained from the pooled empirical model estimated in M1, the absolute values of which will be used in estimating M3. Like M2, the estimation for research question three will also use a fixed effects model. However, only the model assuming strict exogeneity is estimated as follows to test hypothesis 3.1a,

$$PSI_{it} = \gamma_i + Degreeofmisfit_{it}\theta_1 + Constituents_{it}\theta_2 + Hospital_{it}\theta_3 + Year_t\theta_4 + v_{it} \qquad (3)$$

Where PSI_{it} represents the outcome variable postoperative sepsis rate, with *i* indexing a hospital and *t* indexing time. γ_i is the hospital-specific error component. $Degreeofmisfit_{it}$ represents the degree to which a hospital's EHR and its degree of centralization are not in fit based on the absolute residual scores. $Constituents_{it}$ represents a vector for variables, as described in Table 7, which form the constituents of the fit measures. $Hospital_{it}$ represents a vector for variables that may potentially confound the study's relationship. $Year_{it}$ is a vector for year dummy variables from 2006 to 2010 (2005 is the reference year). The terms θ are vectors of parameters for their respective variables. v_{it} is an error term.

To test hypothesis 3.1b, the second specification of M3 will be similar to the first specification, but will contain new $Degreeofmisfit_{it}$ values. The absolute residual values for this variable will be obtained from another regression of M1 that will not only include the structural variable (i.e., degree of centralization) for the first contingency (i.e., task uncertainty), but also the two other structural variables (i.e., level of differentiation and type of integration) that are associated with the minor contingencies (i.e., task complexity and task interdependence). Like M2, robust standard error estimates will be calculated, which are clustered at the hospital level, for both specifications. For both specifications, a significant $Degreeofmisfit_{it}$ variable that is positive would confirm hypotheses H3.1a and H3.1b.

Sensitivity Analyses

The study will perform several forms of sensitivity analysis. For research question one, the empirical model will be applied to the unbalanced panel to verify if the findings of the key variables differed from those obtained with the balanced panel. Alternative definitions of hospital markets will be used, besides the conventional county level measurements, for the proportion of EHR presence variable. These will include core based statistical areas (CBSA) and health service areas (HSA).

For research question two, models will be estimated using a composite adverse event measure for surgical-related safety events in place of the postoperative sepsis measure. The composite measure includes adverse events captured by AHRQ's PSIs for accidental puncture or laceration during procedure, postoperative hemorrhage or hematoma, postoperative wound dehiscence, infection due to medical care, postoperative pulmonary embolism and deep vein thrombosis, iatrogenic pneumothorax, postoperative respiratory failure, postoperative sepsis, and postoperative physiologic and metabolic derangements (Encinosa & Bae, 2011; Encinosa &

Hellinger, 2008). In regard to this study, each measure is assigned an identical weight (i.e., 1/9) based on the number of total AHRQ PSIs used in the composite (i.e., nine AHRQ PSIs for the surgical-related safety events PSI), which follows one of the composite weighting strategies recommended by the AHRQ (Agency for Healthcare Research and Quality, 2008).

A group of HIT applications that directly relates to surgical care will be examined for the second research question. This group will consist of four applications: 1) operating room (OR) scheduling; 2) OR (surgery) – pre; 3) OR (surgery) – peri; and 4) OR (surgery) – post. The latter three applications provide clinicians with information that is relevant to the documentation/management (e.g., clinical ordering, decision support, follow-up procedures, surgical instrument and medications management) of care for patients before, during, and after surgery. All of the OR applications may also help prevent complications in surgery that could be associated with postoperative sepsis events. The effects of a hospital having all four of these applications (namely, the creation of a surgical suite index) and their presence with EHRS1, EHRS2, or EHRS3 in a hospital will be assessed through the use of interaction terms. This approach signals the need for hospitals to have sophisticated applications that not only automate several general clinical functions, but also tasks targeted towards better surgical management.

Additionally, hospitals may require more time and experience with EHR applications before they achieve objectives of better care management. To account for this possibility, the study will explore whether the effect of the level of EHR sophistication on patient safety changes based on the number of years that a hospital had a particular EHRS category during the study period. An interaction of a hospital's EHRS stage with the length of time it had this stage in place is included in an analysis of the second research question's empirical model. Using Stata's

LINCOM function, the potential differential effects of the EHRS groups, based on the length of time the hospital had the technology (i.e., between one and four years) will be tested.

Summary

This chapter covered the research design, data sources and study sample, measurement of study variables, the empirical methodology, and the sensitivity analyses that will be used in this study. A balanced panel of hospitals from six states that provided data for the five-year study period is used to assess the study's three research questions. For the research question one empirical model, an ordered probit model will be used with cluster-robust standard errors to adjust for non-independence/correlation of errors within hospitals. For research question two, fixed effect models will be used with the first specification assuming the strict exogeneity of the EHRS1, EHRS2, and EHRS3 variables, and the second specification using instrumental variables to account for the potential endogeneity of EHR. With regard to research question three, fixed effect models will be used with the first specification using a fit variable that is based on EHR measures and the degree of centralization variable, and the second specification using a fit variable based on the EHR and the degree of centralization, task complexity, and task interdependence variables. The results of this study from these models and their sensitivity analyses are presented in the next chapter.

Chapter 5: Results

Chapter 5 presents the study findings based on the research methodologies discussed in Chapter 4. The first section provides the general descriptive statistics on the variables used in the study's empirical models. The second section reports the results of the empirical models and sensitivity analyses for each of the study's research questions.

Descriptive Analysis

Table 10 provides a comparison of the hospitals in the study sample with all the general, short-term, acute care, and non-federal hospitals present in the AHA data. The average hospital in the study sample had significantly more beds than the average hospital nationally. The study sample also had significantly more system affiliated and teaching affiliated hospitals, but fewer publicly owned hospitals versus the hospitals in the national sample. Although not indicated in the table, it should be noted that all the study sample hospitals were located in urban areas.

The following tables report the means and standard deviations of the key explanatory variables used in each of the study's empirical models. In reference to Table 11, there was an increased likelihood of a hospital's competitor having EHRS2 or EHRS3 technology over the study period. Hospitals also experienced a growth of three percentage points in Medicaid covered patients between the base year and 2009, but did not experience any notable changes in the share of Medicare patients. During the study period, HMO penetration decreased by eight percentage points, while PPO penetration rose by four percentage points in hospital markets. Hospitals were less likely to be affiliated with a centralized hospital system by 2009.

Table 10

Comparison of All General, Short-Term, Acute Care, and Non-Federal Hospitals in the American Hospital Association Annual Surveys Database and Study Sample

	National Sample (*n*=4,860)	**Study Sample** (*n*=404)
Bed size*** *M* (*SD*)	173 (186.91)	324 (228.92)
Ownership *n* (%)		
For-profit	782 (16.10)	70 (17.32)
Public***	1,165 (23.98)	42 (10.50)
Not-for-profit	3,522 (72.47)	292 (72.17)
System affiliated** *n* (%)	2,627 (54.05)	249 (61.66)
Teaching status *n* (%)		
COTH member***	291 (5.99)	57 (14.44)
Minor teaching ***	532 (10.95)	75 (18.53)
Non-teaching***	4,037 (83.06)	272 (67.03)

Note: COTH=Council of Teaching Hospitals. *t* test was performed to compare means of the national versus study samples for the bed size variable and two-proportion z-test were performed to compare the proportions of the national versus study samples for the hospital characteristic variables.*$p < .10$. **$p < .05$. ***$p < .01$

Table 11

Descriptive Statistics for Research Question One Key Explanatory Variables by Year (*n=404*)

	2005		**2006**		**2007**		**2008**		**2009**	
Variable	***M***	***SD***	***M***	***SD***	***M***	***SD***	***M***	***SD***	***M***	***SD***
Hypothesis 1.1										
Presence of EHRS1 in other hospitals	0.30	0.29	0.37	0.33	0.31	0.30	0.28	0.29	0.21	0.26
Presence of EHRS2 in other hospitals	0.11	0.20	0.15	0.23	0.14	0.21	0.25	0.28	0.29	0.30
Presence of EHRS3 in other hospitals	0.06	0.15	0.07	0.14	0.17	0.22	0.20	0.23	0.23	0.26
Hypothesis 1.2										
Share of inpatient days covered by Medicare	0.49	0.13	0.48	0.13	0.48	0.12	0.48	0.12	0.49	0.12

Table 11 (continued)

Variable	2005 M	2005 SD	2006 M	2006 SD	2007 M	2007 SD	2008 M	2008 SD	2009 M	2009 SD
Share of inpatient days covered by Medicaid	0.18	0.12	0.19	0.12	0.20	0.13	0.20	0.13	0.21	0.13
Penetration of HMO in market	0.36	0.21	0.38	0.21	0.31	0.19	0.33	0.18	0.28	0.16
Penetration of PPO in market	0.22	0.15	0.25	0.15	0.30	0.17	0.27	0.13	0.26	0.13
Hypothesis 1.3										
Affiliated with COTH	0.14	0.35	0.14	0.35	0.14	0.35	0.14	0.35	0.14	0.35
Minor teaching	0.16	0.36	0.23	0.42	0.18	0.39	0.19	0.39	0.18	0.39
Hypothesis 1.4										
Centralized cluster	0.13	0.34	0.14	0.34	0.13	0.33	0.11	0.31	0.09	0.29
Moderately centralized cluster	0.19	0.39	0.20	0.40	0.18	0.39	0.19	0.39	0.20	0.40
Decentralized cluster	0.28	0.45	0.26	0.44	0.26	0.44	0.27	0.45	0.27	0.45
Independent hospital system	0.03	0.17	0.01	0.11	0.04	0.21	0.05	0.21	0.06	0.23

Note: EHRS=electronic health record sophistication. COTH=Council of Teaching Hospitals. HMO=health maintenance organization. PPO=preferred provider organization.

