2006

Electronic Medical Records in Acute Care Hospitals: Correlates, Efficiency, and Quality

Abby Jo Swanson
Virginia Commonwealth University

ELECTRONIC MEDICAL RECORD USE IN ACUTE CARE HOSPITALS:

CORRELATES, EFFICIENCY, AND QUALITY

A Dissertation submitted in partial fulfillment of the requirements for the degree of PhD at Virginia Commonwealth University.

by

ABBY JO GILLENORA SWANSON
Master of Teaching, The University of Virginia, 2001
Bachelor of Arts, The University of Virginia, 2001

Director: DR. YASAR OZCAN
PROFESSOR DEPARTMENT OF HEALTH ADMINISTRATION

Virginia Commonwealth University
Richmond, Virginia

July 27, 2006

ACKNOWLEDGEMENT

The purpose of this section is to thank the individuals who have helped to make this work possible. In doing so, they have helped me to achieve a dream. First, without the love, support, friendship, and encouragement of my family, I likely would not have finished this dissertation. Bryan, my new family, has provided me with daily laughter, constant doses of encouragement, plenty of reality checks, and endless amounts of optimism. I am so appreciative of his patience and the support he has given me in my career. My parents are among the greatest inspirations in my life. I am thankful that they have always told me that I am capable of anything. Even more, their unconditional love has always encouraged me to try many new things and to appreciate the learning in every life lesson. My sisters have also been guiding influences in my life. I am thankful to Kelsey for her wonderful example, which has always encouraged me to strive for more. She is kind, bright, successful, and fun, a rare combination. I am thankful to Lindsay for her conviction and bravery. She continues to show me that it is best to follow your heart, and success and happiness will follow.

I am so thankful to the chair of my dissertation, Dr. Yasar Ozcan, who shared his insight and encouragement very freely throughout my dissertation process. Dr. Ozcan is well known for his terrific work and research, yet he always made this project a priority. His ideas were fantastic, and his encouragement and example were always very appreciated. My meetings in his office were so valuable and never failed to clear me of any confusion I had. Without Dr. Ozcan's help, I would never have finished this work as quickly nor would I have been so proud of the final product. For all of these things I am extremely grateful.

I owe a great deal of gratitude to Dr. Stephen Mick. I am especially thankful for his patience, brilliance, meticulous attention to detail, enthusiasm, and love of teaching. I have learned so much from him and hope to follow his example as a mentor in academia.

I am also indebted to Dr. Robert Hurley and Dr. Larry Williams. Dr. Hurley has provided me with a great deal of insight, information, and inspiration with his teaching and feedback on my work. He did all of these things with a wonderful disposition and a good sense of humor, two traits I really admire. Dr. Williams is so accomplished, yet still makes time for students and serves as a wonderful example and resource for all in academia. His passion for his field and opportunities for collaboration are unending, and his attitude is caring and relaxed, which makes him so approachable and appreciated.

I am so grateful for the opportunity I have had to learn from the entire VCU Department of Health Administration. The faculty more than exceeded any hope or expectation I had, and I am so proud to be a graduate of this program. I am extremely thankful for the support I received during my time as a student. I especially thank Dr. Michael McCue, Dr. Diane Dodd-McCue, Dr. Kelly Devers, and Dr. Delores Clement for the help, encouragement, and teaching they provided while I was a student.

I also have learned so much from the other students in this program. I especially thank Nailya Delellis, Michelle Lee, Preethy Nayar, Veronica Sikka, Henry Caretta, Askar Chukmaitov, and Mark Diana for their time, their friendship, and their insight of so many of the issues we discussed.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

Page

ABSTRACT

ELECTRONIC MEDICAL RECORDS IN ACUTE CARE HOSPITALS:

CORRELATES, EFFICIENCY, AND QUALITY

By Abby Swanson, PHD, MT, BA

A Dissertation submitted in partial fulfillment of the requirements for the degree of PhD in Health Services Organization and Research at Virginia Commonwealth University.

Virginia Commonwealth University August 2006

Director: Yasar Ozcan, PhD
Professor, Department of Health Administration

The purpose of this dissertation is to examine the organizational and environmental correlates of hospital EMR use and to examine the relationship between hospital EMR use and performance. Using a theoretical framework that combines resource dependence theory with Donabedian's structure, process, outcome model, a conceptual model is created. To test the hypotheses of this model, logistic regression and Data Envelopment Analysis (DEA) are used. The data included in this analysis come from the AHA, HIMSS, CMS, ARF, and HQA. In the

analysis of hospitals correlates of EMR use, three hypotheses were supported, and one was partially supported. Hospital system affiliation, bed size, and environmental uncertainty were found to be positively associated with hospital EMR use. Hospital rurality was found to be associated with EMR use for all categories except one; at every other level of rurality, as the hospital moves on a continuum from least rural to most urban, the likelihood of hospital EMR use also increases. Hospital EMR use was not found to be associated with teaching status, environmental munificence, competition, operating margin, ownership, or public payer mix.

In the hospital performance analyses, one hypothesis was supported, and one was partially supported. Regarding quality, hospitals with EMRs were found to provide higher quality than those without EMRs. In efficiency performance, only small hospitals with EMRs were found to be more efficient than hospitals without EMRs. No support was found that hospitals with EMRs improve their efficiency over time more than hospitals without EMRs.

Hospital EMR use does vary by certain organizational and environmental characteristics. For this reason, hospitals and policy makers must take action that enables and encourages all hospitals to implement and use EMRs because some hospitals do not have the motivation or resources to begin using EMRs on their own. Hospital EMR use is positively associated with high quality care, thus justifying the practice. Hospital efficiency was not found to be associated with EMR use in medium or large hospitals, but it was found to be associated with EMR use in small hospitals. Interestingly, larger hospitals are more likely to use EMRs than small hospitals. It is possible that the efficiency gains of EMR use in hospitals will not be realized until a standardized, fully interoperable system is developed, allowing health care provides to quickly and easily share the medical charts of their patients.

CHAPTER 1: INTRODUCTION

Purpose of the Research

The purpose of this study is to examine organizational and environmental factors associated with EMR use and to assess the impact EMRs have on hospital performance. It is a fact that a majority of U.S. hospitals are now operating without EMR systems, yet there are some hospitals that have employed EMRs for a number of years. However, little quantitative research has been done to assess the impact EMRs have on hospital performance. The purpose of this research is to identify which hospitals, based on organizational and environmental characteristics, have already implemented EMR systems so as to enable researchers to identify larger trends of hospital EMR use.

This study also hopes to measure and identify differences in performance for hospitals that use EMRs as compared to those that do not use EMRs. Performance is considered to include both the efficiency of processes and quality of outcomes in health care. In this period of cost containment and quality concern, both efficiency and quality have been increasingly demanded from providers such as hospitals. Although there is some projection that EMR use may allow for improvements in both efficiency and quality, there has not been a study to examine this rigorously on a broad scale basis. This study attempts to fill this gap. While much of the research that has been conducted in the area of EMR use has been anecdotal, qualitative, or of a case-study nature, this study will quantitatively evaluate how EMR use influences the processes and outcomes of care.

Introduction

The United States health care system has faced many challenges in recent decades. Health care costs and spending have grown at dramatic rates, and providers have been challenged to contain and reduce these costs through practices such as Prospective Payment Systems, increased competition, and managed care. Attention has also been pointed to the quality of health care with providers, payers, and patients all demanding increased quality of services. Health information technology is both a reason for the increase in cost and quality concerns and an answer to questions of how to improve quality and control costs. Health information technology includes many different components, which attempt to standardize and automate health care. As technology emerges, the expenses of providing novel care with new information and equipment increases drastically, yet new technology may also give providers the ability to perform more efficient and appropriate health care. With regard to quality, new technology may advance the treatment of patients, allowing for better disease management and diagnosis. However, without reliable information about the quality outcomes of current medical practices and the timely dispersion of recommended clinical guidelines, the quality of health care may be slow to evolve. Health information technology (HIT) may change the way health care is provided and influence outcomes in the future.

The Electronic Medical Record (EMR) is a promising new piece of health information technology (Tierney, Overhage, and McDonald 1997, Shortliffe 1999). EMRs are individual computerized documents of patient medical history, treatments, and lab results, which are often coupled with other tools such as computerized physician order entry (CPOE), electronic prescribing, and a multitude of administrative and fiscal functions (Schmitt and Wofford 2002, Shortliffe 1999). While there is some variation in the scope of EMRs, their use is predicted to change the processes of health care drastically while also improving quality and decreasing costs (Brailer 2004, Tierney, Overhage, and McDonald 1997, Burt and Hing 2005). The quality improvements are expected due to the automated nature of EMRs, requiring providers to follow clinical guidelines, while also reducing errors that cause medical harm such as incomplete medical histories, illegible handwriting on paper charts, and prescription interactions (Miller and Sim 2004, Varon and Marik 2002). The potential quality improvements are also expected due to the fact that EMRs will allow data to be collected more completely and quickly to determine the success of clinical interventions (Varon and Marik 2002). Efficiency will be achieved through the reduction of duplicate treatments, the automation of care, and the time that will be saved, as patients' complete medical histories will be readily available (Hannan 1999). It is also expected that EMRs will reduce the need for certain services such as medical transcription and chart storage and management. The reduction or elimination of these services could reveal excess resources that can be directed to other aspects of patient care, which may improve the overall quality of health care.

There is a great deal of evidence to suggest that the EMR may be the wave of the future for American health care (Berner, Detmer, and Simborg 2004). This evidence exists in the form of government initiative, payer interest, some provider practice, environmental pressure, and the availability of EMR products (Berner, Detmer, and Simborg 2004). Up until this point, paper medical records have been maintained, but have been criticized for being inaccurate, illegible, and incomplete (Shortliffe 1999). The ability of paper medical records to assess health care outcomes and monitor public health areas has been disappointing. Not only is the data collection time consuming, but it also may not reflect the nature of the health care experience. Even before the advent of the EMR, health care researchers such as Donabedian criticized paper medical records (1980). Paper medical records may be inaccurate, and they do not always reflect the true nature of interaction between a patient and a physician. It is often the case, too, that when medical records are used as a proxy for measuring the quality of care a patient receives, it is instead the quality of the record that is assessed. In other words, if a health care provider is more detailed in the documentation of an interaction with a patient, a medical record review may reveal that this provider performed greater quality care than another practitioner who may have performed as well but did not document the care in as much detail. With the opportunity of EMRs, the standardization of an interoperable medical record system, with individual patient files that can be shared and transferred among providers nationwide, could ensure uniformity of medical records, allowing for a better measurement of the quality of care provided.

While there is a great deal of hope for a nationally interoperable EMR system, the implementation of EMRs has been slow. Currently, approximately 31% of hospital emergency departments and 29% of hospital outpatient departments use EMRs (Burt and Hing 2005). The barriers to implementation in individual hospitals include the substantial cost of implementation, physician resistance, and a public fear over the security of sensitive health information that exists in an electronic format (Shortliffe 1999¸Rash 2005, Miller and Sim 2004). Each of these barriers represents a valid concern, yet they must be addressed in the interest of health care efficiency and quality improvement. A similarity between the EMR and the banking industry's automated teller machine (ATM) with regard to implementation, buy-in, and security has been noted (Brailer 2005). If banks have been able to, over the last couple of decades, adopt a secure, interoperable system for customers, can the hospital industry also do so? Additionally, adopting a nationally interoperable system will require a great deal of organizational cooperation that may only come with the development of national standards and incentives. However, if substantial improvement in hospital performance is possible through EMR use, policies must be created and dollars must be spent to allow for implementation. The problem, however, is that there have been few studies to date that can show such improvements on a widespread basis through valid findings.

Research Questions

Since little rigorous and quantitative research exists in the area of hospital EMR use, this study attempts to explore it more. Specifically, this study aims to identify organizational and environmental factors associated with the use of EMRs in hospitals as well as to examine how hospital EMR use influences performance in the areas of efficiency and quality. The research questions that will guide the study are:

- What organizational and environmental factors are associated with EMR use in acute care hospitals?
- How do EMRs affect hospital performance?

Theoretical Frameworks

Two theoretical frameworks are used to examine hospital EMR use in this study. First, Resource Dependency theory provides a useful framework for examining organizational and environmental characteristics associated with EMR use. Next, Donabedian's model of structure, process, and outcome will guide the evaluation of hospital performance. In this study, the two theoretical frameworks are joined together to examine the constructs of interest. Further, these two theories aid the development of the conceptual model, specific measures and hypotheses.

Resource Dependency Theory is used to identify organizational and environmental characteristics that influence hospital behavior, before hypothesizing how they affect a hospital's likelihood of using an EMR system. This theory claims that the adoption of organizational structure and practices is not random; rather, it is actively selected by management to prepare for and promote organizational success in times of environmental uncertainty (Zakus 1998). An organization, according to this theory, depends on external sources for inputs that are needed to function and excel (Hatch 1997). Organizations are thus motivated to reduce these dependencies in order to ensure future success (Zinn, Proenca, and Rosko 1997). In this study, organizational characteristics include size, ownership, system affiliation, teaching status, financial resources and public payer mix. Environmental characteristics include competition, munificence, of wealth, and rurality.

Donabedian's structure, process, outcome model is used to examine organizational performance. Donabedian claims that organizations implement structures, which influence processes and outcomes (1980). This theory is joined with Resource Dependency theory as it is suggested that Resource Dependency theory can be used to determine internal and external forces associated with EMR use, which is a hospital structural feature. Structures are fairly stable inputs that allow an organization to function, including equipment, technology, and personnel. EMRs clearly are a structure that are used in some hospitals, and according to Donabedian, this structure will influence a hospital's process and performance

(1980). Previous literature, which is explored in depth in Chapter 2, is in agreement that EMR use will likely affect how care is provided and the outcomes of this care. Since the interest of this study is hospital performance associated with EMR use, performance will be represented through the efficiency of the processes of care and the quality of outcomes of care. Efficiency will include the assessment of how the ratio of inputs to outputs for individual hospitals compares to other hospitals in an effort to determine if the automated nature of EMRs affect how care is provided. Quality of care is measured through ten indicators of hospital quality relating to three clinical conditions and is used to determine if the EMR can improve patient outcomes. These quality measures are provided through the Hospital Quality Alliance and the Centers for Medicare and Medicaid Service and are used frequently in Health Services Research.

Methodology and Data

The data for this study come from several different sources. First, the Health Information and Management System Society (HIMSS) provides information about which hospitals use health information technology systems such as EMRs. The American Hospital Association (AHA) database provides descriptions of hospital characteristics such as size, rurality, teaching status, ownership, public payer mix, and system affiliation as well as input and output data necessary for efficiency analysis. The Area Resource File (ARF) provides information about the per capital income and change in unemployment rates in hospital environments. Hospital financial information, such as the operating margin, are provided from the Centers for Medicare and Medicaid Services (CMS). The quality outcome data come from the Hospital Quality Alliance (HQA) project, coordinated through the Centers for Medicare and Medicaid Services (CMS). All of these data are secondary and include the years 2001 and 2004. Chapter 4 provides more detail about the data, specific variables and measures.

The design of this study includes a two-part analysis. First, a retrospective, cross-sectional analysis is used to examine organizational and environmental factors associated with hospital EMR use. The non-federal acute care hospital in the United States is the unit of analysis. To achieve ideal generality of the results, the entire population of hospitals is included in the study. Several statistical techniques are used in this study to determine specific aspects of hospital EMR use. First, logistic regression is used to define the relationship between organizational and environmental factors and EMR use. Next, Data Envelopment Analysis (DEA) is used to create efficiency scores for hospitals, which are grouped according to whether they use EMRs or not. DEA is a non-parametric statistical technique that uses combinations of inputs and outputs to identify organizations that perform efficiently relative to other organizations. This technique can be used to measure organizational efficiency at any one given point in time, or a DEA Windows Analysis can be calculated to identify how organizational efficiency changes over time. In this study, both a cross-sectional, individual point in time measure of efficiency is calculated, as well as a Windows Score to measure how efficiency changes in hospitals that use EMRs over time. The second part of the study design is a repeated measures design with a non-equivalent control group. To calculate the Windows Efficiency Score to assess efficiency change, data from hospitals in 2001 and 2004 are used, thus allowing for a non-equivalent control design to compare the change in efficiency for hospitals with EMRs to those hospitals without EMRs. Logistic regression is used to assess the relationship among hospital quality and efficiency. Specific aspects of this analysis are described thoroughly in Chapter 4. Finally, logistic regression equations are used to compare the average efficiency scores and quality outcomes of hospitals that use EMRs to those that do not use EMRs. The results of these analyses are expected to provide concrete evidence of trends that surround EMR use, as well as some prescriptive suggestion of how inefficient hospitals with EMRs can improve their performance.