Table 12 notes the increasing presence of EHR over time among the study's hospitals. There was also a substantial rise in hospitals with EHRS2 and EHRS3 by 2009 in comparison to the base year. This increase in presence was by 22 percentage points for EHRS2 and by 15 percentage points for EHRS3 between 2009 and the base year.

Table 13 presents the means and standard deviations for the degree of misfit scores for both specification of the research question three model (i.e., with the single fit measure and the overall fit measure). The distribution of misfit scores ranged between 0.71 to 0.82 for both specifications. The highest level of average misfit occurred in 2007 for both specifications, while the best level of fit was present in the preceding year for both specifications as well.

Table 12

Descriptive Statistics for Research Question Two Key Explanatory Variables by Year (*n=404*)

	2005		2006		2007		2008		2009	
Variable	***M***	***SD***	***M***	***SD***	***M***	***SD***	***M***	***SD***	***M***	***SD***
Hypothesis 2.1										
EHR (EHRS1/EHRS2/EHRS3)	0.54	0.50	0.69	0.46	0.71	0.46	0.80	0.40	0.81	0.39
Hypothesis 2.2										
EHRS1	0.33	0.47	0.40	0.49	0.34	0.47	0.30	0.46	0.23	0.42
EHRS2	0.14	0.35	0.19	0.39	0.17	0.37	0.29	0.46	0.36	0.48
EHRS3	0.07	0.26	0.10	0.30	0.20	0.40	0.21	0.41	0.22	0.42

Note: EHR=electronic health record. EHRS=electronic health record sophistication.

Table 13

Descriptive Statistics for Research Question Three Key Explanatory Variables by Year (*n=404*)

	2005		2006		2007		2008		2009	
Variable	***M***	***SD***	***M***	***SD***	***M***	***SD***	***M***	***SD***	***M***	***SD***
Hypothesis 3.1										
Degree of misfit (specification one: single fit measure)	0.74	0.48	0.71	0.50	0.82	0.52	0.73	0.54	0.76	0.55
Hypothesis 3.2										
Degree of misfit (specification two: overall fit measure)	0.75	0.48	0.71	0.50	0.81	0.52	0.74	0.53	0.76	0.55

Table 14 provides more information about the distribution of the average degree of misfit scores for the research question three model's two specifications by the level of EHR sophistication. For both specifications, the degree of misfit was higher for hospitals with no EHR or EHRS3 in comparison to those with EHRS1 or EHRS2, and the hospitals with EHRS1 had the best level of fit.

Table 15 presents the means and standard deviations of the control variables used in the study's empirical models and the additional fit constituent variables used for research question three averaged over all the study years. The log transformation of variables (e.g., hospital size) was used when their original variables had skewed distributions. On average, a majority of the

Table 14

Distribution of Degree of Misfit Scores by EHR Sophistication Level Averaged Across All Years (*n=404*)

	Specification One (i.e., single fit measure)		Specification Two (i.e., overall fit measure)	
EHRS Level	***M***	***SD***	***M***	***SD***
EHRS0	1.04	0.37	1.02	0.37
EHRS1	0.35	0.26	0.37	0.27
EHRS2	0.50	0.35	0.51	0.36
EHRS3	1.37	0.39	1.36	0.41

Note: EHR=electronic health record. EHRS=electronic health record sophistication.

Table 15

Descriptive Statistics of Control Variables and the Additional Fit Constituent Variables Used for Research Question Three Averaged Across All Study Years (*n=404*)

Variable	*M*	*SD*
Patient Characteristics		
Proportion of hospital patients age 19 through 64	0.48	0.08
Proportion of hospital patients >=65 [reference]	0.38	0.13
Proportion of patients Hispanic	0.14	0.17
Proportion of patients non-Hispanic Black	0.12	0.14
Hospital all-patient DRG case mix	1.32	0.22
Proportion of patients female	0.57	0.05
Average length of stay	4.74	1.04
Proportion of patients major or extreme severity illness	0.14	0.04
Hospital Characteristics		
Proportion of hospital nurses RN	0.93	0.06
High-technology service mix index	14.08	7.58
Lagged total margin	0.03	0.08
Hospital bed size [log]	1.66	0.27
Ratio of FTE and beds [log]	5.54	0.51
Ratio of outpatient visits to total admissions [log]	2.19	0.75
Ratio of RN and total admissions [log]	0.03	0.01
Total surgical operations [log]	9.06	0.61
Ratio of non-ER visits and total admissions [log]	1.41	0.33
For-Profit	0.17	0.38
Public	0.10	0.31
Not-for-profit [reference]	0.72	0.45

Table 15 (continued)

Variable	*M*	*SD*
Community orientation	6.15	3.63
Hospital level of differentiation[a]	0.11	0.04
EHR enterprise application strategy: SDT[a]	0.002	0.05
EHR enterprise application strategy: BOB[a]	0.11	0.31
EHR enterprise application strategy: BOS[a]	0.34	0.47
EHR enterprise application strategy: NS[a]	0.84	0.28
EHR enterprise application strategy: SV[a] [reference]	0.47	0.50
Market Characteristics		
Proportion uninsured (ages 18 through 64 in county)	0.04	0.08
HHI	0.30	0.21
Per capita income [log]	10.59	0.27
Population size [log]	13.49	1.21
Year 2005 [reference]	0.20	0.40
Year 2006	0.20	0.40
Year 2007	0.20	0.40
Year 2008	0.20	0.40
Year 2009	0.20	0.40
California [reference]	0.25	0.43
Arizona	0.07	0.25
Florida	0.27	0.44
Maryland	0.07	0.25
New Jersey	0.12	0.32
New York	0.23	0.42

Note: BOB=best of breed. BOS=best of suite. DRG=diagnosis related group. EHR=electronic health record. ER=emergency room. FTE=full time equivalent. HHI=Herfindahl–Hirschman Index. NS=no strategy. SV=single vendor. RN=registered nurse. SDT=self-developed technology. a=variables used, in addition to the electronic health record sophistication level and the degree of centralization variables, for the construction of the overall degree of misfit variable in the second specification of the research question three model.

patients in the study's hospitals were female. Patients were typically admitted for 4-5 days and 14 percent of the patients in the study's sample had a major or extremely severe illness. A high proportion of the nurses employed in the study's hospitals were RNs. The hospitals provided at least 10 of the 33 high-tech services listed in the AHA Annual Survey, and engaged in at least six of the nine community activities that were listed in the AHA Annual Survey. On average, the hospital markets in the study sample had 4 percent of the population uninsured. Many of the hospitals present in the study sample were located in Florida, California, and New York.

Table 16 provides the means and standard deviations of the alternate variables used in the study's sensitivity analyses. The difference in proportions of other hospitals having EHRS1, EHRS2, and EHRS3 for the CBSA and HSA definitions of the hospital market closely resembled the distribution based on the FIPS county definition of the hospital market. On average, OR-scheduling and OR-Pre were the more popular OR technologies, among the surgical suite applications considered, for hospitals to adopt in the study sample. Almost 60 percent of the study's hospitals also tended to adopt all four of the OR applications (i.e., OR-Scheduling, OR-Pre, OR-Peri, and OR-Post).

Table 16

Descriptive Statistics of Variables Used in Sensitivity Analyses Averaged Across All Study Years (*n=404*)

Variable	***M***	***SD***
Alternative definitions of hospital market (research question one)		
Hospital market defined by core-based statistical area		
Presence of EHRS1 in other hospitals	0.23	0.26
Presence of EHRS2 in other hospitals	0.14	0.20
Presence of EHRS3 in other hospitals	0.11	0.16
Hospital market defined by hospital service area		
Presence of EHRS1 by other hospitals	0.43	1.50
Presence of EHRS2 by other hospitals	0.34	1.18
Presence of EHRS3 by other hospitals	0.15	0.58
Alternative measure for PSI postoperative sepsis rate (research questions two and three)		
PSI composite	0.14	0.04
Alternative measures for EHR (research question two)		
OR-Scheduling	0.78	0.41
OR-Pre	0.77	0.42
OR-Peri	0.67	0.47
OR-Post	0.65	0.48
Surgical Suite Index	0.59	0.49

Note: EHR=electronic health record. EHRS=electronic health record sophistication. PSI=patient safety indicator. OR=operating room. Surgical Suite Index is the sum of a hospital having some or all of the four OR applications: OR-Scheduling, OR-Pre, OR-Peri, and OR-Post.