Significance of the Study

This study has the potential to make an impact on the policy surrounding and practice of EMR use in the United States. While there are indications that EMR use may eventually be standard practice in hospitals in the United States, the fact of the matter is that most hospitals do not have such systems in place now. Because there is a large financial investment associated with implementing and using EMR systems, it is intuitive to study rigorously how they affect care and hospital performance at this point so as to guide future EMR implementation and use.

Especially during this period of cost containment and quality concern in health care, there is pressure for health care providers to make provisions to improve care. It is clear that hospitals do not all have access to the same resources, and this study will identify those that may be at risk of missing the wave of wide spread EMR implementation. Once these hospitals are identified, policies to ease their transition to increased health information technology can be made. For example, if small, rural hospitals are less likely to adopt and use EMR systems, policy makers may need to offer these organizations assistance to ensure that they are using the same technology as other hospitals. However, if EMRs are not capable of creating major improvements in the areas of hospital efficiency and quality, it may not make sense to invest further in this area. If EMR use is associated with greater hospital quality outcomes, it may be easier to justify the cost of implementation in the interest of patient safety. At the same time, since EMR use will change, through its automated nature, the way that health care is provided in the United States, adjustments in hospital resource consumption of inputs and production of outputs may be necessary. EMRs will allow patients to see physicians with their entire medical history already documented, which may reduce the amount of time a physician must spend with each patient. If EMRs can improve hospital efficiency in this way, there may be an excess of physicians in hospitals in the future. DEA will allow for the identification of relatively efficient providers and will also identify, through a slack analysis of excess resource consumption, changes that must be made to inefficient hospitals to improve their performance. For example, if efficient hospitals with EMRs have fewer beds than inefficient hospitals with EMRs, it may be prudent for these inefficient hospitals to reduce the number of beds to increase efficiency.

This study will also contribute to the body of knowledge in the area of EMRs. While a presentation of previous EMR literature is presented in Chapter 2, much of the research of EMRs up to this point has been qualitative, and little exists on a wide scale basis regarding how EMR use affects quality and efficiency. Because this study will include all acute care hospitals in the U.S., it will provide a clearer picture of hospital EMR use, afairly weak area in the previous literature. This study attempts to determine how hospital performance is influenced by hospital EMR use. Specifically, this study aims to determine how EMR use in hospitals relates to efficiency and quality, two areas of specific interest to hospitals, policymakers, payers, and patients.

Description of Future Chapters

The remaining chapters of this dissertation further inform and explore EMR use in acute care hospitals. Chapter two provides a comprehensive overview of previous literature and research in the area of EMRs, while also explaining many of the governmental actions and policy that appear to pave the way for EMR implementation. Chapter two reviews the potential impact of EMRs on cost, quality, and efficiency, while also pointing out barriers to EMR implementation and use. These barriers include provider opposition, the expense of implementation, and patient concern over the security of sensitive medical information. Chapter Three outlines the theoretical frameworks used to guide this study and create the conceptual model. The theories, Resource Dependency and Donabedian's Structure, Process Outcome model, are described and applied in chapter three, where specific hypotheses are also presented. Chapter Four describes the methodology and statistical approaches used to examine EMR use in acute care hospitals. The data used in this study include the HIMSS (Healthcare Information and Management System Society) data, the American Hospital Association (AHA) data, the Area Resource File (ARF), data from the Centers for Medicare and Medicaid Services (CMS), Case Mix Index (CMI) data, and data from the Health Quality Alliance (HQA) data), and are described in Chapter Four. Specific statistical techniques include logistic regression and Data Envelopment Analysis (DEA), a non-parametric technique for measuring organizational efficiency with multiple inputs and outputs. A Windows approach is also used in the DEA analysis to measure efficiency change over time. A test for and solution for possible endogeneity of the model is also presented in Chapter four. Chapter five presents the results of the analysis including efficiency and quality reports of hospitals in the study, along with comparisons of these areas between hospitals with and without EMRs. These results include descriptions, prescriptions for hospital efficiency improvement, and comparisons between hospitals that do and do not have EMRs. Finally, Chapter Six discusses the potential implications and significance of the study, along with limitations.

CHAPTER 2: LITERATURE REVIEW

This chapter explores previous research and literature in the area of electronic medical records. Because this is a relatively new field of study due to the novelty of implementation in hospitals in the United States, there are several gaps in the literature. While these gaps leave some unanswered questions in the area of interest, they also provide the opportunity for new research. This chapter will examine the need for electronic medical records, the evolution of the practice of using electronic medical records, the potential impact that electronic medical records may have on the cost, quality and efficiency of health care, the barriers that are present to nationwide implementation of electronic medical records, and anecdotal evidence through the qualitative research of organizations that have implemented electronic medical records. The previous literature will inform the development of this dissertation, but this study aims to examine the performance of hospitals with EMR systems, thus contributing to the body of knowledge in this area.

Electronic Medical Records

Electronic Medical Records (EMRs) are paperless accounts of health care services, diagnoses, and evaluations. While talk of their use is widespread, there has yet to be a universal name for the practice. In addition to electronic medical records, they have been termed computerized patient records (CPRs), electronic health records (EHRs) and personal health records (PHRs). According to the Institute of Medicine (IOM) the computer-based EMR is, "the electronic patient record that resides in a system specifically designed to support users by providing accessibility to complete and accurate data, alerts, reminders, clinical support systems, links to medical knowledge, and other aides," and is considered essential (Varon and Marik 2002 p.619). While there does not appear to be a clear distinction between any of these names with regard to practice and use, EMRs exist with great variety. Many different applications and formats are becoming available as EMRs continue to evolve. Some include electronic prescribing, computerized physician order entry (CPOE), transferability of medical lab results and history to other providers, standardized clinical pathways, clinical reminders, and a complete medical history. It is this variability that may make interconnection between providers difficult and is the reason that a national standard template may be needed for EMR systems (Thompson and Brailer 2004).

EMRs are an important component of a larger movement to the spread of health information technology (HIT). EMRs are a new technology that may offer drastic changes in the way health care is documented. Increasingly, physicians' practices and hospitals are developing clinical workstations. Shortliffe describes these clinical workstations as:

> Single entry points into a medical world in which computational tools assist not only with clinical matters (results reporting, order entry, access to transcribed reports, telemedicine applications, and decision

> support), but also with administrative and financial topics (admission-discharge- transfer, materials management, personnel, payroll), research (outcomes analysis, quality assurance, clinical trials, implementation of pathways and protocols), scholarly information (digital libraries, biblio-graphic searches, drug information databases), and even office automation (spreadsheets, word processors). At the heart of the evolving clinical workstation lies the medical record in a new incarnation: electronic, accessible, confidential, secure, acceptable to clinicians and patients, and integrated with other, non-patient specific information (1999, p.414).

Through this quote, one may deduce that the impact of EMRs may be varied based on the system and applications used, but EMRs have the potential to alter every area of health care from administrative to clinical to research functions. However, the hope is not that these areas will be merely affected, but that the overall quality and efficiency of health care will improve.

The Need for Electronic Medical Records in the United States

Each year many thousands of medical errors occur in hospitals in the United States. The Institute of Medicine (IOM) estimates that there are 44,000 to 98,000 deaths each year in the U.S. due to medical errors (Kohn, Corrigan, and Donaldson 1999). These deaths occur from drug interactions, pharmacy errors, errors in medical procedures, and the fragmented care that may exist based on the incomplete medical history documentation that accompany the use of paper medical records. Essentially, these human errors lead to unsafe medical care, which can be prevented with the use of a more automated process, such as is found with EMRs. Zwillich adds that these medical errors are the result of prescription errors and other treatment mistakes, which add to the escalation of health care costs and decreases the quality of health care (2005). In *Crossing the Quality Chasm,* the IOM states that, "health care delivery has been relatively untouched by the revolution in information technology that has been transforming nearly every other aspect of society" (2001, p. 15). In many ways this is true. Communication has changed drastically with the advent of e-mail and the Internet, as have many other industries including banking, retail, and even higher education. The personal computer and Internet have made life quicker, more efficient, and more complex all with the introduction of new technologies. Many have questioned why health care has not been part of this growing way of hi-tech structure and processes, especially when health care could stand to improve so much with the use of technologies that already exist (Cushman 1997, Berner, Detmer, and Simborg 2004). Many have pointed out the inability of paper records to deal with the complex health care process as it exists today, as well as their contribution to the medical errors and inefficiency of medical practice (Shortliffe 1999). Varon, and Marik claim that paper records:

> Cannot adequately deal with the enormous volume of information accumulated during a patient's hospitalization and subsequent care, leading to errors in medical management; and they are usually illegible, are often misfiled or lost, are not readily accessible, and are frequently incomplete, with missing reports (2002, p. 617).

These statements link health care errors to quality and lead one to a distinct question, if health care improvements can be made with EMR use, why is implementation so slow to happen?

The federal government, the largest purchaser of health care services in the United States, has expressed interest in the use of EMRs. In the year 2004 alone, the federal government spent more than $900 million in health information technology (Thompson and Brailer 2004). Additionally, the government has proposed that e-prescribing, a common component of EMR systems, may become a requirement for all Medicare provider participants after the implementation of the Medicare prescription drug benefits in 2006 (Thompson and Brailer 2004). This regulative pressure to adopt electronic processes in health care may be indicative of the future, when it may be possible that payer groups, such as Medicare and private insurers, require providers to use EMR systems.

Some have demonstrated that there is drastic geographic variation in health care throughout the United States (Dubios, Batchlor, and Wade 2002, Baucus and Fowler 2002). This variation exists in many areas and practices including Medicare spending, surgical and diagnostic procedures, and the use of medications (Dubois, Batchlor, and Wade 2002, Baucus and Fowler 2002). Hannan claims that EMR use could reduce this geographic variation, which is caused by health care system differences, differences in physicians' practice styles, and differences in the populations of patients served (1999). The EMR would increase physician attention to protocols of care, ensuring that more physicians practice medicine based on proven clinical standards. However, to develop and disseminate these protocols of care, medical outcomes must be measured, which, again, could be more easily accomplished with EMRs.

Another way that the need for EMRs is demonstrated is in the event of natural disasters. In the aftermath of Hurricane Katrina, which devastated the Gulf Coast in 2005, clinicians, patients, and policy makers realized the medical histories of many thousands of patients were completely gone thus impacting their care ("Katrina Highlights the Need for Computerized Medical Records" 2005). As physicians attempted to treat victims of Hurricane Katrina, they reported that they had no medical records and, in some instances, the patients themselves were unable to report their current prescriptions citing only that they take "a blue pill." For comparison, nearly 50,000 Veterans had been patients at the Veterans Health Administration Hospital (VHA) in New Orleans. Because the VHA has EMRs, none of these medical records was lost. Health and Human Services Secretary Mike Leavitt reported that Hurricane Katrina highlighted even more the need for EMRs in the United States. For the many whose medical records were lost, the health care they receive may be more complicated than necessary. Tragically, this health care crisis of absent medical records has the potential to repeat itself with other natural disasters if only paper records are maintained, while the use of EMRs could significantly reduce the impact of natural disasters on individuals' health by providing records that could be backed up at multiple locations so as to not be vulnerable to water or fire damage.

The Evolution of the Electronic Medical Record

Computers have been used in hospitals for many decades now. Beginning in the first part of the 1960s, computers were used for administrative and financial functions in hospitals (Berner, Detmer, and Simborg 2004). However, computers were not initially integrated into every part of health care for several reasons. First, the technology was often unreliable, and administrators and clinicians alike feared that an over-reliance on computers could lead to frustration and information loss. Second, computers were still a young technology requiring large mainframes to function, thus making their widespread use impractical. Third, the workforce of the 1960s and 1970s was generally computer illiterate, which would have required a great deal of training to use the equipment. Finally, because computer technology was still quite new and costly, the expenses made widespread use impossible for many non-profit hospitals and other health care providers, and the financial gains from computer use were not yet demonstrated (Berner, Detmer, and Simborg 2004).

Some federal agencies have been using EMRs for years now. Dr. George K. Anderson reports his first experience with EMRs in the 1970s, as the United States Air Force aerospace medicine researchers performed a clinical study of grounded pilots using mainframe computers and punch cards (Anderson 2004). In addition, the Veteran's Health Administration (VHA) has been using EMRs since the early 1990s, with system performance exceeding that of Medicare (Asch et. al. 2004). Evidence exists that the call to automate clinical processes has existed for several decades, yet this task is not yet complete (IOM 1991). The reason for the lack of EMR use in other realms is not clear.

One of the first federal steps to paving the way for large scale EMR implementation was the Health Insurance Portability and Accountability Act (HIPPA) of 1996. In addition to allowing Americans to switch jobs with more ease and less worry about health insurance coverage, this act also attempted to promote and protect medical information with privacy standards and security measures. By allowing Americans to be more transient with their jobs, it is likely that they are also more likely to relocate geographically with ease, increasing the likelihood that they seek care from more than one physician. This may increase the need for individuals to take their medical history with them easily, and the electronic medical record will allow them to do so (Thompson and Brailer 2004). The HIPAA changes also began to address medical information security issues, and though not directly providing standards for EMRs, their stipulations may have been a step in the right direction.

It is possible that two Institute of Medicine Reports, *Crossing the Quality Chasm* and *To Err Is Human: Building a Safer Health System* emphasized the relationship between patient safety, medical errors, health care quality, and HIT (2001, 1999). These two reports revealed the annual costs, in patient lives, of medical errors and indicated that information technology could improve the quality of the health care system, in part, by reducing medical errors. Following these reports, in 2004, President George W. Bush called for all or nearly all Americans to have EMRs within ten years through executive order 13335 (Thompson and Brailer 2004). To further demonstrate commitment to this goal, Dr. David J. Brailer was named National Health Information Technology Coordinator in the U.S. Department of Health and Human Services. In this capacity, Dr. Brailer, along with Secretary of Health and Human Services Tommy Thompson, released a report, "The Decade of Health Information Technology: Delivering Consumer-centric and Information-rich Health Care," claiming that health information technology, "can give us both better care- care that is higher in quality, safer, and more consumer responsive- and more efficient care- care that is less wasteful, more appropriate, and more available" (2004). The goal of this report was to identify strategies for improving the quality and cost of health care, while also provide specific direction for the health care framework. The strategic framework includes goals and strategies such as informing clinical practice, incentivizing EMR adoption, reducing the risk of EMR investment, promoting EMR diffusion in rural and underserved areas, developing a national health information network, coordinating federal health information systems, encouraging the use of personal health records, and unifying public health surveillance architectures (Thompson and Brailer 2004). These goals and strategies all seem to point to the nationwide use of EMRs as one answer to the questions of the current quality, cost, and appropriateness of healthcare in the United States.

The federal government has further emphasized its commitment to the implementation of EMRs through $139 million in grants and contracts, available from the Department of Health and Human Services (Anderson 2004). These monies will enable smaller health care systems and providers to obtain and implement EMR systems, as well as provide a resource for research associated with EMR use. One of the primary barriers to implementation of EMRs is the cost associated with purchasing and maintaining systems. Perhaps, with the distribution of this money, more health care organizations will be able to use EMR technology. Additionally, the Bush Administration has begun to propose a relaxation of the antikickback rules that govern financial and patient referral interactions between physicians' offices and hospitals (Zwillich 2005). While the purpose of these regulations is to prevent situations in which private physicians may receive financial gain for patient referrals, policy makers believe that changes to these strict rules may increase the likelihood that hospitals with EMR technology will give or sell at a reduced price EMR systems and equipment. The hope is that hospitals will share their EMR technology with physicians' practices that may not otherwise be able to attain it due to the financial cost, while at the same time creating an interoperable system where these physicians could share patient information with hospitals via the EMR.