Empirical Results: Research Question One

Results of ordered probit model.

Table 17 reports the regression results for the research question one model, which explores what organizational and environmental forces are associated with hospitals' having certain EHR applications. The coefficients from this model were converted to marginal effects to provide a meaningful quantitative interpretation of the results. In general, the marginal effects represent the change in the probability of a hospital's EHRS level for a one-unit change of the independent variable. The marginal effects, for this study, were first calculated at the levels of the variables for each observation, and then all the computed effects, for an observation, are averaged. The marginal effects presented below were obtained to specifically explore the association of the key explanatory and control variables and a hospital having EHR (i.e., EHRS1, EHRS2, or EHRS3). The cluster-robust standard errors, which account for heteroskedasticity and the correlation of errors within hospitals due to serial correlation, for the estimated marginal effects are also reported.

Table 17

Ordered Probit Regression Results on Electronic Health Record Presence (*n=404*)

	Marginal Effect	***SE***
Key Explanatory Variables		
Presence of EHRS1 in other hospitals (%)	0.0004	0.0004
Presence of EHRS2 in other hospitals (%)	0.0005	0.0005
Presence of EHRS3 in other hospitals (%)	0.0018***	0.0006
Share of inpatient days covered by Medicare (%)	-0.0005	0.0012
Share of inpatient days covered by Medicaid (%)	-0.0030**	0.0013
Penetration of HMO in market (%)	0.0010	0.0008
Penetration of PPO in market (%)	0.0005	0.0008
Affiliated with COTH	0.0543	0.0479
Minor teaching	0.0105	0.0336
Centralized cluster	-0.0836**	0.0367
Moderately centralized cluster	-0.0903**	0.0397

Table 17 (continued)

	Marginal Effect	*SE*
Decentralized cluster	0.0012	0.0379
Independent hospital system	-0.0098	0.0493
Patient Characteristics		
Hospital all-patient DRG case mix	-0.0787	0.0621
Hospital Characteristics		
Hospital bed size [log]	0.1891***	0.0602
Lagged total margin	-0.0253	0.1437
High-technology service mix index	0.0074***	0.0021
For-Profit	0.1135***	0.0408
Public	0.1178**	0.0462
Community	-0.0080*	0.0042
Market Characteristics		
Per capita income [log]	0.0274	0.0586
Population size [log]	-0.0147	0.0184
Proportion uninsured (ages 18 through 64 in county) [%]	0.0033	0.0036
HHI	0.1408	0.0916
Arizona	0.0998*	0.0591
Florida	0.1218**	0.0482
Maryland	0.2599***	0.0657
New Jersey	0.1192**	0.0577
New York	0.0421	0.0510
Year 2006	0.1480**	0.0703
Year 2007	0.1913***	0.0708
Year 2008	0.2924***	0.0773
Year 2009	0.3272***	0.0781

Note: EHRS=electronic health record sophistication. HMO=health maintenance organization. PPO=preferred provider organization. COTH=Council of Teaching Hospitals. HHI=Herfindahl–Hirschman Index.
*$p < .10$. **$p < .05$. ***$p < .01$

For Hypothesis 1.1, the results suggested that other hospitals having EHRS1 or EHRS2 in a hospital market may not influence a hospital to have EHR. However, hospitals had a statistically significant ($p<0.01$) increase in the probability (0.002) of having EHR as the percent of other hospitals having EHRS3 in the market increased. In regard to Hypothesis 1.2, the results indicated that hospitals' dependence on Medicare or managed care (i.e., HMO or PPO) did not have any significant association with EHR presence, albeit hospitals that depended on Medicaid patients had a lower, statistically significant ($p<0.05$) probability of having EHR. In reference to Hypothesis 1.3, the results suggested that teaching status (i.e., COTH affiliated or minor teaching) was not significantly related to a hospital having EHR. The results also indicated that hospitals belonging to centralized or moderately centralized systems had a lower, statistically significant ($p<0.05$) probability of having EHR when compared to hospitals that were not part of a hospital system. The aforementioned results, however, did not hold for hospitals that were part of a decentralized system or for those that were in independent hospital systems.

In regard to the research question one control variables, hospital size and a hospital having more high-technology services had a positive, statistically significant ($p<0.01$) association with a hospital having EHR. In reference to ownership type, hospitals that were for-profit or public had a positive, statistically significant ($p<0.01$ and $p<0.05$, respectively) likelihood of having EHR when compared to not-for-profit hospitals. Hospitals that had a higher level of community orientation had a negative, marginally significant ($p<0.10$) probability of having EHR. The probability of a hospital having EHR was positive and statistically significant for all the study years after the baseline year (i.e., 2005). Hospitals that were in Florida, Maryland, New Jersey, and Arizona had a positive, statistically significant association with having EHR when compared to hospitals in California.

Results of sensitivity analyses.

Table 18 and Table 19 present the results of the sensitivity analyses related to research question one. The results from Table 18, where the unbalanced panel for the study's sample was used (i.e., Column II), suggested that there were no substantial differences in the marginal effects of the key variables in comparison to the results from the balanced panel (i.e., Column I). In regard to the use of different definitions of a hospital's market, Table 19 provides the marginal effects of other hospitals' having EHR based on the CBSA definition of the market (i.e., Column I) and the HSA definition of the market (i.e., Column II). Presence of EHRS3 among other

Table 18

Ordered Probit Regression Results on Hospitals Electronic Health Record Presence (Balanced Panel Versus Unbalanced Panel)

	Column (I) **Balanced Panel** (*n=404*)		**Column (II)** **Unbalanced Panel** (*n=548*)	
	Marginal effect	***SE***	***Marginal effect***	***SE***
Presence of EHRS1 in other hospitals	0.0004	0.0004	0.0234	0.0374
Presence of EHRS2 in other hospitals	0.0005	0.0005	0.0423	0.0487
Presence of EHRS3 in other hospitals	0.0018***	0.0006	0.1749***	0.0554
Share of inpatient days covered by Medicare	-0.0005	0.0012	-0.0007	0.0011
Share of inpatient days covered by Medicaid	-0.0029**	0.0013	-0.003**	0.0011
Penetration of HMO in market	0.0010	0.0008	0.0006	0.0008
Penetration of PPO in market	0.0005	0.0008	0.0003	0.0007
Affiliated with COTH	0.0543	0.0479	0.0607	0.0426
Minor teaching	0.0105	0.0336	0.0102	0.0299
Centralized cluster	-0.0836**	0.0367	-0.0652*	0.0336
Moderately centralized cluster	-0.0903**	0.0397	-0.0745**	0.0359
Decentralized cluster	0.0012	0.0379	-0.0058	0.0347
Independent hospital	-0.0098	0.0493	-0.0276	0.0492

Note: EHRS=electronic health record sophistication. HMO=health maintenance organization. PPO=preferred provider organization. COTH=Council of Teaching Hospitals. All models included control variables from the original model, but only key explanatory variables related to hypotheses tests are displayed in table.
*$p < .10$. **$p < .05$. ***$p < .01$

Table 19

Ordered Probit Regression Results on Electronic Health Record Presence (Alternative Market Definitions) [*N=404*]

	Column (I) **CBSA Market Definition**		**Column (II)** **HSA Market Definition**	
	Marginal effect	***SE***	***Marginal effect***	***SE***
Presence of EHRS1 in other hospitals	-0.0282	0.0386	-0.0051	0.0036
Presence of EHRS2 in other hospitals	0.0029	0.0613	0.0135*	0.0076
Presence of EHRS3 in other hospitals	-0.0945	0.0652	0.0577**	0.0251

Note: EHRS=electronic health record sophistication. CBSA=core based statistical area. HSA=hospital services area. All models included control variables from the original model, but only key explanatory variables related to hypotheses tests are displayed in table. *$p < .10$. **$p < .05$. ***$p < .01$

hospitals was no longer significantly associated with a focal hospital having EHR when the CBSA definition of the market was used. However, the results were consistent with the original model when the HSA definition of the market was used. The use of the HSA definition, in addition, suggested that the presence of EHRS2 among other hospitals had a positive, marginally significant association with a hospital having EHR.

Empirical Results: Research Question Two

Results of fixed effects model.

Table 20 and Table 21 present the results for specifications one and two of the research question two model, which explores whether hospitals that adopt EHRs have lower postoperative sepsis outcomes relative to those who do not adopt such applications. Table 20 provides results for the relationship of the key explanatory variable: hospital having EHR, on the rate of postoperative sepsis, while Table 21 provides results for the relationship of the key explanatory variables: hospitals' specific level of EHR sophistication (i.e., EHRS1, EHRS2, or EHRS3), on the rate of postoperative sepsis. Both tables contain two columns to provide the results when the key explanatory variables were treated as being endogenous (i.e., Column I) or exogenous (i.e., Column II). The cluster-robust standard errors, which account for heteroskedasticity and the correlation of errors within hospitals due to serial correlation, for the estimated coefficients are also reported.

The instrument variable specification tests for the research question two models suggested that there was no evidence that the instrument variables were correlated with the error term in the over-identification test and the instrument variables were weak. However, the fixed effects strict exogeneity test as prescribed by Wooldridge (2002; p.285), which assesses whether

Table 20

Fixed Effects Regression Results of Electronic Health Record and Postoperative Sepsis Rate (*n=404*)

	Column (I) Fixed Effects Model with Instrument Variable		Column (II) OLS Fixed Effects Model	
	Coefficient	***SE***	***Coefficient***	***SE***
Key Explanatory Variable				
EHR (EHRS1/EHRS2/EHRS3)	3.1898	9.9279	1.4134*	0.7889
Patient Characteristics				
Hospital all-patient DRG case mix	1.1055	2.3613	0.9300	2.1243
Proportion of patients major or extreme severity illness	40.7606*	23.9564	39.9363*	23.4059
Average length of stay	-0.7411	1.0728	-0.7200	1.0738
Proportion of hospital patients age 19 through 64	35.8546	21.9761	36.3467*	21.7924
Proportion of patients female	-25.5350	22.9095	-28.2519	18.7197
Proportion of patients non-Hispanic Black	-8.2905	12.1612	-8.0288	12.4917
Proportion of patients Hispanic	1.6433	3.2907	1.8306	3.2347
Hospital Characteristics				
Proportion of hospital nurses RN	-4.8850	11.7204	-5.4261	11.7038
Ratio of RN and total admissions [log]	-46.8720	89.2650	-39.7445	77.0409
Ratio of FTE and beds [log]	1.1100	3.4447	1.3791	3.0947
Share of inpatient days covered by Medicare	-4.4338	5.1577	-4.3834	5.2129
Share of inpatient days covered by Medicaid	8.6557	5.4820	8.4200	5.3519
Hospital bed size [log]	2.2395	6.0905	2.0023	5.9478
Centralized cluster	2.1340	4.9036	1.5876	4.0383
Moderately centralized cluster	1.2500	4.9399	0.6165	3.6997
Decentralized cluster	2.1384	5.4516	1.3643	3.7915
Independent hospital	-1.4274	4.3310	-1.8552	3.8315
High-technology service mix index	-0.1020*	0.0589	-0.1006*	0.0588
Ratio of non-ER visits and total admissions [log]	-0.7085	1.8277	-0.8595	1.6820
Ratio of outpatient visits and total admissions [log]	-0.1717	1.0031	-0.1189	1.0000
Total surgical operations [log]	-1.8630	1.8717	-2.0531	1.6780
Lagged total margin	-5.3374	6.2875	-5.4750	6.3872
HHI	6.3440	12.2209	6.1251	12.3208
Market Characteristics				
Penetration of HMO in market	-2.1672	3.5647	-2.0347	3.3954
Penetration of PPO in market	-2.8957	4.2688	-2.3247	3.3194
Per capita income [log]	-2.2244	14.2570	-2.7908	13.8278
Proportion uninsured (ages 18 through 64 in county)	-9.3589	14.9392	-8.2615	13.8617
Population size [log]	-7.8820	18.6781	-7.7425	18.2008
Year 2006	0.2692	4.1638	0.7469	3.0712
Year 2007	1.3057	4.4645	1.8091	3.3334
Year 2008	0.6000	5.7668	1.3664	3.5881
Year 2009	0.7214	5.7363	1.4985	3.4857
Constant			160.8851	320.3312

Table 20 (continued)

	Column (I) Fixed Effects Model with Instrument Variable		Column (II) OLS Fixed Effects Model	
	Coefficient	***SE***	***Coefficient***	***SE***
Instrument Variable Specification Tests				
Over identification test (p-value)	0.23			
Weak identification test (F-Statistic)	1.87			
Fixed effects strict exogeneity test (p-value)	0.62			

Note: EHR=electronic health record. EHRS=electronic health record sophistication. ER=emergency room. FTE=full time equivalent. DRG=diagnosis related group. HHI=Herfindahl–Hirschman Index. HMO=health maintenance organization. OLS=ordinary least squares. PPO=preferred provider organization. RN=registered nurse. COTH=Council of Teaching Hospitals. **p* < .10. ***p* < .05. ****p* < .01

Table 21

Fixed Effects Regression Results of Electronic Health Record Sophistication Level and Postoperative Sepsis Rate (*N=404*)

	Column (I) Fixed Effects Model with Instrument Variable		Column (II) OLS Fixed Effects Model	
	Coefficient	***SE***	***Coefficient***	***SE***
Key Explanatory Variable				
EHRS1	-9.4975	14.9834	0.9601	0.7897
EHRS2	-6.4108	21.9502	2.0067*	1.1732
EHRS3	4.1669	14.6251	2.7095***	1.0098
Patient Characteristics				
Hospital all-patient DRG case mix	1.8453	2.7455	1.1577	2.1198
Proportion of patients major or extreme severity illness	40.7742	28.2063	40.3148*	23.3242
Average length of stay	-1.3697	1.3961	-0.8039	1.0732
Proportion of hospital patients age 19 through 64	39.7432	29.0663	36.9088*	21.9497
Proportion of patients female	-49.7364	32.4940	-29.2910	19.1941
Proportion of patients non-Hispanic Black	-11.7516	14.2211	-8.5521	12.2122
Proportion of patients Hispanic	3.4666	6.0810	1.7967	3.2314
Hospital Characteristics				
Proportion of hospital nurses RN	-5.1917	14.6213	-5.2768	11.6835
Ratio of RN and total admissions [log]	-8.6581	108.9352	-41.6220	76.9023
Ratio of FTE and beds [log]	3.3725	4.0300	1.5066	3.1094
Share of inpatient days covered by Medicare	-5.4920	6.8758	-4.4753	5.2323
Share of inpatient days covered by Medicaid	6.8345	6.2547	8.3266	5.3489
Hospital bed size [log]	3.2931	6.3243	2.3608	5.9296
Centralized cluster	0.7834	5.8270	1.8913	4.0932
Moderately centralized cluster	-0.3079	6.2670	0.9806	3.7693
Decentralized cluster	-1.2182	7.2236	1.5952	3.8631
Independent hospital	-1.5226	5.0436	-1.5264	3.8864
High-technology service mix index	-0.1198*	0.0716	-0.1039*	0.0591
Ratio of non-ER visits and total admissions [log]	-1.7327	2.1134	-0.8801	1.6698
Ratio of outpatient visits and total admissions [log]	0.0881	1.6937	-0.0892	0.9920
Total surgical operations [log]	-3.5951	2.7364	-2.1834	1.6824

Table 21 (continued)

	Column (I) Fixed Effects Model with Instrument Variable		Column (II) OLS Fixed Effects Model	
	Coefficient	***SE***	***Coefficient***	***SE***
Lagged total margin	-3.6846	7.1129	-5.0692	6.3602
HHI	4.4126	15.7755	5.9452	12.4844
Market Characteristics				
Penetration of HMO in market	-1.9465	4.9634	-2.0206	3.3891
Penetration of PPO in market	-0.1766	5.2088	-2.3747	3.3149
Per capita income [log]	-6.7066	16.0044	-2.9374	13.8861
Proportion uninsured (ages 18 through 64 in county)	-9.9251	21.8762	-8.7742	13.7699
Population size [log]	-3.6908	30.7199	-7.9263	18.4255
Year 2006	1.4740	5.2159	0.6109	3.0498
Year 2007	1.3378	6.3356	1.5338	3.3015
Year 2008	1.2217	6.5872	0.9062	3.5677
Year 2009	0.8608	6.3349	0.9403	3.4640
Constant			165.2004	323.9737
Instrument Variable Specification Tests				
Over identification test (p-value)	0.18			
Weak identification test (F-Statistic)	0.34			
Fixed effects strict exogeneity test (p-value)	0.65			

Note: EHRS=electronic health record sophistication. ER=emergency room. FTE=full time equivalent. DRG=diagnosis related group. HHI=Herfindahl–Hirschman Index. HMO=health maintenance organization. OLS=ordinary least squares. PPO=preferred provider organization. RN=registered nurse. COTH=Council of Teaching Hospitals. *$p < .10$. **$p < .05$. ***$p < .01$

the instrumental variable is endogenous, suggested that the EHR variable and the specific levels of EHR sophistication can be treated as exogenous in the research question two model. Hence, the discussion of the results in Tables 20 and 21 focuses on the Column II findings of the fixed effects model assuming exogeneity.

For Hypothesis 2.1a, the results from Table 20 suggested that the EHR was associated with a higher, marginally significant ($p<0.10$) rate of postoperative sepsis – a result that was counter to the hypothesis. Similarly, for Hypothesis 2.1b, the results from Table 21 suggested that EHRS2 was associated with a higher, marginally significant rate of postoperative sepsis. Moreover, EHRS3 was associated with a higher, statistically significant ($p<0.05$) rate of postoperative sepsis when compared to hospitals that did not have EHR sophistication.

In regard to the control variables used for the research question two model, the results from Table 20 and Table 21 were similar: hospitals with a higher proportion of patients with a major or severe illness and those with patients between the ages of 19 and 64 (when compared to 65 and over) were associated with a higher, marginally significant rate of postoperative sepsis, while hospitals that had a greater number of high-technology services were associated with a lower, marginally significant rate of postoperative sepsis.

Results of sensitivity analyses.