Leapfrog, a coalition of large employers in the U.S. with the goal of influencing health care quality and patient safety, recognizes the potential value of EMRs to health care providers. Leapfrog currently encourages health care organizations that participate in their plan to implement and adopt certain features that have been shown to increase health care safety, efficiency, and quality, such as the use of hospitalists and CPOE. CPOE, or computerized physician order entry, is a common feature of some EMR systems, which begs the question: will EMRs be the next Leapfrog provider participant promoted practice (Hillman and Given 2005)?

Corporations have already begun to respond to the attention that has highlighted the potential impacts of EMRs. Not only do companies such as Seimens and IBM provide EMR systems, new companies have emerged. ONFILE, for example, sells an EMR directly to individual consumers with the claim that hospitals will be able to access such a record, containing medical history, diagnostic results, and doctors' notes, in emergency situations. In addition, VeriChip Corporation of Delray Beach, FL, has begun implanting FDA approved computer chips into the arms of individuals who wish to carry their EMRs with them at all times. Approximately 10,000 Americans have also placed their EMRs on the internet through a free online service ("Senate Wants Patients to Carry Own Electronic Medical Records" 2005). The emergence of these companies and availability of their services and products may indicate that EMRs are here to stay.

The Potential Impact of Electronic Medical Use in Hospitals

Cost

The quickly rising cost of health care is an area of great concern for payers, policy makers, patients, and providers. In fact, the U.S. spends more per capita on health care than any other country, while the quality of health care may not be as high or higher than countries that use fewer resources (Reinhardt, Hussey and Anderson 2004). While it may still be too early in the evolution of EMRs to determine real cost savings associated with the practice, many projections indicate that, while implementation will cost money, EMRs may eventually reduce overall health care spending. Thompson and Brailer indicate that these cost savings range from \$78 billion to \$112 billion per year across all payers based on an interoperable system (2004). A positive rate of return could be all the promise that health care providers need to invest in EMR systems.

Some estimates of the cost savings of EMR use do, however, exist. Price estimates that EMR practice could save health care payers and patients millions of dollars each year through the earlier dissemination of lab results to multiple providers (2005). Currently, the often-fragmented health care system results in overuse and duplication of services. If the information itself was easily and quickly transferable, it is likely that cost savings may be possible. Similarly, another report estimates that the savings associated with EMR use could be in excess of \$77 billion each year if an interoperable system exists (James 2005). There is not currently any consensus with regard to how much EMRs may cost to implement.

While these estimates predict very large cost savings, the reality is that the cost savings of EMR implementation may exist in many arenas. First, EMRs are expected to save money on the storage, creation, and existence of paper medical records. If medical histories are all electronic, and physicians are using them in exam rooms and during procedures, it is likely that more complete notes will be made. In addition, there will be no more costs for paper medical record transcription, storage, and pulling, not to mention time lost searching for missing records.

Second, EMR cost savings are expected through the decrease of medical errors. By linking patient records to other electronic tools such as clinical pathways, drug interaction alerts, and computerized physician order entry (CPOE), clinical errors are expected to decline. In fact, Thompson and Brailer cite several studies that indicate how cost savings through the prevention of medical errors are possible (2004). First, laboratory and radiology testing that is inappropriate or redundant can be prevented, reducing the practice of these tests by 9% to 14% (Bates et. al. 1999, Tierney et. al. 1997). Considering how expensive these tests can be, this cost savings may be substantial. Second, they claim that "excess medication usage" will be decreased by 11% (Teich et. al. 2000). Finally, the use of EMRs is expected to reduce hospital admissions by 2%, with each admission costing an average $16,000 (Jha et. al. 2001). These cost savings would be the result of a less fragmented health care system based on the electronic prompts that doctors could use to more closely monitor patients' afflictions. Additionally, dangerous medical errors often lead to costly treatments to correct the potential damage of errors. Clinical pathways through EMR use may decrease or nearly eliminate these errors and the costs associated with their occurrence, an important component of health care quality.

Another cost savings through EMR use is expected with the more appropriate use of diagnostic testing and results. Some claim that health care is currently overused and often duplicated by multiple providers for single patients (Price 2005, Bates et. al. 1999). EMRs, connected with clinical guidelines can ensure that proper testing is done for patients. The electronic results of diagnostic testing provides information that is easily shared with other health care providers, when appropriate, decreasing the duplication of services. In a randomized study at Brigham and Woman's hospital, the use of computerized notifications of tests that were redundant or unnecessary for patients revealed cost savings (Bates et. al. 1999). According to this study, a computerized system that identified inappropriate use of diagnostic procedures found more than 900 redundant laboratory tests in more than 11,000 patients in a fifteen-week period. This type of computerized system is a component of many EMR systems and was found in this study to save approximately $35,000. While this type of system may be in conflict with the practice of defensive medicine, which aims to provide an excess of diagnostic tests and procedures to prevent any physician liability if a condition is not properly diagnosed, these cost savings are substantial. Unfortunately, this study did not report any information about changes in clinical outcomes, quality of care, or patient satisfaction.

Finally, the use of EMRs may increase billing accuracy (Schmitt and Wofford 2002). It is conceivably difficult for administrative staff to read paper records of physicians' treatment for patients and to then bill the payer groups accordingly. If physicians enter procedural and diagnosis information immediately into the computer during the exam or immediately afterwards, the potential connectivity with these records and a billing system, this standardization is expected to increase accuracy (Terry 2002).

The benefits of an expensive innovation must be weighed against the costs. One study attempts to examine the costs versus the benefits of EMR use in primary care (Wang et. al. 2003). The authors of this study examine the financial costs and savings associated with their own EMR implementation at Partner's HealthCare System in Boston, Masssachusetts. Although data limitations did not allow for the analysis to extend to any other health care provider, the authors report that their internally developed electronic medical record software saved the health system $86,400 per primary care provider over a five-year period. These savings accumulated primarily in the area of decreased radiology use, decreased billing errors, and increased charge capture. Of course, the generality of these findings must be questioned since the study included only one health care organization with a small sample of primary care providers examined. Nevertheless, similar cost savings may be possible in other health care organizations through the use of EMR technology.

In a related article, researchers report the financial analysis conducted as Virginia Mason Medical Center contemplated the adoption of an EMR system (Schmitt and Wofford 2002). This 280-bed hospital employs about 400 physicians and also has a research center and many outpatient clinics. A clinical advisory team investigated the cost and benefits of implementing an EMR system and concluded that the financial investment would be $19 million over a seven-year period, but that the eventual annual financial benefit to the hospital would be an estimated $17,587,393. These savings came in the form of eliminated staff positions for those who entered data and maintained charts, the reduction of adverse drug events, a reduction of time spent managing laboratory and radiology testing orders, an enhanced charge capture, and the faster submission of claims to payers (2002). Each of these cost savings indicates an increased efficiency through the reduction of inputs that was expected to lead to eventual cost savings at the hospital. Over the seven-year period of payment for the system, the present value of the system, while considering all aspects of the projection, was estimated as more than $31 million, thus strongly supporting the case for hospital-wide EMR adoption and use. EMR implementation at Virginia Mason Medical Center is currently underway.

Quality

Quality health care has been defined as, “doing the right thing at the right time in the right way to achieve the best possible results” (AHRQ 2006). Quality health care has many components including error reduction and patient safety. These two important components of health care quality, error reduction and patient safety, may be especially affected through EMR use, which applies standardized clinical pathways, CPOE, and other clinical reminders and indicators of possible prescription interactions and potentially dangerous medical procedures. According to AHRQ, quality health care, "means striking the right balance of services by: avoiding underuse, avoiding overuse, and eliminating misuse" (http://www.ahrq.gov/consumer/guidetoq/guidetoq4.htm 2006). Based on this notion and the available features of EMRs, the quality of health care stands to benefit potentially from the use of EMRs. Some have suggested that the use of EMRs may increase the quality of health care by drastically reduce many of the patient deaths caused by physician errors (Anderson 2004). It has even been said that, "of all the health information technology (IT) in use, the electronic medical record (EMR) has the most wide-ranging capabilities and thus the greatest potential for improving quality" (Miller and Sim 2004). This claim is based on the evidence of previous research, discussed below, to show that health care quality is improved because of the features of EMRs, including electronic documentation, chart viewing, prescription and test ordering, care management reminders, analysis and reporting, billing, and messaging (Miller and Sim 2004).

First, patients in the U.S. seek health care from a number of providers over a lifetime. From birth until death, Americans seek care from general providers as well as specialists. In an article outlining the need for EMRs, David Brailer states that, "Americans can and do choose to get care from whomever they want: more than 500,000 office-based physicians, approximately 5,000 community hospitals, more than 1,600 certified nursing facilities, and many other care settings" (Brailer 2005). One current problem is that many individuals do not keep records of their medical history to share with new providers. Brailer claims that the lack of integration of providers leads to fragmentation, which leads to errors and duplication (2005). As physicians will attest, the more complete the picture of an individual's health history through documentation, the more complete the assessment regarding that patient will be. EMRs will allow patients to carry their complete medical history easily to any provider, or it may be quickly accessed if a national system is developed. According to the IOM:

> the meticulous collection of personal health information throughout a patient's life can be one of the most important inputs to the provision of proper care. Yet, for most individuals, the health information is dispersed in a collection of paper records that are poorly organized and often illegible, and frequently cannot be retrieved in a timely fashion… (Crossing the Quality Chasm 2001).

Some claim that time lost through the re-retrieval of clinical information that makes initial consultations and care less effective may be regained through better documentation in EMRs (Garrido et. al. 2005).

Second, as the IOM reports, physician errors result in many tens of thousands of deaths each year. These errors undoubtedly affect the quality of health care. EMR use may reduce these mistakes by omitting poorly handwritten patient charts, physician orders, or provider notes, and through other EMR integrated health information technology. If a physician is using an EMR system that is connected to standardized clinical pathways or procedures, dangerous drug interactions and inappropriate testing or treatment may be avoided. While technology is not better than the human mind at treating patients, tools may assist physicians in providing care by avoiding mistakes. In an effort to improve the quality of care, the IOM calls for, "the elimination of most handwritten clinical data by the end of the decade" (Crossing the Quality Chasm 2001).

One study reports a comparison of quality of care between patients at the Veteran's Health Administration (VHA), which has had EMRs for more than a decade, and patients in a national sample who were treated at community hospitals (Asch et. al. 2004). By studying 596 patients from twelve VHA facilities and 992 patients from a randomized national sample between 1997 and 2000, the authors conclude that in areas such as adjusted overall quality, chronic disease management, and preventative care, quality was significantly higher, but not for acute care. Using a cross-sectional comparison technique, the authors claim that the VHA's EMR system is associated with higher levels of patient care quality. However, the appropriateness of measures, sampling methods, and comparability of the two groups of male patients leave these conclusions to be questioned. First, these measures are regularly used indicators of quality at the VHA. For this reason, it is possible that they guide hospital performance and the care that is provided in the VHA more than in the compared community hospitals that may rely on other measures of quality. Second, the sampling methods may threaten the validity of the study. The comparison group, males who received care at community hospitals in the previous 12 months, was recruited by telephone, thus eliminating any subject who did not have a phone and had not been to a hospital in the previous year. This group may not be representative of patients in community hospitals. Finally, the comparability of the two groups can be questioned based on the way that the VHA and community health centers function. The VHA serves only veterans who have likely had access to health care through the military throughout their lives. This may mean that they have received more preventative care than the comparison group. Additionally, community hospitals may practice medicine differently than the VHA based on financial reimbursement as community hospitals may be under more pressure to control costs for patients without means of paying for services. Finally, this study includes only men in the sample, making it non-representative to a population that includes women. Nevertheless, the VHA is moving forward with its EMR system, now providing veteran patients with personal health records in an online electronic format called My Health*e* Vet (Thompson and Brailer 2004).

Another study boasts that EMR implementation could improve the quality of health care by reducing variation in processes and outcomes, while also reducing health care costs (Tierney, Overhage, and McDonald 1997). According to this study, EMRs can enable health care information such as lab results to be shared quickly and easily between providers (Tierney, Overhage, and McDonald 1997). Thompson and Brailer agree with this claim and state that, based on previous research, "variations in regional patterns are principal determinants of differences in health status across rural and urban populations" (2004). By interconnecting health care providers, best practices can be more easily disseminated and followed, thus reducing the geographic variations of care.

Certain health care screenings appear to be carried out more effectively with the use of EMRs, thus making the health care process quality higher. Spencer et. al. claim that EMRs used in conjunction with continuous quality improvement lead to drastic improvements in documentation and screening for smoking status at the Family Medicine Clinic in Eau Claire, Wisconsin (1999). In this study, an EMR software program called Practice Partner was used to improve the quality and efficiency of health care, in part, by screen prompters for clinic staff. Specifically, the clinic wanted to determine if a computerized prompt to screen for smoking status would increase the number of patients who were asked their smoking status and provided smoking cessation counseling if appropriate. One of the computerized prompters was customized to the clinic to ask patients of smoking status to increase staff attention to this question. The screening rate of smoking status for patients rose from 18.4% to 80.3% in two weeks, with the rate of smoking cessation counseling with appropriate documentation rising from 17.1% to 48.3%. These gains are drastic and demonstrate the possibilities of improved health care process and documentation quality with the use of a customized EMR.

Additionally, researchers have examined how EMR use affects patient populations with specific afflictions. In one such study, researchers compared two groups of patients from one single-specialty outpatient cardiology practice (Kinn et.

al. 2001). Three physicians in this practice volunteered to implement EMRs and an attached software device for real time lipid management called Virtual Lipid Clinic. Patients from these three physicians were compared with a control group of similar patients randomly chosen from other physicians in the same practice. After twelve months, significant differences between the patients with the traditional paper charts and those with the new EMR system emerged. Patients with the EMRs were more likely than those without the EMR to be on an appropriate drug, to reach lipid related goal levels, to have better medical documentation of treatment and symptoms, and to be receiving a particular form of lipid-lowering therapy. Based on these findings the authors conclude that the EMR and the Virtual Lipid Clinic tools, "provide a great opportunity to positively reinforce physician behavior and enhance the quality of patient care" (Kinn, et. al. 2001). These positive outcome results were attributed largely to the real time data that were available to physicians because of EMR use, enabling them to respond more quickly while monitoring patient progress. However, these findings also provide limited generality because the represent the experience of one organization and patients with one particular condition.

The Joint Commission on Accreditation of Healthcare Organizations also recognizes the potential impact that EMRs may have on quality. While this agency has not yet mandated EMR use, Burt and Hing claim that AHRQ, "indirectly promotes adoption of EMR and CPOE by measuring hospital compliance with patient safety standards needed for accreditation," a goal that, though not explicitly stated, clearly can be improved through the use of health information technology (2005, p. 4).

Ultimately, EMRs may help improve quality by merely allowing care and treatment to be more transparent. A longitudinal picture of an individual's health, provided through an EMR, may show a complete record of care received to indicate proper diagnoses and whether treatments worked. This could provide safer, evidence-based practices for physicians in a time-efficient manner since the data themselves could be aggregated and would be immediately or nearly immediately accessible in electronic format (Anderson 2004). Additionally, it was suggested that one flaw in paper medical record use with regard to quality is that the measure of quality through medical record review may merely assess the quality of the documentation on the record itself, rather than the quality of health care provided (Donabedian 1980). For example, if one is attempting to assess the quality of medical care through paper medical record review, more complete documentation is likely to make the care appear to be higher quality when it is possible that the clinician merely did a more thorough job of recording the care. This flaw of paper medical records in the assessment of quality is likely to be eliminated since EMRs have automated fields, making documentation more standardized and complete.