Sensitivity analyses were performed for research question two to explore whether the results for the hypothesis were consistent. Table 22 provides the results when the dependent variable for the research question two model was the PSI composite, which was a measure based on nine surgical related PSI indicators. The results do not suggest any statistically significant relationship between hospital EHR and the PSI composite.

Table 22

Fixed Effects Regression Results of Electronic Health Record and Patient Safety Indicator Composite (*N=404*)

Specification One (EHR)		
	Coefficient	***SE***
EHR (EHRS1/EHRS2/EHRS3)	0.0018	0.0014
Specification Two (EHRS Level)		
	Coefficient	***SE***
EHRS1	0.0024	0.0015
EHRS2	-0.0004	0.0020
EHRS3	0.0027	0.0021

Note: EHR=electronic health record. EHRS=electronic health record sophistication. All models included control variables from the original model, but only key explanatory variables related to hypotheses tests are displayed in table.
**p* < .10. ***p* < .05. ****p* < .01

Table 23 presents the results of the link between four, targeted HIT applications, related to surgical operations, and postoperative sepsis or the PSI composite. The results suggested that the individual OR applications considered did not have a statistically significant relationship with postoperative sepsis or the PSI composite (i.e., Column I). The findings were also not

Table 23

Fixed Effects Regression Results of Operating Room Applications on Postoperative Sepsis Rate and Patient Safety Indicator Composite (*N=404*)

	Column (I)		Column (II)		Column (III)	
Dependent Variable: PSI Postoperative Sepsis Rate						
	Coefficient	***SE***	***Coefficient***	***SE***	***Coefficient***	***SE***
OR-Scheduling	0.7056	1.4567				
OR-Pre	0.4416	1.1892				
OR-Peri	-0.0333	1.2823				
OR-Post	0.6564	1.3055				
Surgical suite index			1.6194*	0.8825	1.1737	1.3682
EHRS1					1.0734	1.2181
EHRS2					-0.3494	1.7787
EHRS3					3.8771*	1.9912
Surgical suite index * EHRS1					-0.4040	1.6690
Surgical suite index * EHRS2					2.6175	2.0455
Surgical suite index * EHRS3					-1.7872	2.4577
Dependent Variable: PSI Composite						
	Coefficient	***SE***	***Coefficient***	***SE***	***Coefficient***	***SE***
OR-Scheduling	-0.0005	0.0020				
OR-Pre	-0.0001	0.0027				
OR-Peri	0.0012	0.0027				
OR-Post	-0.0006	0.0029				
Surgical suite index			0.0011	0.0014	-0.0016	0.0022
EHRS1					0.0004	0.0022
EHRS2					-0.0033	0.0034
EHRS3					0.0017	0.0037
Surgical suite index * EHRS1					0.0042	0.0028
Surgical suite index * EHRS2					0.0048	0.0039
Surgical suite index * EHRS3					0.0023	0.0042

Note: EHRS=electronic health record sophistication. OR=operating room. All models included control variables from the original model, but only key explanatory variables related to hypotheses tests are displayed in table.
*$p < .10$. **$p < .05$. ***$p < .01$

statistically significant when a summary index variable (i.e., the surgical suite index, which is a sum of a hospital having any of the four OR applications used in the sensitivity analysis) for the OR applications was included (i.e., Column II) or when the index was included with the individual levels of EHR sophistication and their interactions with the index variable (i.e., Column III). The summary index variable did have a marginally significant association with a higher rate of postoperative sepsis. A similar finding was also present with the EHRS3 variable in Column III.

Table 24 provides the coefficients for the effects of EHR sophistication on the rate of postoperative sepsis and the PSI composite based on the number of years that a hospital had a particular EHRS category during the study period. For hospitals with EHRS1, those with this level of sophistication for one year experienced a higher, statistically significant likelihood of poor patient safety performance vis-à-vis the PSI composite. Hospitals with EHRS2 for two and three years were associated with higher, statistically significant rates of postoperative sepsis. Similar results were also present for hospitals that had EHRS3 in their first three years of adoption.

Empirical Results: Research Question Three

Results of fixed effects model.

Table 25 reports the coefficients from the research question three model, which explores if hospitals that have a better fit between their organizational structure and technology have lower postoperative sepsis outcomes relative to those who do not have this type of fit. The table contains two columns to provide the results for the first and second specifications of the empirical model, which contain different degree of misfit and constituent variables. The first specification incorporated a degree of misfit measure based on the hospital's EHRS level and degree of centralization, while the second specification incorporated an overall degree of misfit measure based on the hospital's EHRS level, degree of centralization, level of differentiation, and type of integration. The cluster-robust standard errors, which account for heteroskedasticity and the correlation of errors within hospitals due to serial correlation, for the estimated

Table 24

Fixed Effects Regression Results of Electronic Health Record Differential Effects on Postoperative Sepsis Rate and Patient Safety Indicator Composite Over Time (*N=404*)

	EHRS1				**EHRS2**				**EHRS3**			
	PSI Postoperative Sepsis Rate		**PSI Composite**		**PSI Postoperative Sepsis Rate**		**PSI Composite**		**PSI Postoperative Sepsis Rate**		**PSI Composite**	
Year(s)	***Coefficient***	***SE***	***Coefficient***	***SE***	***Coefficient***	***SE***	***Coefficient***	***SE***	***Coefficient***	***SE***	***Coefficient***	***SE***
1	0.6896	0.9300	0.0039**	0.0017	1.9930	1.2785	-0.0007	0.0022	2.8199***	1.0436	0.0009	0.0021
2	1.1620	0.8044	0.0013	0.0015	2.3436**	1.1545	-0.0008	0.0021	3.0909***	1.1403	0.0035	0.0023
3	1.6344	1.1818	-0.0012	0.0021	2.6941**	1.3521	-0.0008	0.0026	3.3619**	1.6943	0.0061*	0.0033
4	2.1068	1.7645	-0.0038	0.0029	3.0446*	1.7665	-0.0008	0.0034	3.6329	2.4084	0.0086*	0.0046

Note: EHRS=electronic health record sophistication. PSI=patient safety indicator. All models included control variables from the original model, but only key explanatory variables related to hypotheses tests are displayed in table. *$p < .10$. **$p < .05$. ***$p < .01$

Table 25

Fixed Effects Regression Results of Fit on Postoperative Sepsis Rate (Specifications One and Two) [*N=404*]

	Column (I) Specification One (single fit measure)		Column (II) Specification Two (overall fit measure)	
	Coefficient	***SE***	***Coefficient***	***SE***
Key Explanatory Variable				
Degree of misfit	0.936	0.864	0.806	0.834
Fit Constituent Variables				
EHRS1	1.634	0.994	1.534	0.948
EHRS2	2.471*	1.261	2.394*	1.251
EHRS3	2.391**	1.047	2.422**	1.058
Centralized cluster	1.690	4.081	1.615	4.138
Moderately centralized cluster	0.766	3.755	1.394	3.901
Decentralized cluster	1.380	3.853	0.736	3.810
Independent hospital system	-1.670	3.868	-1.797	3.943
EHR enterprise application strategy: SDT			-4.705*	2.559
EHR enterprise application strategy: BOB			-1.478	1.901
EHR enterprise application strategy: BOS			0.898	1.281
EHR enterprise application strategy: NS			2.616	1.741
Level of differentiation			8.126	37.676
Patient Characteristics				
Hospital all-patient DRG case mix	1.003	2.138	1.141	2.151
Proportion of patients major or extreme severity illness	39.997*	23.414	40.039*	23.006
Average length of stay	-0.800	1.079	-0.870	1.090
Proportion of hospital patients age 19 through 64	37.161*	21.958	36.664*	22.108
Proportion of patients female	-29.679	19.164	-30.213	20.776
Proportion of patients non-Hispanic Black	-8.751	12.313	-9.813	12.490
Proportion of patients Hispanic	1.518	3.269	1.533	3.275
Hospital Characteristics				
Proportion of hospital nurses RN	-5.122	11.764	-4.889	11.820
Ratio of RN and total admissions [log]	-45.827	77.475	-43.286	77.585
Ratio of FTE and beds [log]	1.427	3.113	1.226	3.158
Share of inpatient days covered by Medicare	-4.228	5.282	-3.843	5.227
Share of inpatient days covered by Medicaid	8.692	5.405	8.619	5.394
Hospital bed size [log]	2.162	5.931	1.810	5.954
High-technology service mix index	-0.106*	0.060	-0.105*	0.060
Ratio of non-ER visits and total admissions [log]	-0.791	1.668	-0.921	1.681
Ratio of outpatient visits and total admissions [log]	-0.098	0.992	-0.103	1.003

Table 25 (continued)

	Column (I) Specification One (single fit measure)		Column (II) Specification Two (overall fit measure)	
	Coefficient	***SE***	***Coefficient***	***SE***
Total surgical operations [log]	-2.158	1.689	-2.064	1.695
Lagged total margin	-5.389	6.338	-5.566	6.367
Market Characteristics				
Penetration of HMO in market	-1.920	3.376	-2.318	3.351
Penetration of PPO in market	-2.464	3.301	-2.293	3.315
Per capita income [log]	-3.098	13.915	-2.739	14.005
Proportion uninsured (ages 18 through 64 in county)	-8.847	13.745	-8.155	13.759
Population size [log]	-8.394	18.450	-12.038	18.257
HHI	6.045	12.469	6.245	12.416
Year 2006	0.602	3.046	0.853	3.052
Year 2007	1.533	3.303	1.835	3.305
Year 2008	1.009	3.571	1.300	3.575
Year 2009	1.031	3.470	1.341	3.474
Constant	172.952	324.001	218.389	319.800

Note: BOB=best of breed. BOS=best of suite. COTH=Council of Teaching Hospitals. DRG=diagnosis related group. EHRS=electronic health record sophistication. ER=emergency room. FTE=full time equivalent. HHI=Herfindahl–Hirschman Index. HMO=health maintenance organization. NS=no strategy PPO=preferred provider organization. RN=registered nurse. SDT=self-developed technology. SV=single vendor. *$p < .10$. **$p < .05$. ***$p < .01$

coefficients are also reported.

The results did not provide support for Hypotheses 3.1a and 3.1b: the coefficients for the degree of misfit variables were both not statistically significant. In regard to the constituent variables and the control variables, the results were generally consistent with those obtained in the ordinary least squares fixed effect regression model used in research question two. In particular, the adoption of EHRS3 was, again, associated with a higher, statistically significant ($p<0.05$) rate of postoperative sepsis when compared to hospitals that did not have EHR.

Results of sensitivity analyses.

Table 26 provides the results when the dependent variable for the research question three model was the PSI composite. Although the coefficients were negative for both specifications of

Table 26

Fixed Effects Regression Results of Fit and Patient Safety Indicator Composite (*N=404*)

	Column (I) Specification One (single fit measure)		Column (II) Specification Two (overall fit measure)	
	Coefficient	*SE*	*Coefficient*	*SE*
Key Explanatory Variable				
Degree of misfit	-0.001	0.002	-0.001	0.002
Fit Constituent Variables				
EHRS1	0.001	0.002	0.002	0.002
EHRS2	-0.001	0.002	-0.001	0.002
EHRS3	0.003	0.002	0.003	0.002
Centralized cluster	0.007	0.005	0.007	0.005
Moderately centralized cluster	0.013***	0.005	0.013***	0.005
Decentralized cluster	0.012**	0.005	0.012**	0.005
Independent hospital system	0.013**	0.006	0.013**	0.006
EHR enterprise application strategy: SDT			0.003	0.010
EHR enterprise application strategy: BOB			-0.006	0.004
EHR enterprise application strategy: BOS			-0.005**	0.002
EHR enterprise application strategy: NS			-0.002	0.003
Hospital level of differentiation			0.109	0.080

Note: BOB=best of breed. BOS=best of suite. EHRS=electronic health record sophistication. NS=no strategy. SDT=self-developed technology. SV=single vendor. All models included control variables from the original model, but only key explanatory variables related to hypotheses tests are displayed in table. *$p < .10$. **$p < .05$. ***$p < .01$

fit, the results were not statistically significant, and hence, consistent with the results obtained in the main fixed effects model with the postoperative sepsis dependent variable.

Summary

This chapter provided descriptive and multivariate analyses to address the study's three primary research questions. The findings from the research question one model suggested that hospitals had a significant increase in the probability of having EHR as the percent of other hospitals having EHRS3 in the market increased or when the percent of Medicare patients increased within a hospital. Conversely, hospitals had a significant decrease in the probability of having EHR when the percent of Medicaid patients increased within a hospital or when the hospital belonged to centralized or moderately centralized systems. Sensitivity analyses using an unbalanced panel and different definitions of a hospital market generally confirmed the results of the main analyses from the research question one model.

Findings from the research question two model suggested that EHR was associated with a higher, marginally significant rate of postoperative sepsis. More specifically, EHRS2 and EHRS3 were associated with a significantly higher rate of postoperative sepsis when compared to hospitals that did not have EHR sophistication. Results from the sensitivity analyses provided mixed support for the main analyses. In particular, the results did not suggest any statistically significant relationship between EHR and the PSI composite; the use of OR applications were also not significantly associated with lower rates of postoperative sepsis or the PSI composite. However, hospitals that had EHRS1 for one year experienced a higher, statistically significant likelihood of poor patient safety performance vis-à-vis the PSI composite. Hospitals with EHRS2 for two and three years were also associated with higher, statistically significant rates of postoperative sepsis. Similar results were present for hospitals that had EHRS3 in their first three years of adoption.

The findings from the research question three main model and sensitivity analyses did not provide support for either Hypothesis 3.1 or 3.2: the coefficients for the degree of misfit variables were both not statistically significant. However, EHRS3 was, like in the research question two model results, associated with a significantly higher rate of postoperative sepsis when compared to hospitals that did not have EHR. The next chapter will provide a detailed summary of the research findings and discuss some their implications.

Chapter 6: Discussion

Recent developments in HIT provide a potential opportunity through which hospitals may be able to improve their patient safety records. Specific to this study, EHRs are a promising form of HIT that may improve patient safety in hospitals (Furukawa et al., 2010a; Kazley & Ozcan, 2008). Postoperative sepsis, a type of adverse patient safety event, is an important patient safety issue that various functionalities of EHR could help address; EHR, as a result, may help improve the patient safety performance of a hospital.

This study attempted to examine three research questions: 1) what organizational and environmental forces are associated with hospitals' having certain EHR applications; 2) will hospitals that adopt EHRs have lower postoperative sepsis outcomes relative to those who do not adopt such applications; and 3) will hospitals that have a better fit between their organizational structures and technology have lower postoperative sepsis outcomes relative to those who do not have this type of fit. Empirical models were used to examine the relationship of key explanatory variables with hospital EHR presence and postoperative sepsis performance, while controlling for factors related to patient, hospital, and market characteristics. Chapter 5 presented detailed results from the empirical models. Chapter 6 will first present an overall summary of these findings. The findings will then be interpreted by each research question in turn. Lastly, the limitations of the study are noted, and the implications of the findings and suggestions for future research will also be reviewed at the end of this chapter.

Summary of Study Findings

Table 27 presents the eight hypotheses tested in this study and indicates whether the hypotheses were supported based on the findings of the empirical models, which were previously described in Chapter 5.

Table 27

Assessment of Study Hypotheses

Hypothesis	Hypothesis Supported
Research question one: Hospital EHR presence	
1.1: The degree of local diffusion of EHR adoption in a market will be positively related to the likelihood that an individual hospital adopts EHR.	Partial
1.2: Hospitals' dependence on managed care and Medicare will be positively related to EHR adoption, while dependence on Medicaid will be negatively related to EHR adoption.	Partial
1.3: Teaching hospitals will have a higher likelihood of adopting EHR than non-teaching hospitals.	No
1.4: The degree of centralization in a hospital's system will be positively associated with EHR adoption.	No
Research question two: Performance effects of EHR	
2.1a: Adoption of EHR is associated with lower postoperative sepsis outcomes.	No
2.1b: The degree of EHR sophistication is associated with greater reductions in postoperative sepsis outcomes.	No
Research question three: Hospital Fit and EHR performance	
3.1a: Higher degree of fit between a hospital's EHR sophistication and degree of centralization will be associated with greater reductions in postoperative sepsis outcomes.	No
3.1b: Overall degree of fit between a hospital's EHR sophistication and degree of centralization, level of hospital differentiation, and type of hospital integration will be associated with greater reductions in postoperative sepsis outcomes.	No

Note: EHR=electronic health record.

Hospital electronic health record presence.

This study drew on Oliver's (1991) organizational theory framework, which integrated Institutional Theory and Resource Dependence Theory, to examine the nature of EHR presence among hospitals. Using an ordered probit model, the study tested four hypotheses that helped explain how hospitals may or may not adopt EHR.

In regard to hypothesis 1.1, the results suggested that the presence of EHRS1 and EHRS2 by other hospitals in a hospital market may not provide sufficient motivation for a hospital to have EHR. A possible explanation for this could be that such HIT may be easier to integrate with existing work processes and hospitals might not need too much effort to have applications related to EHRS1 or EHRS2. However, the presence of EHRS3 among other hospitals might signify a perceived higher level of healthcare quality, which may also correlate with gains in organizational legitimacy (DiMaggio & Powell, 1991) or the ability to appease the expectations of important stakeholders (Pfeffer & Salancik, 1978).

The findings did support the notion that hospitals with a high proportion of Medicaid patients may place a lower value on having EHR or may have less capital to invest in such technology (McCullough, 2008). But, having a high proportion of Medicare patients or high penetration of HMO or PPO in a hospital market did not positively predict the presence of EHR among hospitals. The aforementioned types of hospitals may have still been evaluating the value of EHR for their organizations, and hence not actively pursued certain types of EHR applications during the study period explored.

The results for hypotheses 1.3 suggested that teaching hospitals were not significantly more likely to have EHR than non-teaching hospitals. Other studies, however, have found that academic hospitals were more likely to have EHR than non-teaching hospitals (e.g., McCullough, 2008; Wang et al., 2005). It may be that the teaching and non-teaching hospitals evaluated did not significantly vary in EHR presence because of the specific states or the time period used in this study.