Efficiency

While there are studies of quality and cost differences for hospitals with EMRs, there is a void in the area of how EMRs affect hospital efficiency. Some claim that this increased efficiency is inevitable with the introduction of EMRs, but the evidence is not clear. The VHA system claims that its use of EMRs has led to the discontinuation of dictation services, patient education has improved, computerized clinical pathways have ensured that patient care is complete, and that the overall physician efficiency is improved because the information flow is much more "enhanced" as test results are not lost (Fletcher et. al. 2001). While these claims are not supported specifically by any rigorous methodology, they indicate that EMRs may increase efficiency in hospitals. However, the lack of research in this area justifies the need for the study herein proposed. In addition to cost reductions, three hospitals affiliated with St. Elizabeth Medical Center in Kentucky noted increased efficiency when they computerized their clinical workflow in early 2000 (Slutzsky 2004). Once the hospital began to calculate its annual cost savings of more than $545,000 per year, it also realized that there was a forty percent reduction in the phone calls and faxes to the lab and medical records department because physician staff can easily find results online. In fact, St. Elizabeth's lab volume has increased 40 percent over this period without any increase in clerical staff to handle the inquiries. Wait times for stat and critical results went from 10 to 24 hours to zero, with abnormal labs flagged for immediate attention (Slutzsky 2004 p.3). These results indicate a large increase in efficiency that may be attributed to the use of at least one component of EMRs in hospitals. However, these findings are not the result of a rigorous study; rather, they were found retrospectively and cannot be attributed exclusively to EMR use without controlling for possible confounding factors.

Similarly, a large ear, nose, and throat physician practice in Raleigh, North Carolina found similar efficiency improvements when it upgraded its EMR system to exclude any paper documentation ("A Giant Step Forward: A Specialty Practice Goes Entirely Paperless by Combining Electronic Document Management Technology with Its Existing EMR" 2002). The practice elected to eliminate paper copies of information through strategies such as scanning insurance cards and billing completely on the computer, though EMRs had previously been used for new patient information. Part of the motivation of this practice was to be proactive with the HIPAA guidelines as the practice feared that excessive paper might not protect patients' medical information. Now physicians in the practice enter their own ICD-9 and DRG codes for patients. A large portion of the efficiency improvements emerged in the billing area. Now, the practice has eliminated 75% of the personnel time in the area of claims, which the practice generates internally. In addition, the turnaround time for accounts has decreased drastically. Finally, the practice was accustomed to hiring four summer employees to catch up on the paper trails that existed at a cost of about $20,000. Now, because of the new computerized system, only one summer employee is required, costing $4,000, and the practice expects that this may be further reduced. While these findings are somewhat valuable, their rigor must be questioned due to the inclusion of only one practice, thus affecting the applicability of the findings to other medical specialties and organizations. Additionally, this practice was already somewhat accustomed to EMR use and may have already faced the challenges of implementation since this study only reported the results of a system upgrade. Thus, the decreased efficiency associated with EMR use may have already taken place in this practice, and it was the effect of the system upgrade that was examined.

Other organizations have also adopted EMR systems gradually, with similar efficiency improvements. The Primary Care Medical Center of Murray, Kentucky implemented an EMR system in 2000 and followed it a year later with a computerized billing system (Terry 2002). The physicians in this practice enter clinical information on "pen tablets," a form of portable computers. Nurses and administrators also have hand held computers that ease a patient's navigation through the practice, alerting providers when the patient has checked-in, paid the co-pay, and given vital signals to the nurse. Because of the new system, which relies heavily on computerized documentation and communication, nurses claim they now have more time with patients since they do not have to waste time pulling and updating charts. Physicians agree that the system is responsible for efficiency improvements, especially since they now receive lab results electronically. Finally, administrators at the practice claim, "far more charges are being captured and far fewer claims are being denied. Equally important, the doctors can defend their charges—and they can't blame billing clerks for errors" since the physicians enter their own procedure codes (Terry 2002 p. 4). Again, the validity of these findings should be questioned due to the gradual implementation of the EMR system over two years in a single practice, which likely influenced the efficiency of this practice since staff had more time to adjust.

While the improved efficiency likely does not take place immediately, researchers at Cedars-Sinai Medical Center in California sought to determine how much additional time nurses used for documentation during EMR implementation (Korst et. al. 2003). Using a standardized and validated instrument of nurse activity, observers recorded documentation time over a fourteen-day period as the nurses documented using both the traditional paper method and the new computerized method. Overall, this study reported that computer documentation required less time than paper documentation, and that, "the total amount of time spent documenting on both paper and computer was comparable to reports based on paper charting alone" (2003 p. 28). These conclusions are important because they indicate that computer documentation and charting are quicker and more efficient than paper charting and documentation. This study also indicates the anticipated time lost during EMR implementation may not be as great as anticipated. While the presence of an observer in any hospital unit may affect employee performance, the researchers note that this is not likely an influence in this study because there was a high level of comfort with the observer. Additionally, the sampling method was not random since it included nurses working in a single unit. Future studies may wish to address not only this sampling weakness, but also to investigate how EMR implementation affected the quality of patient care.

Finally, another area that may improve in efficiency through the use of EMRs is public health monitoring and bioterrorism alerts. In the current state of health care, public health and bioterrorism are monitored with limited data. With EMRs, data would be more available and up-to-date with an interconnected electronic system. Epidemics could be more quickly identified and addressed. The events of September 11, 2001, have created an awareness of the potential threat of terrorism in the United States (Berner, Detmer, and Simborg 2004). EMRs could help with, "disease surveillance, threat monitoring, and reporting…if properly configured and linked, can play a key role in alerting public health officials to health emergencies so that proper countermeasures can be taken" (Anderson 2004 p.1). The federal government expects similar improvements in the promotion of public health. Thompson and Brailer claim that real time data would better allow officials to denote an outbreak and then to deal with it accordingly (2004). Without the real time data, the task of analyzing and disseminating public health data is less effective.

Barriers to the Implementation of Electronic Medical Records

While the benefits of EMRs are numerous, so are the barriers to implementation. Health care providers, policymakers, and payer groups have avoided paying the cost of EMR implementation in hospitals and physician offices. Others, including patients themselves and other advocates for privacy, have questioned the security of sensitive health information in electronic format. Finally, physicians and other health care providers have expressed concern over the introduction of a new practice, such as EMRs, in health care, because of the implications, such as a loss of professional autonomy and loss of time through learning the system that will likely accompany it.

One barrier to widespread EMR adoption and use is the financial cost. Providers struggle to justify the initial investment of an EMR system, and others worry that maintenance costs based on use and technological advancements could be extreme. In actuality, the cost of implementing a system is difficult to estimate based on the great variation in EMR systems' features and uses, yet several estimates have been made. Leapfrog estimates that a 200 bed hospital can expect to spend $1 to $7 million to implement an EMR system (Burt and Hing 2005 p.4). Other estimates indicate that the cost of EMRs for most Americans could be "tens of billions of dollars a year, just for the computer and telecommunications infrastructure" (Cushman 1997 p.2). This estimate, one must remember, does not necessarily include any of the necessary technological upgrades or system maintenance, which could be frequent and costly. The U.S military has invested $2.8 billion worldwide to develop its electronic medical record system (Cushman 1997). Clearly, with such substantial costs associated with EMR implementation, hospital administrators and policy makers want to know if such an investment is worth it in terms of efficiency and eventual cost savings. While these estimated costs of implementation of EMR systems for hospitals range greatly, it is with good reason. As mentioned at the beginning of this chapter, EMRs exist in many different forms from simple to complex, and there is great variance in the level of adoption of EMRs already in use. According to the Health Information and Management System Society (HIMSS 2004), some of the components of EMR systems may include abstracting, dictation, chart deficiency, chart tracking/locator, encoding, master patient index, medical record imaging, and transcription. Burt and Hing claim that EMRs can be include, "medical history, patient demographics, nurse's notes, electronic prescription and diagnostic orders, and evidence-based decision-support tools" in the clinical realm as well as non-clinical functions such as, "billing, quality management, outcome reporting, and public health disease surveillance and reporting" (2004, p. 2) Hospitals and physicians practices may not only use systems with any combination of these features, but there may also be variance in terms of their level of adoption and use. A provider that retrospectively attempts to add older paper medical records to the new electronic format may spend more than a provider who only plans to maintain the current and future patient records in electronic format. Hospitals and other health care providers may adopt EMR systems in waves, beginning first with features such as electronic prescribing and gradually implementing a fully automated EMR system to perform every administrative, clinical and financial function possible. Since EMR systems can currently be purchased from a number of different sources, it is also likely that the prices will vary based on the market, the novelty of the system, and the level of interoperability desired. Essentially, the cost of implementation is difficult to determine. However, researchers have indicated that, "we have enough estimates. They suggest, as persuasively as such estimates can, that well-implemented EMRs have the potential to improve health care at an acceptable cost," and that health care providers needed to begin implementation, "yesterday" (Walker 2005, p. 1118).

Second, although some claim that the technology security to protect sensitive medical information is available, Americans are still anxious about EMR use. Patients fear exposure of private medical information through accidental transmission of paperless medical records. In fact, 70% of people surveyed by Harris Interactive, the thirteenth largest online market research firm in the world, are "somewhat" or "very concerned" that personal medical information would not be secure, 69% are "concerned" that their medical information could be shared without their knowledge, and half are "unsure" if the benefits of EMRs outweigh the risks (Rash 2005). Many patients worry that medical information could be leaked to employers or insurance companies that will discriminate against them. Public distrust is clearly a large barrier in terms of EMR implementation, as patients who fear the use of health information technology may not be as forthcoming with medical information.

The public's concern over privacy with regard to EMRs is not unfounded. In 1995, after conducting a survey, Ernst and Young reported that, "57% of the health care institutions responding reported an information security-related loss in the last two years" (Cushman 1997 p.8). Computer hackers continue to access private, electronic banking information, which may indicate that electronic information is not yet as secure as it must be before it may be introduced in health care. Ultimately, strict guidelines and standards, as well as cryptographic or monitored access should exist. With the proper systems in place, medical information privacy may be more secure if an electronic trail would alert providers if information had been compromised than with the use of paper medical records.

Finally, some physicians and other health care providers have strongly opposed the introduction of EMRs in hospitals (Berner, Detmer, and Simborg 2004, Miller and Sim 2004). A study examining the EMR implementation experience from nurses and physicians in an emergency department at a large urban teaching hospital reports mixed perceptions among the sample (Likourezos et. al 2004). Three months after training and implementation of the EMR system, researchers used a survey to learn about the previous computer experience, perceptions of EMR use, and concerns about EMRs with regard to quality of patient care from 37 physicians and 78 nurses. The findings indicate that the subjects found it easy to use the EMR system overall, but these same respondents did not expect that the EMR system would improve the quality of patient care, make patient care less expensive, decrease patient waiting time, decrease the number of diagnostic tests, or reduce the number of emergency room visits. However, these same survey respondents report that they believe that EMRs will improve health care in the U.S. and that they would prefer for all providers to maintain EMRs for other patients as well as for themselves. These findings, while helpful in gauging provider perceptions and attitudes towards EMRs, must be treated with caution since the sample size is small and made up of subjects who had prior computer experience unlike some members of the health care workforce, and the survey took place very shortly after implementation, which may not have allowed respondents to fully learn the system and realize the benefits or problems.

Another study examined both patient and provider perceptions of EMR implementation (Earnest et. al., 2004). Examining a practice for patients with congestive heart failure, both quantitative and qualitative analyses were conducted. Again, the sample in this study was small and consisted of only seven physicians and 107 patients. The practice instituted a system called SPPARO (System Providing Patients Access to Records Online), which allowed patients access to their medical records through a secure Internet site and online communication with clinicians. The patients in the experimental group reported overall satisfaction with the system based on its ability to help them learn about medical decision-making, reinforce their memory about their illness, increase their participation in their care, streamline the flow of information, and confirm their test results with ease. The patient complaints were few; however, some patients did raise concerns over the security of their medical information online and their ability to understand some of the medical terms that appeared in their records. The physicians in this study had initially raised four primary concerns including, “bypassing the physician as the information gatekeeper, educating patients with the medical record, preventing versus creating medical errors, and documenting sensitive information” (Earnest et. al. 2004, p. 1). However, each of these concerns was laid to rest after the initial period of EMR use. Again, this study involves a single medical condition and a small sample size, so the results may not be valid and reliable. This study, as in several others, indicates that physicians may have concerns up front about implementing EMRs, but these concerns are often forgotten and relieved once the system is in place.

The Experience of Others in Electronic Medical Record Implementation

Although there has been discussion of a nationwide system of electronic medical records for several years, an interactive system has yet to emerge. This nationally interoperable EMR system would allow patients, payers, and providers throughout the country to document and widely share health information for individuals quickly using computers, but would require a standardized format, confidentiality regulations, nearly unanimous support, and a large financial investment (Thompson and Brailer 2004). This type of a system has not yet emerged; however, several health care providers have already implemented EMRs and reported their experiences. While the overall adoption of EMRs has been slow, it has not been completely stagnant. The Center for Disease Control (CDC) released a study that reports that from 2001 to 2003, 17% of physicians’ offices, 31% of hospital emergency rooms, and 29% of hospital outpatient departments in the U.S. used EMRs (Burt and Hing 2005).

Kaiser Permanente, the largest non-profit health care delivery system in the United States, has been a leader in health care for many years. After fully implementing EMRs for all members to replace paper medical records in two regions for ambulatory care, researchers sought to evaluate the effect of the new practice on health care use and quality of care (Garrido et. al. 2005). Using a retrospective, age-adjusted serial cross sectional design with comparisons with national and regional averages of health care utilization, the study concludes that health care utilization decreased while quality remained the same or increased with the introduction of EMR use in the two regions of interest. The quality of health care was assessed using specific process measured from the Health Plan Employer and Data Information Set (HEDIS), a nationally recognized set of indicators in the area of quality of health care. The authors of this study offer several possible explanations for why health care utilization decreased. First, they claim it is possible that the EMR provided complete clinical data, which allowed them to provide care more efficiently through phone calls and more effective first consultations that did not require a great deal of time to update the medical history. It was also suggested that the clinical support tools associated with the EMRs may have guided clinical decision making in such a way as to make it quicker, more accurate, and more effective. One important aspect of the research design of this study is the fact that observations and data collection points took place repeatedly to account for the, "natural lags in implementation and impact" (Garrido et. al. 2005 p.2). Since any change to an established work process may take a period of adjustment before the benefits of the new system may be realized, it is important to consider, as the researchers in the aforementioned study did, that the health care improvements associated with EMR use may not be immediately evident. Additionally, Kaiser Permanente is a closed system, which likely limits the generality of these findings.

As the United States began to contemplate a move to all electronic medical records, other countries took note and action. Australia, New Zealand, and England have all implemented some form of EMRs (Bates et. al. 2003). In fact, more than half of the primary care physicians in Sweden, the Netherlands, and Australia have implemented and use EMR systems (Asch and Bates 2004). A majority of Israeli hospitals are using EMRs, but the variability of the systems is also great; twenty-one out of twenty-six hospitals responded and reported using EMRs, but indicated that 27 different types of EMR systems are currently used in these hospitals (Lejbkowicz et. al. 2004). In Oman, a middle-eastern country that was named in 2000 as the most efficient health system in the world by the World Health Organization, EMR use is widespread by physicians in practices and in hospitals (Al Farsi and West 2005). Previous research in Oman regarding physician satisfaction and EMR use states that a majority of physician respondents to a survey report that the EMR system improves communication between departments, improves the quality of patient care, accurately eases the retrieval and documentation of patient information, reduces medical errors, and increases productivity (Al Farsi and West 2005). The concerns these physicians had about EMRs include the security and confidentiality of patient records, the underutilization of the system, the speed of the system, and the disease coding mechanism.

In underdeveloped areas, EMR use has also been explored. Diero et. al. used personal data assistants (PDAs) and an existing EMR system to follow the care of patients with acute respiratory illness in a rural health center in Kenya (2006). Since this part of Kenya is especially restricted with limited health care resources while respiratory tract infects account for one quarter of all deaths in Kenyan hospitals, the goal of EMR use in this medical center was to tract the patients to better study the disease patterns and outcomes of care. The researchers in this study conclude that EMRs and PDAs can provide important tools for clinical research, which will help these countries to better treat patients and utilize resources. Again, since this study was limited in scope, the findings may not be generalizable to other organizations.

A majority of general physician practices in the United Kingdom also adopted electronic medical records, and the overall response from both patients and providers has been positive (Dobbing 2001). Shortly after implementation, researchers claim that overall clinical guideline adherence is improved based on the use of EMRs. One particular study reports on the experience of Island Health, a general medicine practice in London. This particular practice indicates that in ten years, there have been no patient objections, and that staff is also highly satisfied with the EMR system. The administrative tasks have become faster and more reliable, with patient EMR information available immediately without the hassle of lost paper records.