In regard to a hospital's degree of centralization, the study found that hypothesis 1.4 was not supported, and a hospital being part of a centralized or moderately centralized system was less likely to have EHR in comparison to hospitals that were not part of a hospital system. The aforementioned results were contrary to hypothesis 1.4, and additional research is required to validate whether similar results hold when alternative measures of the degree of centralization are used as well.

Some of the control variables used in the empirical model also had significant associations with EHR presence: specifically, hospital size, the provision of high-technology services, ownership type, community orientation, the study time period, and the state in which the hospital was located.

Hospitals that were bigger in size (measured by bed size) may attract greater attention, and are thus more vulnerable to social pressures to have EHR (Meyer, 1979); furthermore, the potential presence of slack resources (Baron & Hannan, 1994) in these organizations could also help with EHR presence. Hospitals that have had prior experience with innovative technologies (measured by the high-technology service mix index) may be predisposed to have EHR (Walston et al., 2001) with the help of work-practices and routines that can easily adapt to new technology. For-Profit and Publicly owned hospitals were both more likely to adopt EHR than not-for-profit hospitals. This behavior may be present among not-for-profit hospitals due to their pressure, as tax-exempt organizations, to yield to community needs and to provide services that may not be profitable (Clement, Smith, & Wheeler, 1994). Concomitantly, there was a lower likelihood that hospitals with high levels of community engagement had EHR, which is a finding that has been supported by the research of Encinosa and Bae (2011) as well.

The findings suggested that the presence of EHR in hospitals significantly increased over the study period in reference to the base year, which is a general trend that has been acknowledged in other studies as well (e.g., Jha et al., 2010). The study findings also suggested that hospitals situated in the states of Florida, Maryland, New Jersey, and Arizona were more likely to have EHR than hospitals in California. The aforementioned patterns of EHR presence among states are similar to the findings present in the studies by Furukawa et al. (2008) and Jha et al. (2010).

Performance effects of electronic health record.

This study used Donabedian's (1980) framework to assess the performance of hospital EHR in relation to postoperative sepsis rates. Using a fixed effects model, the study tested two hypotheses that helped explain how hospitals might reduce the rate of postoperative sepsis with the help of EHR. In regard to hypothesis 2.1a, the results suggested that the relationship between EHR and a higher postoperative sepsis rate was marginally significant. Further exploration, through hypothesis 2.1b, indicated that EHRS1 did not have any association with the rate of postoperative sepsis: this may be due to the limited role such technology could play in the "changing of nurse workflow and processes" (Furukawa et al., 2011; pg. 325). But, EHRS2 and EHRS3 were significantly linked to increased rates of postoperative sepsis. Like Furukawa et al. (2011), the results from this study's sensitivity analysis suggested that EHR may be associated with poor patient safety performance, at least in the early periods of implementation.

The above noted findings could reflect the presence of a learning curve that may also be connected to workflow disruptions in care delivery processes that could in turn lead to higher postoperative sepsis rates. Another plausible explanation is the transformations in workflow not only from the EHR, but from the emergence of new practices (Hilligoss & Zheng, 2012). Namely, EHR (especially, EHRS2 and EHRS3) may increase the capability to document (i.e., detection and reporting) the incidents of postoperative sepsis (Gunningberg, Fogelberg-Dahm, & Ehrenberg, 2009). EHR could also lead to an over-reliance by clinicians to use it as a "peripheral brain" (McAlearney, Schweikhart, & Medow, 2004; p.4), which automatically performs previously manually based tasks. Such reliance then could lead to errors of omission or commission, where clinicians may miss important data because a system does not prompt them to such information or clinicians may comply with incorrect directives, presented by an application, even when it runs counter to an individual's medical training (Coiera, Westbrook, & Wyatt, 2006).

Some of the control variables used in the empirical model also had significant associations with postoperative sepsis rate: specifically, patients with a major or severe illness, patients between the ages of 19 to 64 (when compared to 65 and over), and hospitals that had more high-technology services. Greater rates of postoperative sepsis arose in hospitals with patients that had a major or severe illness, which may be due to such patients being more susceptible to postoperative sepsis due to a poor immune system. Counter to general expectations, patients in the age group 19 to 64 were marginally associated with a higher rate of postoperative sepsis in comparison to patients in the 65 and over category. The type of surgery obtained and the behavior (e.g., lifestyle) of patients in the 19 to 64 age group after the surgery may provide some plausible explanations as to why patients in this age group may be more susceptible to postoperative sepsis than the older age category.

As expected, hospitals with more high-technology services were linked to lower postoperative sepsis rates. This finding supports the general premise of the Structure-Process-Outcome framework that more advanced structures (i.e., more technology) could help improve care processes that can, in turn, influence safer care outcomes (Donabedian, 1980).

Hospital fit and electronic health record performance.

This study relied on Donaldson's (2001) rendition of Structural Contingency Theory to assess whether hospitals that had a better fit between their organizational structure and type of EHR technology were associated with lower postoperative sepsis rates relative to those who did not have this type of fit. Using a fixed effects model, this study tested two hypotheses to explore the links between a single fit measure and overall fit measure and the rate of postoperative sepsis. Both hypotheses did not present any significant associations between the fit measures and the rate of postoperative sepsis. It may be that a nonlinear relationship was present between the constituent fit variables, which may not be accurately depicted in the fit measure used in this study. Relatively low between-group and within-group variance for the fit measures may have also contributed to the lack of statistically significant results. More work in regard to the concept of fit between hospital structure and EHR is needed, and some areas worth exploring are discussed later onwards in this chapter.

Some of the control variables and fit constituent variables used in the empirical model also had significant associations with postoperative sepsis rate. For the control variables, these included: patients with a major or severe illness, patients between the ages of 19 to 64 (when compared to 65 and over), and hospitals that had a greater number of high-technology services. For the fit constituent variables, these included: presence of certain EHR applications and EHR enterprise application strategy.

The nature of the findings for the relationships of the above noted control variables and the presence of certain EHR applications with hospital postoperative sepsis rate have already been discussed under the findings of the research question two model. In reference to EHR enterprise application strategy, hospitals that had a self-developed technology (SDT) EHR enterprise application strategy were associated with lower postoperative sepsis rates in comparison to hospitals that had a single vendor (SV) EHR strategy. A plausible explanation for this finding could be that hospitals with an SDT strategy were able to have a higher level of work integration and customization (Fareed, Ozcan, & DeShazo, 2011) than hospitals with an SV strategy. Although hospitals could have had a high level of integration with an SV strategy, the level of customization may have been limited to the EHR design specifications of the vendor that a hospital contracted with to acquire most of its EHR applications. A higher level of work integration and customization could provide better care delivery through the enhanced coordination of effective care delivery procedures, which are also focused on the specific needs of a patient.

Study Limitations

Although the proposed study has several strengths and makes important contributions to the literature in the study of HIT, there are important limitations that need to be noted. In regard to the construction of the EHR variables, HIMSS does not identify whether a hospital's specific unit had adopted an EHR application. This precludes the ability to identify whether surgical units may or may not have had an application. Also, the system used to categorize EHR sophistication represents a theoretical approach that was conceptualized by experts in the HIT field, and thus the measure has face validity, but may still require validation through statistical tests.

Only the structural and outcome dimensions of Donabedian's (1980) framework were operationalized in this study. The incorporation of a process dimension could help identify whether hospitals that adopt EHR are actually transforming work processes, which could in turn help reduce the rate of postoperative sepsis.

The availability of information on the total length of time a hospital had an application is limited in HIMSS. Hospitals that had an application for a longer period of time may have gained more experience with their technology and capitalized on the benefits it potentially offered. Further, it is important to realize that although a hospital may have successfully adopted an EHR application, the extent and caliber of their use across facilities may still vary. Variation in use may be due to a factor such as resistance from clinicians to effectively incorporate the applications into their work processes.

Issues such as non-random selection and measurement error are bound to be present among administrative datasets such as AHA, HCRIS, HIMSS, and HCUP. However, these datasets have been validated (especially the AHA), used in several past empirical studies, and the measures constructed from them have been generally viewed as being reliable. Besides, they represent the few datasets that provide standardized information on hospitals that can be used in health services research.

Studies that have previously used Structural Contingency Theory have predominantly relied on survey measures to gauge various contingencies and structural dimensions of an organization. The use of administrative datasets may not provide the same flexibility as survey instruments in obtaining insightful information about intra-organizational features (Alford, 1974). However, Hyderbrand (1974) argued that datasets such as the AHA Annual Surveys can be used to obtain meaningful measures of hospital intra-organizational features (e.g., differentiation of medical services) that “may well tell you as much as, if not more than, an in-depth analysis of one delivery system” (p. 491-92).

Lastly, although the measurement approach used to evaluate fit in this study has the advantage of providing the level of fit or misfit for each organization, a main drawback to this method of measuring fit is that it compares an organization’s performance to an ideal level. While there may be several optimal profiles of fit, they are only limited to a linear conceptualization in this study; any organizations that lie outside of this concept of fit are treated as being in misfit (Donaldson, 2001). It is important to, therefore, note that the true correlation between fit and performance may tend to be understated (Donaldson, 2001). Despite these shortcomings, the study results provide some important implications for theory, health policy and practice.