In the United States, some physicians' offices have implemented various forms of EMRs. At Greenhouse Internists, a Philadelphia practice for more than a decade, EMRs were implemented on July 14, 2004 (Baron et. al. 2005). Like many other physicians, the staff in this practice was anxious about the cost, privacy, and efficiency of the EMR system they planned to use. With regard to cost, the system itself will cost $40,000 per year for support to the system and regular updates, along with a $24,000 annual fee for the next five years for the implementation itself. However, the authors note that they have already seen savings of $45,000 per year for transcription and another $20,000 for an eliminated staff position. With the costs of printer cartridges and other supplies, the practice expects to break even, but the physicians noted positive feedback about using the EMR system. The article claims that:

> We communicate more quickly and clearly with patients on the telephone and by letter, transmit important clinical information (albeit on paper produced automatically by our system) more efficiently to specialists, and spend less time paging through charts to find out what the previous cholesterol values (for example) had been (Baron et. al. 2005, p.6).

The physician comments here indicate that differences in care can be made through EMR use and, in this instance, this change happened quickly.

Even as early as 1996, the potential benefits of EMR systems with computer-assisted decision support in hospitals began to emerge. At a 520-bed hospital in Utah, a study took place to examine the association between EMR use and antibiotic practice guidelines, which can drastically influence health care outcomes (Pestontnik et. al. 1996). According to this seven-year study, antibiotic use, the associated costs, and the resilience sometimes associated with excessive antibiotic use improved with EMR use and the clinical reminders and guidelines associated with the EMR system. This study, cited by other proponents of EMRs, showed an overall antibiotic use decrease of twenty-two percent, overall mortality rates decreased by one percent, antibiotic resistance remained stable, appropriate use of post-surgery antibiotics increased from forty to higher than ninety-nine percent, and adverse antibiotic drug events decreased by thirty percent (Hannan 1999). In addition, the cost of antibiotics per patient was more than cut in half (Pestontnik et. al. 1996). This strong evidence emerged nearly a decade ago, leaving all to wonder, where is the momentum for EMR adoption?

One meta-analysis exists in regard to EMRs. Using articles published between 2000 and 2003, twenty institutions' experience with EMRs or CPOE, the researchers report a summary of findings (Delpierre et. al. 2004). Overall, the studies consistently found increased user and patient satisfaction, but the improvements to quality of care and patient outcomes were not strongly evident. In most of the studies included, the sample sizes were small.

Perhaps the greatest challenge that all EMR implementers have reported is the transfer of existing paper medical records to electronic format (Dobbing 2001, Spencer et. al. 1999). Even for an individual physician, the transfer of old paper records to the electronic format is overwhelming and difficult. Dr. Bruce Yaffe, a New York internist and gastroenterologist, implemented an EMR system in 2002, but the system is still not fully functional because the cost of adding the old clinical information in paper format to the new electronic format would have "sunk" the practice financially (Kranhold 2005). In an attempt to complete the integration of the EMR system, this practice has three staff members scanning data at a rate of seventy patients per day.

The Potential Contribution of this Study

While this chapter provides a great deal of information regarding what has been learned in previous research, it also reveals gaps in the field of EMRs. Since EMR use is a relatively new practice, little is known about where EMRs are being used and why. Some health care providers such as physicians and hospitals are using EMRs for patients, but there is no indication of what leads these individuals and organizations to employ EMR systems. The previous research primarily has been descriptive or qualitative. While there is value to these types of analyses, it does not explore the forces surrounding EMR use or the impact or EMR use on health care. Additionally, many of these studies have included very small sample sizes or patients with specific medical conditions, not allowing for generality of the findings.

Another gap in EMR research exists because few, if any, studies have effectively used theory to examine this HIT trend. This study uses theory to determine organizational and environmental factors associated with EMR use in hospitals whereas many previous studies have examined only organizational characteristics. By examining the relationship between EMR use and hospital and environmental determinants of this strategy, the hospitals that are less likely to use EMR systems are also identified. From a policy perspective, this may alert policymakers of hospitals that may need assistance to implement EMRs, consistent with President Bush's initiative regarding near nationwide EMR use in the next decade.

Another large gap in the literature of EMR use relates to use of rigorous methods to examine the impact of EMRs on health care. While some studies have examined individual organization's use of EMRs, no study has rigorously examined the relationship between EMR use and organizational performance with a large sample. The implication of such findings may guide further EMR implementation in the United States. The aforementioned literature in this chapter indicates that EMRs are expected to improve efficiency and quality; yet, there are no reliable findings to back up this claim. Another problem in the previous literature is that many of the studies have relied on estimates of EMR system cost and savings to determine the value and impact of EMR use, yet the reliability of these estimates is not documented. This study attempts to fill this gap by examining hospital EMR use with actual data and rigorous methods. After all, if EMRs do not improve organizational performance, their use may not justify the financial investment associated with purchasing and implementing EMR systems.

Finally, little is apparently known about specific EMR applications. In other words, EMR use in health care organizations exists. However, there is great variability in the applications that may be associated with EMR use, ranging from administrative to financial to clinical. It is this variability that may challenge or prevent the development of an interoperable EMR system in the future. For reasons discussed in Chapter 4, this study only examines fully automated EMR systems according to the HIMSS definition. However, this gap in the literature may also provide an area for exploration in future research.

Chapter Summary

This chapter summarizes previous research in the area of EMR systems, efficiency, and performance. Essentially, while there are significant barriers to EMR implementation in the United States, the benefits may be substantial. Federal regulations such as HIPAA and trends in the cost containment efforts in health care indicate that widespread EMR adoption and use is a strong possibility for the future. Additionally, hospitals and physician practices that have already begun using EMR systems report improvements in quality, efficiency, and cost savings. While barriers such as the initial financial investment of an EMR system and concerns over information security breeches are valid, health care providers in the U.S. and abroad have overcome these barriers. To realize the complete benefits of EMRs while protecting the sensitive medical information of patients, standards and systems of security must be developed and followed.

One answer to the cost containment battle of health care is to improve efficiency, by way of reducing waste and inputs while increasing outputs. Organizational performance stands to improve with appropriate processes and structures such as EMR systems, which clearly can improve health care efficiency. Measuring hospital performance using DEA will allow a relative comparison to determine optimal levels of inputs and outputs along with the identification of inefficient organizations and their respective areas of resource slack.

CHAPTER 3: THEORETICAL FRAMEWORK

Introduction

This chapter presents the theoretical frameworks and conceptual model used to evaluate the efficiency and quality of EMR use in acute care hospitals, as well as to examine environmental and organizational characteristics associated with EMR use. Two theories are presented separately and joined together as they are applied to hospital EMR use. First, Resource Dependency Theory is used to examine which hospitals have already begun to use EMR systems. The hypotheses derived from this theory examine the market and organizational characteristics that influence EMR use in hospitals. Second, Donabedian's Structure, Process, Outcome model will guide the study of the performance of hospitals. Through the application of Donabedian's theory, the influence of EMR use on organizational processes and outcomes will be studied. The conceptual model bridges these two theories as a way to examine the evolution, practice, and performance of EMR systems in hospitals. While it may seem that these theories exist independently, in this instance, they are sequentially joined together to examine the continuum of care at the hospital level, examining internal organizational factors and external environmental influences that affect the structures in hospitals that ultimately lead to the processes and outcomes of health care. In this model, the hospital structural feature examined is EMR use.

Resource Dependency Theory

Resource Dependency Theory is an open systems, natural theory that was developed in 1978 by Pfeiffer and Salancik. Resource dependency theory assumes that organizations are not in control of all of the resources they need to survive, and that many of their strategies for survival include attempts to reduce their dependence on external resources in times of uncertainty (Shortell and Kaluzny 2000). These organizational resources may include, "raw materials, labor, capital, equipment, knowledge, and outlets for its products and services" (Hatch 1997, p. 78). In other words, organizations that are highly dependent on external sources for inputs are vulnerable and may seek to become more independent by securing necessary resources from the environment. Thus, organizations are strongly influenced by their environments as they have the ability to "interpret their environments and actively modify the elements contained therein" (Proenca et. al., 2003, p. 61, Hatch 1997). While resource dependency theory recognizes the role of competition between organizations regarding input resources, it requires that they may become interdependent on one another through joined forces if it will lead to more secure supplies of resources during times of great uncertainty (Zinn, Proence and Rosko 1997). For example, two organizations that need and compete for the same resource or resources may work together to acquire them if they are more able to secure the necessary input through a joint effort, coalition or network (Shortell and Kaluzny 2000).

Many previous studies have applied Resource Dependency Theory to health care settings. These applications have hypothesized and examined why organizations have adopted flexible benefit plans and how skilled nursing facilities have evolved in the face of organizational and environmental change (Barringer and Milkovich 1998, Banaszak-Hall, Zinn, and Mor 1996). Proenca, Rosko, and Zinn used Resource Dependence, linked with Institutional Theory, and Organizational Adaptation, to examine the association between organizational and environmental factors and hospital provision of prevention and health promotion services (2002). Zakus used Resource Dependency theory to examine community participation in primary care in Oaxaca, Mexico (1998). Another study used Resource Dependence to examine organization and environmental determinants of non-profit hospitals joining a hospital alliance membership or contract management (Zinn, Proenca, and Rosko 1997). Lucas et. al. used Resource Dependence theory, in conjunction with Institutional theory, to examine which nursing facilities adopted Continuous Quality Improvement (CQI) (2005). These studies use Resource Dependency Theory to show how the environment guides organizational strategy. According to Scott, it is at the environmental level that, "the interests, the resources, the dependencies of a given organization are best examined and its survival tactics probed" (2000, p. 127).

Resource Dependence Theory is a clear choice for examining hospital EMR Use. Hospital EMR use represents a fairly new organizational strategy or behavior, and this study examines the environmental and organizational reasons for EMR use.

According to Resource Dependence theory, *environmental uncertainty* influences the variability and complexity in organizations face when obtaining resources (Dess and Beard 1984). Measured by *munificence* and *concentration*, uncertainty in the environment may lead organizations to attempt new strategies to secure resources and survive. As uncertainty in the environment increases, organizations may increase their attempts to stabilize and attain resources and relationships to secure these supplies of resources in order to survive (Zakus 1998). According to Proenca et. al., "Organizational responses are aimed at lowering the level of uncertainty in the environment by securing a stable flow of resources" (2003, p. 61). Munificence is the abundance of resources and is a determinant of organizational strategy, and concentration refers to the density of resources in the environment (Zinn, Proenca, and Rosko 1997). In other words, in an environment that is certain, access to resources may not warrant organizational strategy or action. However, if an environment is very uncertain, an organization may be more likely to adapt.

Hospitals have existed in an environment that has changed drastically over the last twenty years, leading to a great deal of uncertainty (Lee and Alexander 1999). This uncertainty has led to "changes in organizational structure or behavior that may reflect accommodations intended to secure a stable flow of resources from the environment" (Zinn, Proenca, and Rosko 1997, p. 69).Through the cost containment efforts and the quality improvement efforts, hospitals have gained a great deal of responsibility for the financial risk of patient care and the quality outcomes of health care (Lee and Alexander 1999). Changes such as the Prospective Payment System (PPS) and the introduction of managed care have contributed to this environmental uncertainty for hospitals. For quality, trends such as Continuous Quality Improvement (CQI) and accreditation from agencies such as JHACO have increased the pressure for hospitals to improve patient safety and outcomes. As technological advances continue and the financial risk is continually shifted to hospitals and other health care organizations, it likely that this environmental uncertainty will continue. As noted in Chapter 2, hospital EMR use may lead to decreased overall costs and increased quality of care, thus making it one possible hospital strategy in an environment of uncertainty. According to Resource Dependence Theory, hospital strategy and action are motivated by environmental uncertainty, and managers are actively able to influence organizational survival through strategies to respond to the environment and its pressures (Zakus 1998). Hatch contends that the environment may provide a powerful constraint on organizational action and may use this power to influence cost, services, or products (1997). If organizations are to survive in an environment of uncertainty, they must identify their resource dependencies and adapt their organizations accordingly (Scott 2003).

Resources can include capital, technology, human resources, and information. Resources needed for organizational survival as assessed based on their *scarcity and criticality*, and proponents of this theory believe that the most powerful organizations, not necessarily the most efficient, survive in the market because more powerful organizations are better equipped to attain the resources they need to survive (Hatch 1997, Scott 2003). Resource dependency analysis involves the anticipation of resource dependencies as the scarcity and criticality of resources is determined, and resources that are deemed the most scarce and critical are given the highest priority (Hatch 1997). To do so, managers at organizations attempt to identify resource dependencies, or inputs that the organization needs to function. Access to these resources is sought based on their scarcity and criticality. Hospitals depend heavily on patients and revenue to function. Without these resources, it is impossible to attain or maintain other resources, such as staff, equipment, or supplies, making patient revenue critical. The scarcity of this resource depends upon the availability and competition in the market. Since most hospital revenue comes from patient services and the associated charges, hospital leaders may seek to secure patient demand by offering state-of-the art technology and services, such as EMRs. If patients have control over where they are able to receive covered services, they may elect to go where the services offered are advanced in some way. By appealing to patients, hospitals are able to secure a constant source of financial input, thus reducing their vulnerability. However, based on organizational power, these organizations do not have equal resources or access to resources (Zakus 1998). According to Scott, “Unequal exchange relations can generate power and dependency differences among organizations; hence, organizations are expected to enter into exchange relations cautiously and to pursue strategies that will enhance their own bargaining position" (2000, p. 197). When examining hospital EMR use, not all hospitals have the same ability, based on power, to implement such a practice, but as Hatch states, "the power distribution then explains the outcomes of selection" (1997, p. 290).

Hospital leaders who believe that EMR use may lead to increases in quality, safety, and efficiency may see EMR use as a way to reduce dependence on an uncertain environment, thus prompting organizational action, which could increase the likelihood of organizational survival. According to Shortell and Kaluzny:

> In regard to quality, the resource dependence perspective would emphasize the importance of continuous improvement and total quality management for demonstrating value to purchasers of care. To accomplish this, the organization needs resources from the Environment in the form of measurement tools, information systems, and technical expertise to produce valid data on the processes and outcomes of patient care. An organization's ability to exert influence over its environment will depend on how successful it is in demonstrating continuous improvement relative to that of other organizations that patients and purchasers can choose (2000, p. 22).

This quote clearly shows the relationship between hospital behavior and the use of EMRs, according to the Resource Dependency theory. In essence, hospitals that wish to secure resources from the environment will try new strategies and practices to attract demand for their services. In addition to using EMRs to attract patients, some hospitals may depend upon external organizations to store paper medical records and may see the exchange of these records with other providers for diagnostic results as being a risk to their independence. At the same time, these hospitals are monitored by organizations including Medicare, Medicaid and regulated by the Joint Commission for the Quality of Healthcare Organization (JCAHO), Leapfrog, private insurance companies, and other agencies. If the data and documentation are more automated through EMR use, it is possible that organizations may see this as a strategy for reducing dependence or achieving independence since EMRs may allow them to more easily generate quality or cost reports instead of having inspectors or medical records reviews. Many of the organizations may value the certification they receive from these agencies as a resource, but may wish to more easily document their compliance with the necessary rules. This documentation may occur more easily with EMRs, which could reduce the number of external agency audits a hospital may undergo. By maintaining such certifications, hospitals are further securing patient demand as a resource since patients with a choice of locations for care will likely elect to go to the hospital that offers a certification of their quality of care.

One criticism of this theory is the question of whether or not managers are able to identify all of the resources necessary for an organization to survive (Hatch 1997). Because some resources may not be identified right away or they may change in unpredictable ways, it is possible that organizational leaders may not anticipate and plan for these resources with their strategies and identification of dependencies. This is a possible weakness of managers, according to this theory. However, the value of this theory is evident in that there are some resources that managers may identify as crucial to organizational performance, and they may act to secure the steady input of these resources from the environment.