Implications of the Findings

Theoretical implications.

This study adopted several organizational theory frameworks to examine hospital EHR adoption and EHR performance. The advantage of applying these theories was to obtain a comprehensive perspective on the issues explored in this study. Nonetheless, many of the study’s hypotheses were not supported. Further modifications or extensions of the theoretical frameworks, which could build upon the general concepts already proposed in this study, may be warranted.

Oliver’s (1991) integrated theoretical model presented some hypotheses that were partially supported by the study’s empirical evaluations. Additional research is suggested to further evaluate the hypotheses that were not significant from this model. Such research may include the use of different research designs, samples, and alternate measures of the key constructs.

It is essential to note that the Structure-Process-Outcome model is limited by its ability to present a strong causal linkage between EHR and postoperative sepsis. The model was primarily designed to provide researchers with the ability to classify structures, processes, and outcomes, and possibly identify interrelationships that may exist between these three dimensions. Hence, the capacity to explicate the drivers of EHR that can specifically affect postoperative sepsis performance may be restricted by the Donabedian (1980) framework. More research is needed to determine the causal connections between EHR, the processes related to improving postoperative sepsis, and postoperative sepsis outcomes.

In regard to one of the study's main findings, for example, the significant relationship between EHRS3 and the higher rate of postoperative sepsis, ran counter to the hypothesis (2.1b) generated from the Structure-Process-Outcome portion of the study's conceptual model. The underlying driver, however, behind the higher rate of postoperative sepsis may have been due to the better documentation of postoperative sepsis events (Gunningberg et al., 2009), which is a behavior that might need to be accounted for in future assessments of EHR performance, particularly when using the Donabedian (1980) framework. Such an approach may help account for any bias against findings that could link EHR with lower rates of postoperative sepsis (Furukawa et al., 2011).

Based on this study's results, the use of the Structural Contingency Theory to evaluate EHR and postoperative sepsis performance could be questioned. Notwithstanding, organizational theorists, as early as Woodward (1965), have demonstrated that the appropriate fit between organizational structure and technology can lead to high performance. Other studies (e.g., Mohr, 1971; Pennings, 1975), however, were unsuccessful in finding significant relationships between fit and performance. In light of such failed attempts, Pfeffer (1997; p.162) acknowledged that "the empirical support for the consonance [fit] hypothesis has been inconsistent. But that could conceivably be remedied by more careful studies and measures."

In the spirit of the above statement by Pfeffer, this study calls on researchers to consider the need for a more subtle application of EHR fit. Some of the areas that researchers, who plan to use Structural Contingency Theory to assess EHR fit and performance, need to consider include: the identification of potentially non-linear fit relationships, the measurement of fit at the unit level in order to capture dynamics present at this level that may not be reflected at the organizational level, and the use of other measures to operationalize the theory's key constructs.

Additionally, this study incorporated constructs (i.e., degree of centralization, level of differentiation, and type of integration) that have been traditionally used in the research studies based on Structural Contingency Theory. The versatility of the theory, however, lends itself to the further development of other constructs (e.g., level of clinician's autonomy), which could help better match the theory to the issue of EHR fit and performance. Qualitative explorations, for example, could be used to help identify new, and potentially more appropriate, structural dimensions, within a hospital, that best fit with the various levels of EHR used in this study.

Healthcare policy implications.

During the period evaluated in this study, policymakers and other institutional actors in the healthcare system had a firmly established view that the mere adoption of HIT, such as EHR, by hospitals can help improve patient safety (Cresswell & Sheikh, 2012). There is increasing appreciation, however, in the policy arena that such an expectation in relation to EHR is unrealistic (Cresswell & Sheikh, 2012). Simply motivating hospitals to adopt EHR could potentially lead to harmful outcomes (Waegemann, 2013) as identified in this and other studies. Policymakers need better understanding of the driving forces behind hospital adoption of such technology, and whether incentives provided to hospitals are appropriately designed to motivate the adoption and effective use of EHR technology. Hence, policymakers may need to focus their attention on motivating hospitals to adopt a clear set of effective EHR functionalities with the most potential to improve patient safety: an idea that may be reflected in contemporary notions of EHR meaningful use.

Although the meaningful use of EHR among hospitals is a stepping stone towards the ideal use of EHR, policy makers need to also consider actions that help identify, monitor, and prevent the incorrect use of EHR that can lead to adverse patient outcomes. One example is the Food and Drug Administration (FDA) Safety and Innovation Act of 2012, which had called for the Department of Health and Human Services to propose a regulatory framework to protect patient safety pertaining to HIT such as EHR use (U.S. Congress, 2012; section 3187). In one scenario, it was proposed that the FDA should monitor EHR as a Class III medical device[8] (Institute of Medicine, 2012). However, the implementation of such regulations could also bring forth barriers (e.g., delayed release time for EHR technology due to additional safety related testing requirements) to EHR adoption and use that need to be addressed.

Practical implications.

Developing the necessary infrastructure and support for a successful EHR system in hospitals is a daunting task, especially since EHR is still regarded by many as an evolving HIT. Even though the meaningful use guidelines set forth by the Office of the National Coordinator for Health Information Technology (ONC) has provided some structure for healthcare providers

[8] Class III medical devices are highly regulated technologies that require stringent pre-market evaluations of their safety and effectiveness. Other examples of Class III medical devices include: pace makers and pulse generators.

to follow with EHR adoption, clearer guidance is needed so that organizations “can align activities related to patient safety with the activities required to support a safe EHR-enabled health care system” (Sittig & Singh, 2012; p.1854).

Healthcare administrators need to look beyond the meaningful use requirements and track the potential deviations from standard EHR processes that could negatively affect the quality of healthcare delivery for their organization (Shea, et al., 2013). Such incidents could be driven by factors such as: breakdowns in care processes, changes in workflow, resistance to change by clinicians, and increases in workload (Shea et al., 2013).

Although this study did not find a significant relationship between hospital fit and EHR performance, it is still important for healthcare administrators to carefully evaluate their resource capacities, structural dimensions, and social dynamics within their organization and match these appropriately with the correct EHR functionalities to help avoid poor patient safety outcomes. The application of a framework for successful EHR adoption, which could additionally track care quality performance before and after EHR implementation, could also provide guidelines on how to identify and mitigate new or unexpected risks that may arise from the use of an EHR system (Sittig & Singh, 2012).

Future Research

There are three primary areas of research that can be explored as extensions to this study and its findings. These areas include:

1) The evaluation of post-meaningful use (i.e., post 2009) EHR adoption and EHR performance among hospitals: An examination of this type could help evaluate whether the findings from this study are still consistent or if they might change based on the increasing focus on meaningful use by policymakers and other stakeholders in the healthcare industry;

2) An assessment of the nature of negative consequences linked to EHR: Future research could identify how errors related to EHR use might occur and what measures could be taken to prevent them. Such studies can provide beneficial insights for policymakers and researchers who are involved in the design and creation of a regulatory framework for monitoring the safety of EHR use; and

3) Further exploration of topics related to EHR fit and performance: Research of this form may include attempts to measure hospital unit-level structural dimensions and whether these features fit with certain types of EHR to potentially lead to better patient safety performance in comparison to hospital units that do not have such fit.

Conclusion

Encinosa and Bae (2011) posited that the adoption of EHR is increasingly becoming an essential part of the effort to improve patient safety in hospitals. Along with other researchers such as DesRoches et al. (2010), they cited a series of major policy initiatives, which were launched as early at 2004 and culminated in the enactment of the 2009 HITECH Act that had related provisions for EHR meaningful use in the 2010 ACA. However, the utility of such initiatives hinges on the successful adoption of potentially patient safety improving HIT, such as EHR. In order for this to occur, policy makers and healthcare administrators may to consider an expanded understanding of EHR and its relationship to patient safety performance.

This study used an organizational theory lens to explore three research questions: 1) what organizational and environmental forces are associated with hospitals' having certain EHR applications; 2) will hospitals that adopt EHRs have lower postoperative sepsis outcomes relative to those who do not adopt such applications; and 3) will hospitals that have a better fit between their organizational structures and technology contingency have lower postoperative sepsis outcomes relative to those who do not have this type of fit. The study used longitudinal data, from 2005 to 2009, for six states; and used econometric models to test eight study hypotheses. Key study findings suggested that hospitals had a significant increase in the probability of having EHR as the percent of other hospitals having EHRS3 in the market increased. Conversely, hospitals had a significant decrease in the probability of having EHR when the percent of Medicaid patients increased within a hospital or when the hospital belonged to centralized or moderately centralized systems. Also, the study findings suggested that EHR was associated with a higher, marginally significant rate of postoperative sepsis. Specifically, EHRS2 and EHRS3 were associated with a significantly higher rate of postoperative sepsis when compared to hospitals that did not have such EHR sophistication.

Aside from some limitations, the study findings provide new insights for the advancement of organizational theory, future policy discussions, and practice related considerations. The findings also present several new research opportunities that need to be explored to better understand the nature of EHR adoption and patient safety performance in hospitals.

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Vita

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