Environmental uncertainty is possibly the greatest predictor of organizational strategy and action, according to Resource Dependence theory. As discussed earlier, hospitals are currently facing environmental uncertainty, and EMR use may be one strategy to combat this uncertainty. Additionally, though Resource Dependence theory views managers as active participants in organizational strategy, no hospital management variables are included in the model. The reason for this is two-fold. First, the purpose of this project is to examine specific organizational and environmental determinants of EMR use, and management style is very difficult to measure. Additionally, the data available for this research do not provide any management level variables, and acquiring these data would require a different approach and be costly.It is, however, likely that proxy management variables are represented through ownership and system affiliation, though the exact relationship between these variables is not examined in this study. Second, the structural feature of interest in this study is EMR use. The purpose of this study is not to examine the decision-making process associated with EMR adoption or use, which would likely require a very different approach. Figure 1 provides the first part of the conceptual model employed to examine EMR use in hospitals. This conceptual model is built from a Resource Dependence Framework and will later be joined with Donabedian's Structure, Process, Outcome Theory to examine hospital performance and EMR use.

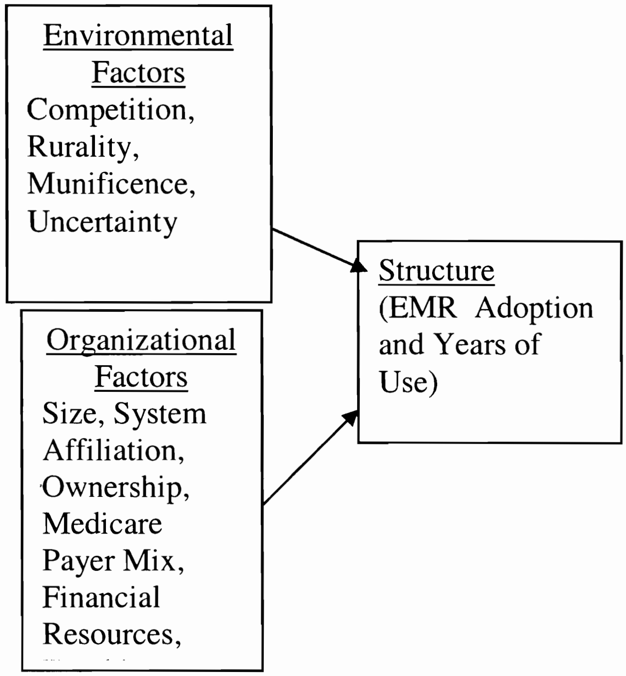

Figure 1: Conceptual Model of Hospital EMR Use Derived Through Resource Dependency Theory

Theory Application and Hypotheses

Financial Resources

Because previous research and literature have identified many barriers to EMR implementation and use, the influence of these challenges must be examined using theory. The organizational barriers, as mentioned in the previous chapter, include cost, concerns over information security, and physician buy-in. Perhaps the greatest of these barriers for any individual hospital is the cost. With adequate financial resources, hospitals are likely more able to purchase the often-expensive

EMR systems and equipment. However, not all hospitals have the financial means or the motivation to implement and use EMR systems.

H1: Hospitals with greater financial resources are more likely to use EMRs.

Environmental Uncertainty and Payer Mix

Resource Dependency theory claims that in times of environmental uncertainty, organizations will seek to reduce their vulnerability by increasing their independence, thus improving their chances to succeed. Based on this insight, one would expect hospitals in uncertain times to attempt to be on the cutting edge to secure the inputs their organization requires to function. In the instance of hospitals, as aforementioned, critical resources include patients and the revenue that is collected based on their service. Zinn, Proenca, and Rosko state that, "The public payer sector has experienced the greatest amount of environmental uncertainty in recent years" (1997, p.71). The reason for this great uncertainty is that Medicare and Medicaid reimburse hospitals at prices below the cost of providing services (Zinn, Proenca, and Rosko 1997). Additionally, CMS has often elected to reimburse less to hospitals that do not participate in their voluntary initiatives. For example, the Health Quality Alliance, of which CMS is a member organization, began collecting quality indicator variables from hospitals and reimbursing hospitals that do not participate in this initiative .4% less than those that do participate (HQA 2005). For hospitals that depend greatly on CMS for reimbursement and financial resources, this reduction of money may be a significant incentive for compliance, thus prompting the organization to action. Since the federal government is such a large purchaser of health care services, and it has indicated a desired move to an entirely interoperable EMR system within ten years, hospitals may suspect that using an EMR system may become a CMS provider requirement in the future (Brailer 2004). The government may encourage the use of EMRs before their use becomes mandated through hospital grants to implement or study EMRs, higher payments for hospitals with EMRs, or it may begin by making them a Medicare of Medicaid requirement for reimbursement. While this is speculation at this point, it represents the type of strategizing that hospital management must do to function in an uncertain environment. It is also possible that the federal government's indications that EMR use is in the future of our country may create more uncertainty in the environment, thus leaving hospitals seeking strategies such as EMR use to ensure continued input resources, such as funding and contracts with large payer groups such as CMS.

H2: Hospitals with a high percentage of Public reimbursement are more likely to use EMRs.

Competition

The level of competition in an external environment, according to Resource Dependency Theory, is a large predictor of organizational strategy and action (Lucas et. al. 2005). In an area with a great deal of competition, hospitals must compete for the same resources, thus making inputs potentially scarcer. In areas with a large amount of health care competition, hospitals are under more pressure to distinguish themselves from competitors, thus securing their market share of patients. If patients have more choices, they may elect where to go for health care and will likely choose a hospital that offers new or better services such as EMRs. On the other hand, if a hospital is located in an area without competition, patients have fewer choices regarding where to seek care, and thus, hospitals are under less pressure to make their services and facilities more appealing. Hospitals may reason that EMRs will make them more appealing to the patient population in an area of high competition where patients have choices of where to receive care. Because of this, it is expected that hospitals in areas of greater competition will be more likely to use EMRs. In this study, the level of competition will be measured using a calculated Herfindahl index.

H3: As environmental competition increases, the likelihood of hospital EMR use increases.

Rurality

In the organizational environment, hospitals in more rural areas face unique challenges. Rural hospitals often report lower rates of occupancy, and more financial and social pressures, thus making their comparison to urban hospitals in the areas of financial performance and efficiency difficult (Williams 2005). These rural hospitals also generally serve a smaller stream of patients. Part of the reason for this trend is that rural areas may have fewer provider choices than more urban areas. Larger cities have larger populations and more hospitals than rural areas, making competition among these providers more intense. A hospital that exists in a rural area may be the only option for residents, thus not causing the hospital to compete with others in the environment. For this reason, one expects that hospitals in rural areas would be less likely to take actions, such as EMR adoption, to attract patients that have no other provider choice in their area. According to Demiris, Patrick, and Boren, regulative and legislative efforts have recently been made to address patient safety; however, "most practical initiatives have focused on urban settings and academic medical centers; as a result rural hospitals and other clinical settings are mostly excluded from these efforts" (2004, p. 157). Balosky reports that, "larger, more affluent markets can support" new health care practices better than smaller markets (2005 p. 339). Rural hospitals have fewer beds in most instances than larger urban hospitals. The patient population is smaller for a rural hospital than for an urban hospital, also causing a rural hospital to bring in fewer financial resources through insurance reimbursement and payment for patient care. Since EMR systems are costly, rural hospitals may not have the financial resources to implement such a system, and little is known about the "limitations of existing software, hardware, and human resources infrastructure to support an electronic reporting system" currently in place in rural hospitals (Demiris, Patrick, Boren 2004, p. 158). Rural hospitals are also less likely to have complex tertiary services since their patient population is smaller and not likely to provide enough demand (Williams 2005). At the same time, in rural areas, access to complex health information technology may not be as readily available as it is in a more urban area, so hospitals may not have the means in geographic proximity to obtain and EMR system. This will likely make it more difficult for rural hospitals to adopt EMR systems, as compared to urban hospitals.

H4: Rural hospitals are less likely than urban hospitals to use EMRs.

Hospital Size

Organizational Power is often associated with organizational *size* since larger organizations may have more financial and human resources with which to attain necessary inputs from the environment (Lucas et. al. 2005, Zinn, Proenca, and Rosko 1997). More powerful organizations may also be those that control vital resources in an environment, and for this reason, these organizations may be in a better position to name the terms of exchange and to survive (Hatch 1997). The power associated with size allows hospitals to more easily achieve economies of scale for services, and the larger the purchases made by an organization such as a hospital, the more negotiation power that organization will have with suppliers. According to Williams and Torrens hospital size allows organizations to, "implement information systems and other care management technologies" (2002, p. 204). This claim is consistent with Resource Dependency Theory. Hospitals that are larger will have more ability to acquire and use EMRs because they will have more revenue to purchase a system and more personnel to implement and maintain a complex EMR system. Larger hospitals also tend to have more complex services, which may be associated with EMR use. Hospital size has been measured in a number of ways in health services research. In this study, size is measured through the total number of beds set up and staffed.

H5: Larger hospitals are more likely to use EMRs.

Hospital Ownership

Hospital ownership may also guide organizational strategy, based on differences in organizational missions. For-profit hospitals have been accused of operating with a greater profit margin, thus allowing them to sustain greater financial gains (Clement and Grazier 2001, Williams and Torrens 2002). If this is the case, they will have more financial resources than non-profit or public hospitals to attribute to purchasing an EMR system. To add to this, for-profit hospitals generally pursue organizational efficiency and financial gain more than public and non-profit hospitals that provide a great deal of charity care, in part based on their missions (Williams 2005). Harrison and Sexton studied hospital ownership finding that non-profit hospitals are more likely than non-profit hospitals to, "be in communities with lower HMO (health maintenance organization) penetration and more elderly patients" as well as to have, "a lower ROA (Return on Assets), lower debt, higher occupancy rates, older facilities, and higher operating expenses per discharge," indicating that they are not as efficient as their for-profit counterparts (2004, p. 201). However, on the other hand, McKay, Deily, and Dorner reported that in both 1986 and 1991, for-profit hospitals were the least efficient overall, while non-profit hospitals are the most efficient, and public owned hospitals are in between these in efficiency performance (2002-2003). With regard to cost, for-profit hospitals have been found, "more expensive for Medicare," than non-profit hospitals, causing speculation that they have, "greater incentive to maximize reimbursements from payers by various means including formal and informal contractual relationships with other suppliers of health care services" (Sloan et. al. 2001 p.17). It appears, according to this study, that for-profit hospitals may not be as efficient if they are also the most costly considering that hospitals are reimbursed from Medicare based on services performed on patients according to the DRG (Diagnostic Related Groupings) system. Essentially, each of these studies illustrates the fact that differences in hospital performance, based on ownership, exists, though not all of them tell a consistent story regarding hospital ownership and performance. Although the research regarding the success of for-profit hospitals in attaining better efficiency is mixed, it is plausible that they would be more likely than hospitals with other types of ownership to pursue a system such as EMRs, which could improve organizational efficiency and increase profits. Since EMR use is expected to improve hospital efficiency drastically through automation, decreased medical chart maintenance, and reduced duplication of services, it seems likely that for-profit hospitals would be eager to use this new technology. For-profit hospitals may view EMR use as a way to both increase efficiency and attract a steady influx of paying patients, who might prefer to go to a hospital that offers EMRs over one that does not. In this way, for-profit hospitals can view EMR use as a way to better secure necessary resources such as patients while maintaining their mission to generate a profit through increased efficiency. Essentially since for-profit hospitals may have more financial resources available to purchase an EMR system and more of an interest in increasing organizational efficiency in the interest of increased profits, one may expect that they would be more likely than non-profit and public hospitals to use EMRs.

H6: For-profit hospitals are more likely than public or non-profit hospitals to use EMRs.

Hospital System Affiliation

Organizational size also relates to interdependence, which refers to organizations that work together to function and requires some coordination of efforts. *Competition* between *interdependent* organizations is an important component of resource dependency theory that recognizes that similar organizations may be attempting to maintain autonomy by securing the same resources. When describing the Resource Dependence theory, Hatch claims that, "competition over raw materials and customers is one source of potential influence" of organizational strategy and behavior (1997, p.79). The scarcer a resource is, the more competition will generally exist for that resource, leading organizations to strategies to attain the resource. The *interdependence* of organizations is based on the notion that organizations are interconnected through the environment as they work to secure the resources they need for survival. According to Resource Dependence theory, organizations seek ways to avoid and reduce dependency on suppliers through *buffering and bridging* tactics. *Buffering* attempts to protect the technical core of an organization and includes internal tactics such as coding, stockpiling, leveling, forecasting, and adjusting scale (Scott 2003). *Bridging* utilizes external strategies to secure resources and includes bargaining, contracting, co-optation, hierarchical contracts, joint ventures, strategic alliances, mergers, associations, and government connections (Scott 2003). One example of interdependence is hospitals that share management, as in the case of system-affiliated hospitals. In the 1990s, many hospitals joined health care systems as a strategy to face a very uncertain environment, and many of these system affiliations still exist (Bazzoli et. al. 1999, AHA 2003). System affiliation, according to Resource Dependence Theory, may be viewed as a bridging tactic intended to create alliances for the purpose resource acquisition and better negotiation through purchasing on a larger scale. Like size, system-affiliation also allows hospitals to have access to more resources such as personnel and revenue. System-affiliated hospitals also may have more negotiating power with external organizations or suppliers in the environment. This is because the larger the purchase of an organization, the more power the organization may have to negotiate the terms of purchases, such as price, availability, and delivery of service. According to Zinn, Proenca, and Rosko, “Membership in a hospital chain may provide greater access to financial and administrative resources at the corporate level” (1997, p. 70). Hospital systems, in many instances, will implement companywide programs and policies. An EMR system would likely be implemented on a system-wide basis, allowing the hospitals within a system to share resources and communicate medical information more easily.

It is important to note, however, that not all hospital system affiliations are the same (Bazzoli et. al. 1999). Hospital system affiliations vary with regard to their levels of centralization, differentiation, and integration (Bazzoli et. al. 1999). According to Bazzoli et. al., "The level at which services are organized and provided (i.e., centralization) represents a key structural dimension with important implications for decision making and accountability" (1999, p. 1685). Hospital systems that are highly centralized are associated with, "centrally organized individual hospital delivery, physician arrangements, and insurance product development" (AHA 2003, p. 26). In highly centralized hospital systems, the hospitals are likely to rely on a managing organization to make most organizational decisions and policies, including the decision to use EMRs. In less centralized hospital systems, the individual hospitals are more likely to develop their own organizational practices and policies, including EMR use. Additionally, it is likely that hospital systems that operate with more centralization have more resources at the system level to use to strategize for success. In other words, these hospitals associated with system organization for operational practices are more likely to have EMRs because the larger system organizations are more likely to have the resources to attain a structure such as an EMR system. Also, a centralized health system could invest in a single EMR system to use in each of its individual hospital members, thus creating greater economies of scale by sharing the one system throughout several organizations. According to Lee, Alexander, and Bazzoli, hospital members of systems may benefit from system practices such as, "centralized information gathering, processing, and dissemination," which may be "cost-efficient" for hospitals that could not afford to perform these processes independently (2003, p. 177). A taxonomy of hospital systems, which includes centralized health systems, centralized physician/insurance health system, moderately centralized health systems, decentralized health systems, and independent hospital systems, is presented in Chapter 4, thus allowing for the distinction of health systems based on centralization of decision making. This taxonomy essentially presents the types of health systems in ordinal categories. Because the level of centralization is also associated with organizational size and power, Resource Dependence predicts that the larger, more powerful organizations, such as hospital systems that are making decisions centrally for multiple hospitals, are more likely to use EMRs. Thus, the hospital members of these centralized systems are more likely to use EMRs than the hospital members that make decisions independently of the systems because the centralized systems will have more power and resources with which to attain EMR systems.

H7: As a hospital's relationship with a system moves along a continuum from no affiliation to highly centralized systems, the likelihood of EMR use increases.

However, there is still a component of interdependence associated with EMR use. The federal government speaks of EMRs as an interoperable system that will allow providers to better communicate with one another regarding particular patients. It is possible that, if an interoperable system is developed, that the level of interdependence between providers may increase. Physicians and other clinicians may begin to depend upon one another more as they increase the continuum of care associated with sharing patient information through EMRs, but the aforementioned hypothesis stands since system affiliated hospitals may already be more accustomed to sharing the care of patients and their information. Zinn, Proenca, and Rosko claim that in times of great environmental uncertainty, "one strategy is to enter into cooperative exchange relationships with other organizations in order to secure and stabilize resource flow" (1997, p. 73). So, while an interoperable EMR system that allows medical records to be transferred rapidly from one organization to the next may increase interdependence, this may merely represent a bridging strategy of hospitals who are responding to the desire to secure resources including patient demand, reimbursement, and the medical histories of their patients. Additionally, if the EMR systems are purchased from a vendor and include a service contract, instead of being produced "in-house," the dependence of hospitals upon these external vendors is likely to increase through organizational bridging. Again, this may represent an organizational strategy to secure resources by acquiring a new technology.

Hospital Teaching Status

Teaching hospitals provide a great deal of charity care and medical research, as well as provide the training and education of many of the nation's heath care workforce. Teaching hospitals, which assume multiple roles, "face numerous challenges including the provision of care to medically underserved communities" (Williams 2005, p.80) Some have speculated that these hospitals are in financial danger based on the increased expense associated with the medical training of staff and providing a great deal of charity care. Rosko reports that teaching hospitals, "provide larger volumes of uncompensated care than non-teaching hospitals" (2004, p. 37). According to Retchin and Wenzel, academic health centers can easily adapt to the use of EMRs because they, "have the expertise to resolve remaining software issues, the components necessary for the integrated delivery, a culture for innovation in clinical practice, and a generation of future providers that can be acclimated to the requisites for computerized records" (1999, p.493). However, Balosky claims that the teaching hospital has, "lost its significance as the preferred setting for high technology treatment" (2005, p. 344), yet Rosko claims that, "teaching hospitals frequently compete on the basis of providing superior quality," a strategy that may be consistent with EMR use (2004, p. 40). Ultimately, teaching hospitals are those that may not have the financial resources to adopt EMRs, but where EMR use would make sense based on the medical training that takes place. However, since teaching hospitals are often providing cutting edge technology, which is also expensive, it is likely that EMR use is more common in teaching hospitals. Another reason for this increased likelihood is that medical training occurs in these hospitals, and younger medical trainees tend to be more comfortable with computers as they have recently used them in school. Because of this, the staff resistance to EMR use may not be as great as in other hospitals.

H8: Teaching hospitals are more likely to use EMRs.

Environmental Uncertainty

According to Resource Dependence theory, it is environmental uncertainty that may motivate organizational action or strategy (Hatch 1997). Organizations in areas of greater uncertainty are more likely to take action to secure resources than organizations in areas of less uncertainty. After all, organizations that have certain access to necessary resources do not need to strategize to secure inputs from the environment, and organizations in uncertain environments must adapt to their surroundings in order to survive (Scott 2003). Hospitals have not recently existed in certain environments, thus prompting the need to strategize for organizational survival (Proenca, Rosko, and Zinn 2002, Ginn, Young, and Beekun 1995, Lee and Alexander 1999). Since EMRs may lead to greater hospital performance and outcomes as well as increasing efficiency, some hospitals may use EMRs as a strategy to combat this environmental uncertainty (Brailer 2004). For this reason, it is likely that hospitals in areas of greater environmental uncertainty are more likely that those in areas of less environmental uncertainty to use EMRs.

H9: Hospitals in environments of more uncertainty are more likely to use EMRs.

Munificence

Finally, to be more specific about uncertainty, munificence represents the availability of resources in the environment (Zinn, Proenca, and Rosko 1997). Munificence is, "the level of resources available in the local market" (Lee and Alexander 1999, p. 932). Since hospitals seek financial resources in the form of patient payments or insurance coverage, it is possible to tie environmental munificence for hospitals to the amount of financial resources in the hospitals' markets since the level of financial resources available locally "determines the amount of input to hospital operations" (Lee and Alexander 1999, p.932). After all, hospitals in areas where the amount of financial resources are more abundant are more likely to have the support for high cost services and technology such as EMR. Zinn, Proenca, and Rosko have hypothesized that hospitals in areas of less munificence (wealth), hospitals are more likely to join together in alliances (1997). This may be because in areas of more munificence, hospitals are more likely to compete with one another for patients, thus leading to the adoption of EMRs as a means of competing, while hospitals in areas of less munificence (wealth), hospitals face more uncertainty and must work together to face this uncertainty. Additionally, in these financially wealthy regions, hospitals may be more motivated to appeal to potential patients because they know that the patients can afford to be selective in their health care and pay for services received. Balosky reports that, "Markets with greater per capita income supported higher cost hospitals" (2005, p. 340). Because of this, hospitals may reason that in environments of greater financial munificence, they are more likely to recover the money spent investing in an EMR system than in an environment of less financial munificence.

H10: Hospitals in areas of more munificence are more likely to use EMRs.

Impact of EMR Use on Hospital Quality and Efficiency

While the Resource Dependency Theory is quite useful to examine the environmental and organizational characteristics associated with EMR use, Donabedian's Structure, Process, Outcome provides a more dynamic view of organizational performance. Because of this, Resource Dependency Theory will be joined with Donabedian's Structure, Process, Outcome framework, which provide a useful tenets for examining organizational structural variance, process characteristics, and the associated health care outcomes of these factors. While not an actual theory, Donabedian's framework emphasizes the relationship among tenets in organizations. The Structure, Process, Outcomes model will examine the role of EMRs in hospital outcomes as well as how each of these components relates to one another. Specifically, the next theory will examine the relationship between EMR use and hospital efficiency and quality since Donabedian emphasized the relationship between these constructs.

Efficiency and Quality

Donabedian has been credited by some for providing the first theoretical framework to examine health care quality (Mick and Wyttenback 2003). This framework includes the examination of the relationship between organizational structures, processes, and outcomes. According to this framework, it is the relationship between structure and process that leads to the outcomes of health care. These outcomes may include health care quality, efficiency, and effectiveness. However, a link between Donabedian's framework and general Systems Theory is evident. Systems Theory claims that organizations are made up of interdependent parts, and that the combination of these parts influences how the organization functions (Scott 2003, Hatch 1997). According to Scott the parts that make up organizations vary so, "While these features underlie the similarities exhibited by all systems, they also suggest bases for differences among them" (2003, p. 83). Hatch states that according to Systems Theory, "Each part is conceived as affecting others and each depends upon the whole" (1997, p. 35). These statements indicate that different organizations have different features and practices that influence the processes of the organization and lead to different outcomes. The description of the relationships of Systems Theory is consistent with components of Donabedian's Structure, Process, Outcome framework. Essentially, general systems theory acknowledges that outputs are the result of organizational inputs. Likewise, Donabedian also cites several other theoretical frameworks, including those from

Sheps, De Geyndt, and Dror, as providing validity to his own work, based on the similar components each includes for evaluating health care organization performance (1980). For example, Sheps' framework includes prerequisites, elements of performance, clinical evaluations, and effects of care. De Geyndt's framework includes structure, content, process, outcome, and impact. Finally, Dror's framework examines input, structure, process, nominal output, and real output. According to Dror, input includes manpower and the time, knowledge, equipment, and energy and drive needed for production. The main difference between these models is the level to which they are broken down, as some contain more specific components than others. Ultimately, they examine very similar components and how they relate to health care outcomes and Donabedian cautions that he offers the framework, "as a guide, not a straightjacket," meaning he intends for its applicability to be flexible and adjusted (1980, p. 89). Each of the three components of the framework, structure, process, and outcome, represents a component of organizational performance, and when they are combined, and the relationships amongst them are examined, the most complete evaluation is possible. Donabedian writes that outcomes, "reflect all contributions of all the practitioners to the care of the patient" and can provide, "an inclusive integration measure of the quality of care" (1980, p. 120). For these reasons, this model has been selected to guide the research relating to EMR use and peformance. Figure 2 illustrates Donabedian's model.

Donabedian's Structure ⟹ Process ⟹ Outcome

Figure 2: Donabedian's Structure, Process, Outcome Model

Structure includes the resources that are needed for an organization to function. Donabedian defines structure as, "the relatively stable characteristics of the providers of care, of the tools and resources they have at their disposal, and the physical and organizational setting in which they work," and claims that structure, "includes the human, physical, and financial resources that are needed to provide medical care and embraces the number, distribution, and qualifications of professional personnel, and so, too, the number, size, equipment, and geographic disposition of hospitals and other facilities" (1980, p. 81). Structure includes organizational inputs and provides organizations with the capacity to do the work (Scott 2003). Without the appropriate structure, an organization is unable to function at its optimal ability. Structure is the environment in which care is provided, and it "influences the kind of care that is provided" and "increases or decreases the probability of a good performance" (Donabedian 1980 p. 81-82). Because of this, a change in the structure may ultimately lead to a change in the outcome. The complexities of outcomes in health care and the relationships between structure, process and outcome are further emphasized by Scott, who claims that, "Outcomes are never pure indicators of quality of performance since they reflect not only the care and accuracy with which work activities are carried out but also the current state of technology and the characteristics of the organization's input and output environments" (2003, p. 353-364). This statement reflects the perspective of the structure, process, and outcome model as it states the influence that both structure and process have on the quality of care and indicates that the measures of quality do not stand-alone. Donabedian states that, "good structure, that is, a sufficiency of resources and proper system design is probably the most important means of protecting and promoting the quality of care" (1980, p. 82). Structure includes human resources, facilities, equipment, organization, information systems and records, financing, management and amenities and governance (Starfield 1992). This theoretical framework emphasizes the necessity of having an adequate organizational structure to positively affect the processes and outcomes of health care.

Process includes "the set of activities that take place between providers and patients" (Paganini 1993, p. 7). Process may also include clinical decision-making and the protocols and procedures that are used in health care. Scott claims that process measures, "focus on the quantity or quality of activities carried out by the organization" (2003, p. 366). According to Donabedian,, the structures in health care directly influence the processes, and processes directly, in turn, affect the outcomes (1980). After all, the number of employees, the equipment that is available, the facilities where care takes place, the organization, and management all directly impact how things are done. For example, management, as a structure, may implement procedures that must be followed, such as specifying the order in which care must be given or when vital signs must be measured, and those procedures will affect the process of care. Processes of care include diagnostic procedures, diagnosis, therapy and management, utilization, acceptance, understanding, and compliance (Paganini 1993). Processes of care can be efficient or inefficient, and Scott claims that they "assess effort rather than effect" (2003, p. 366). This distinguishes efficiency from measures of outcomes since assessing a process can include looking at the quantity of outputs in a work situation without considering their effects solely on the end result (Scott 2003). However, without the proper structure, processes will almost certainly be inefficient due to a lack of necessary input resources, as an organization cannot produce the optimal amount of outputs without appropriate inputs including the correct number and type of staff and equipment. Efficiency is the ratio of inputs to outputs, with the notion that situations that produce the most outputs with the least inputs are the most efficient. Efficient processes exist when the appropriate structure is in place, and adequate resources are available. At the same time, it is possible that organizations without the necessary input resources will be ineffective as opposed to or in addition to being inefficient. Being ineffective may mean that the processes do not lead to the desired outcomes. In the instance of health care, an ineffective hospital is one that does not provide appropriate care to patients in a timely manner. For example, a hospital that does not provide tertiary care would likely not be effective in treating patients with complex conditions such as those in need of a specialized burn unit or an organ transplant unit.

The outcomes of health care are complex and have many components. Donabedian defines outcomes as, "a change in a patient's current and future health status that can be attributed to antecedent health care" (1980, p. 82-83). Quality is a construct that often includes components such as patient satisfaction, adverse clinical affects, mortality, and effectiveness of treatments. While efficiency and quality are related concepts, one does not necessarily guarantee the other, and in many cases, trade-offs are made so that one may be achieved over the other. The outcomes of health care are the products of the structures and processes that lead to them. Donabedian claims:

> While 'process' is the primary object of assessment, the basis for the judgment of quality is what is known about the relationship between the characteristics of the medical care process and their consequences to the health and welfare of individuals and of society, in accordance with the value placed upon health and welfare by the individual and society (1980, p. 79-80).

This statement ties quality to efficiency, for in many instances, quality comes with increased costs, and few have the ability to spend limitless amounts of money to increase their quality of health care.

Donabedian's structure, process, outcome model provides a useful theoretical framework for examining the influence EMRs may have in hospitals, though it is important to note that Donabedian's structure, process, outcome model does not actually predict any directional relationships; instead this framework describes the interdependence of and relationships between components of organizations. Because of this, researchers must use this framework to acknowledge the influence that organizational structures, processes, and outcomes have on one another and rely on previous research and logic to determine the direction of the construct relationships. To apply this framework in this study, the influence of structure on process and outcome is examined and described n the context of hospitals and EMR use. Through previous research and projections made by policy makers, it is clear that the expectation is that EMRs will improve the cost, quality, and efficiency of health care. Each of these components is a health care outcome, according to the descriptions provided by Donabedian. EMR systems are a health care structural feature, according to Donabedian's model. Because they are a fairly stable information system, EMRs are part of the environment of care. It is the structure that influences the process of care, and ultimately leads to the outcomes of care. EMRs are expected to make processes more automated, standardized, and efficient. These improved automated processes are expected to lead to fewer medical errors and oversights, thus improving health care quality or outcomes. If the automated EMR processes are in fact more efficient, they will waste fewer resources on providing care, thus enabling providers to give attention to other aspects of patient care. It is this other attention that will also, in addition to the decreased medical errors, ultimately improve patient care. Figure 3 presents the sequential combination of Resource Dependency Theory and Donabedian's Structure, Process, Outcome Model and the application to hospital EMR use.

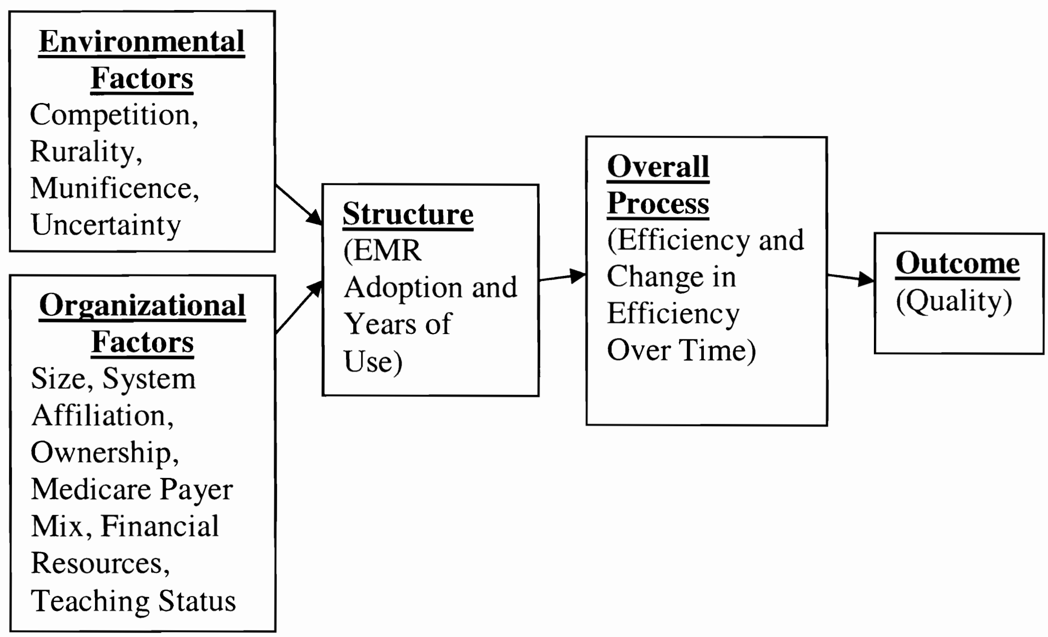

Figure 3: Conceptual Model of Hospital EMR Use Derived through Resource Dependence and Structure, Process, Outcome Framework Theory Application to EMRs

Since not all hospitals currently have EMR systems, there is variation in their structures. However, hospital structures are not randomly selected. As the Resource Dependency framework explains, hospitals without adequate resources to obtain EMR systems may not have the means to reduce their dependency on external resources and secure their necessary inputs. As health care organizations, hospitals in particular, seek to adopt structures that will lead to good performance in both processes and outcomes, many will look to technology in the coming years. These outcomes may relate to quality or efficiency.

Donabedian's model claims that structures influence both processes and outcomes. Thus, logic deduces that a structural change such as EMR usemay drastically change health care. According to Ozcan, "To increase productivity within the hospital as a whole, it is necessary to better match the appropriate resources (the inputs) with the care to be provided (the outputs)" (2005, p.214). While this may seem fairly intuitive, hospitals must recognize that the often incomplete and inaccurate traditional paper records are not conducive to providing high quality patient care in an efficient manner, and a change to the structure, in the form of EMR use, may increase the likelihood of increasing performance. EMR systems have been shown to reduce the number of employees needed to provide care based on their reduced dependency on transcription and medical chart maintenance. Thus, according to Donabedian's framework, as a structure, EMRs will change the process of care in some ways. For example, if these employees are no longer needed to deal with the paperwork of medical care, it is possible that the resources they required may be redirected to other aspects of care, thus influencing the environment of care. Since certain structures enable hospitals to achieve their optimal performance levels through appropriate organization, resources, staff, and equipment, the use of EMRs can greatly affect the processes of care. In this study, efficiency is examined as a process component.

EMR use in hospitals represents a change in structure, according to Donabedian's definitions of structure (1980). Some may consider this change to structure a type of reengineering as the EMR structure will change how care is provided. According to Ozcan, reengineering suggests, "a radical design of business processes to achieve dramatic improvements in performance measures: quality and cost, service and speed" (2005, p. 122). The use of EMRs promises to do just this by assigning a more appropriate structure to hospitals. As a structure, EMRs will drastically change the resources available to hospitals and their staff with regard to technology. This hospital structure will be a large predictor of the processes and outcomes of health care. After all, without the correct structure and tools, it is unlikely that an organization can reach optimal performance (Donabedian 1980). Reengineering, as with EMR use, aims to "eliminate delays and duplications in health care delivery so recovery is speeded and costs are reduced" (Ozcan 2005 p. 123). Essentially, reengineering is a structural change that intends to affect both the process and outcomes of the organization, consistent with Donabedian's description of the relationship between the same three constructs: structure, process, and outcome.

As Donabedian's model predicts, the structure achieved through EMR use will affect the processes of care. Providing the proper structure for an organization is a key element of performance. Without the correct structure, an organization may fail or be ineffective. With the proper structure, and organization can thrive in performance, increasing both efficiency and quality (Donabedian 1980). To increase organizational productivity, Ozcan claims that inputs and structures must be appropriately matched with "work load patterns" and continues to say that, "A successful match requires adequate communication, technological advances, cooperation, timeliness, attention to patient and physician convenience, and tradeoffs," a statement consistent with Donabedian's framework (2005, p. 215). EMRs could provide each of these to hospital structure, thus improving the physician and patient interaction by making it more efficient and of higher quality by the nature of the EMR structure: automated, precise, customizable, and ready-to-go. EMRs can provide clinical pathways, computerized physician order entry (CPOE), computerized prescription orders, and a more complete documentation of patients' medical history, both recent and expanded. This will, of course, influence the interactions of physicians and patients since physicians will, in many cases, provide care with a computer in hand rather than a paper chart. While this will require new provider skill to ensure that patient satisfaction with the interaction is not affected, it will likely make the process more efficient, since physicians can have all of the patient's medical information at their fingertips, ensuring that they have the complete picture of the patient's medical history for better diagnosis and treatment. Physicians who use EMRs will not be required to complete the processes associated with medical record transcription, such as voice recordings after the appointment to document the care, which is associated with a structure of paper medical records.

The use of EMRs should provide clinicians with the ability to follow guidelines and automated processes of care, without the time consuming task of maintaining a paper medical record. Each of these factors will likely increase the efficiency of the process. Also, the efficiency improvements will exist because care will not be duplicated as often since diagnostic test results can be shared between providers, and clinical pathways will ensure that appropriate care guidelines are followed based on symptoms, rather than ordering excessive amounts of tests and procedures to treat a patient. Because of this, one would expect that hospitals that are able to share and receive EMRs would spend less time and fewer resources than those without EMRs who will depend upon paper records and the traditionally slow and unreliable file sharing associated with paper patient medical records. Essentially, according to Donabedian's model, the processes of care change as the structure changes, as is the case with hospital EMR use (1980).

H11: Hospitals with EMRs are more efficient than hospitals without EMRs.

Efficiency Change Over Time

However, implementation of any complex medical process is not immediate as it takes time to implement and adjust to a new structure. The benefits of any new practice are expected to be more realized over time, as challenges of the new systems are addressed and staff become more familiar with the processes the new practice. Scott claims that, "Some organizations insist that their full effects may not be apparent for long period following their performance" (2003, p. 365). This may be especially true of EMR use. To allow for organizational adjustment to a new structure, this model considers EMR use and length of time of EMR use to represent the hospital structure of interest. Previous research indicates that two of the greatest barriers to EMR use are staff resistance and concerns of the patient care time lost while staff learn to use EMRs (Earnest et. al. 2004, Miller and Sim 2004, Korst et. al. 2003, Kranhold 2005). For these reasons, hospital efficiency improvements expected through EMR use may not be as great in the first year of use as they will be later on, when the system structure and practice is more familiar to and accepted by the staff, the challenges of the system have been addressed, and policies and practices have been adjusted. For this reason, the time since implementation will indicate if the structure is familiar or not. The expectation is that the longer and EMR system is in place up to a point, the more familiar the staff will be with it and the more performance improvements will be visible. Donabedian states that structure, "influences the kind of care that is provided" and "increases or decreases the probability of a good performance" (1980, p. 81-82). The influence of a structural change may not happen immediately, and part of this influence relates to the amount of time the structure has been in place. For this reason, the model identifies EMR use and years of EMR use as indicators of how the processes and outcomes are impacted. In other words, one does not expect a hospital that has used EMRs for one week to use them as efficiently as a hospital that has used them for three years. It is true for both hospitals that the EMR structure is influencing the processes and outcomes of care, but it is likely that the EMR structure is influencing them in different ways based on how long the structure has been in place. For example, it is possible that a brand new EMR system may slow the work processes and decrease quality for a short period of time as the staff adjusts to using it. While efficiency improvements are expected immediately due to the automated nature of EMRs, the full efficiency benefits will not be immediately realized as the staff and procedures of the new EMR structure adjust to the change.

H12: Hospitals with EMRs will increase their efficiency over time.

Quality

One of the biggest expectations surrounding EMR use is the anticipated quality improvement. Outcomes such as quality, according to Donabedian's (1980) model, are the direct result of both structure and process. Proponents of EMR use claim that they will reduce medical errors through standardized clinical pathways to ensure that evidence-based medicine practice directs care, through the decrease of adverse prescription use based on an automated interaction detection, and through the automated access physicians may have to patient laboratory and other diagnostic results (Thompson and Brailer 2004, Hannan 1999, Ashe et. al. 2004). Also, EMRs will eliminate mistakes that may occur based on illegible handwritten medical records. In this way, the changes in the processes of care achieved through EMR (structure) use will lead to improved health care quality (outcome). It is expected that fewer patients will have adverse effects due to prescription interactions or reactions, missing medical information, inappropriate care, or a misread patient record. Essentially, it is the process changes caused through EMR use (structure) that will lead to better quality. Since hospitals with EMRs are expected to be more efficient in their processes, it is possible that the newfound slack resources, such as staff time, may be devoted to better patient care. It is likely that this process change, found through increased efficiency, can lead to improvements in health care quality. In other words, the hope is that the staff that were used to maintain paper records and document, by hand, patient medical events and histories may now be able to devote this excess time to improved patient care.

H13: Hospitals with EMRs will report higher quality than those without EMRs.

Proponents of hospital EMR use have claimed many potential improvements in health care. Donabedian's structure, process, outcome model provides a loose framework that is joined with logic and previous research to examine how and where these improvements may exist, while allowing for the development of specific hypotheses. This model emphasizes not only the health care outcome improvements, but also shows the influence structures and processes may have on improvements in hospitals. Table 1 summarizes the hypotheses made in this chapter.

Chapter Summary

In this chapter, two theoretical frameworks are provided and sequentially combined to create a conceptual model that examines determinants and outcomes of EMR use in hospitals. Resource Dependency Theory provides a model for

Table 1: Summary of Hypotheses

H1: Hospitals with greater financial resources are more likely to use EMRs.

H2: Hospitals with a high percentage of Public reimbursement are more likely to use EMRs.

H3: As environmental competition increases, the likelihood of hospital EMR use increases.

H4: Rural hospitals are less likely than urban hospitals to use EMRs.

H5: Larger hospitals are more likely to use EMRs.

H6: For-profit hospitals are more likely than public or non-profit hospitals to use EMRs

H7: As a hospital's relationship to a system moves along a continuum from no affiliation to highly centralized systems, the likelihood of EMR use increases.

H8: Teaching hospitals are more likely to use EMRs.

H9: Hospitals in environments with more uncertainty are more likely to use EMRs.

H10: Hospitals in areas of more munificence are more likely to use EMRs.

H11: Hospitals with EMRs are more efficient than hospitals without EMRs.

H12: Hospitals with EMRs will increase their efficiency over time.

H13: Hospitals with EMRs will report higher quality than those without EMRs.

---

determining organizational and environmental factors that contribute to the likelihood that EMRs are used in hospitals. It is at this point that Resource

Dependency Theory bridges into Donabedian's Structure, Process, Outcome Theory, since EMR use is a component of structure. If a hospital has an EMR system, this structure will affect both the processes of care, as they will likely be more automated and efficient, and the outcomes of care in the area of health care quality. Length of use of an EMR system is also a component of structure and likely influences the processes and outcomes of care. These two combined theories guide the development of the conceptual model, hypotheses, and measures of this study, which examines hospital use of EMRs.

CHAPTER 4: METHODOLOGY

Introduction

The purpose of this chapter is to present the methodology for examining EMR use in hospitals. The research questions of this study include: What factors are associated with EMR use in acute care hospitals? And how does EMR use affect hospital performance? This chapter presents a two-stage analysis research design, population and sample, measurement of variables, data sources, analysis plan, and specific statistical approaches to be used in the study including logistic regression and Data Envelopment Analysis (DEA). This chapter also presents a classification scheme to explore hospital performance and EMR use.

Research Design

The research design used to answer the first and second research questions is a non-experimental, retrospective cross-sectional format with a non-equivalent control group, which means that there is only limited control over the independent variable, EMR use. A second research design is also herein presented, which presents observations at two points in time to assess the change in efficiency between 2001 and 2004 for the Malmquist Index. These two research designs are referred to as Research Design A and Research Design B, respectively. In Research Design A, EMR implementation has taken place at various times in the last decade or so, but the observation of the hospitals occurs at one point in time ex post facto. There are two groups; one includes hospitals that use EMRs and one that includes hospitals that do not use EMRs. These groups will be compared to one another to determine factors associated with EMR use as well as the impact that EMR use has on performance. The observation takes place in 2004. The research design is illustrated in Figure 4:

Group		time 2004
G1	(X)	O3
G2		O4

Figure 4: Research Design A

There are several strengths associated with this type of research design. First, since the study is conducted retrospectively, there is no chance of attrition. Second, as is noted later in this chapter, this portion of this project will include the entire population of interest. This population is all non-federal acute care hospitals in the United States. Including the population to determine organizational and environmental factors associated with hospital EMR use reduces any threats to the generality of the findings. The reasons for not including federal hospitals in the population and analysis are provided later in this chapter. Including the entire population also eliminates the risk of selection bias and the risk of the sample not being representative of the population. Additionally, this entire study will use secondary data, which greatly reduces the chance of demand characteristics, experimenter expectancy effects, and carry-over since trained surveyors designed the tools and collected these data. Since a comparison group is included in the study, the risk of history or maturation is low since an extraneous event would likely affect all groups. Additionally, since this study is a retrospective analysis of how hospitals have performed in their own environments, there is no chance of observing them in a setting that is unrealistic. This threat to external validity is referred to as a non-representative research context and occurs when observations take place in a laboratory or other unnatural setting. The rationale behind this threat is that subjects may behave differently outside of their natural environment for a number of reasons, including demand characteristics, the notion that subjects may act accordingly since they know experimenters are watching them.

However, this type of research design also has several threats to internal validity. These threats include the lack of randomization of the independent variable, and group composition effects. The lack of randomization of the independent variable means that the hospitals have self-selected into the groups through their use or lack of use of EMRs. This may further mean that the groups are not equivalent, making group composition effects a validity risk. To reduce the impact of this threat to validity, the model includes all variables that the researcher views as potential determinants of hospital EMR use based on organizational theory. The first analysis of this study, completed with logistic regression, seeks to identify organizational and environmental determinants of hospital EMR use. The results of the initial research question identify clear organizational and environmental differences between hospitals that do and do not use EMRs, thus perhaps showing that they are not equivalent. In other words, the hypotheses of this study predict that hospitals with EMRs are different in their organizational and environmental characteristics from those that do not have EMRs. The extent of these differences will be explored as part of the first research question. However, it is still possible that this model is at risk for endogeneity based on the fact that the logistic regression analyses of efficiency and quality will not clearly distinguish if the performance is the result of EMR use or the determinant of EMR use. A test and treatment for this endogeneity are discussed later in the chapter in the analysis plan section.

Research Design B is used for the Windows analysis used in DEA to assess efficiency changes over time. The Windows Analysis approach requires two observations. To do so, a DEA score will be calculated for hospitals with EMRs in 2001 to 2004 and hospitals without EMRs in 2001 or 2004 to determine efficiency changes. Since it is possible and even likely that hospital efficiency changes for EMRs may not occur immediately, there is a need to determine if EMRs improve hospital efficiency over time. To do so, a repeated measures, retrospective, non-experimental design with a non-equivalent control group is used. The observations consist of the input and output variables in 2001 and 2004 to measure efficiency using DEA. This design will allow the study to examine the change in efficiency between the period of 2001 and 2004. The Windows Analysis Approach, a DEA method used here, is discussed later in this chapter. Again, the researcher does not have control over the treatment of interest, the use of EMRs in non-federal acute care hospitals; thus, due to the lack of control over this independent variable (EMR use), the design is non-experimental. The hospitals included in this analysis will be those that used EMRs in 2001 and in 2004 and those that did not have EMRs in either 2001 or 2004. The group of hospitals without EMRs will serve as the non-equivalent comparison group to control for extraneous factors that may affect hospital performance during this period. The rationale is that any extraneous environmental factor or event that influenced hospital performance during this time period would have affected both hospitals in a similar way. The difference between the performances of the two groups will allow for the determination of hospital efficiency change associated with EMR use. This design, with two observations can be illustrated as shown in Figure 5.

		2001	**2004**
G1	(x)	O1	O3
G2		O2	O4

Figure 5: Research Design B: Repeated Measures Design with a Non-equivalent Control Group

This non-experimental design also has several strengths. These strengths include the lack of pretest sensitization, the lack of reactive arrangement, the lack of group composition effects, and the chance to examine how efficiency changes over time. Since the observations are conducted retrospectively, there is no chance of pretest sensitization. The lack of comparison group relieves any chance of group composition effects. Since the observations are conducted in natural settings, there is no chance of reactive arrangements. Additionally, by examining the data at two points in time, it is possible to assess the changes in efficiency from one point to the next. Since all hospitals that used EMRs in 2001 are included in this study, the group is representative of the population of interest.

However, this type of design is also susceptible to several validity threats. First, it is difficult to conclude with any certainty that the efficiency change is the result of EMR use. Any change in efficiency could be attributed to any number of practices, as it is possible that both the environment and organization have changed between the two observations. However, to control for this, the period between the two observations is brief, with the hope that any maturation of the organization or other environmental change may be limited and that extraneous events would also be limited. Extending this period between observations may increase the risk of history or an event influencing the hospital performance results of interest. Additionally, the Windows Analysis score measures the difference in efficiency and the changes in efficiency due to technology, so it is essentially using an econometric technique called first differencing. This technique helps to reduce the risk of endogeneity and the influence of confounding factors. Another weakness lies in the fact that the researcher has no control over the independent variable, EMR use in hospitals, and thus has no randomization for the group or treatment. Since EMR use is not a random behavior for hospitals, rather it is a strategy used by some, there is a reisk of selection bias. Essentially, this means that the hospitals studied have been self-selected as they implemented EMRs systems prior to or in the year 2001. A test for and solution for this possible endogeneity problem is presented in this chapter in the Analysis Plan Section.

Study Population and Sample

The unit of analysis in this study is the individual, acute care hospital. The population of interest includes all general medical and surgical acute care, non-federal hospitals in the United States. According to the American Hospital Association database (AHA), there are approximately 6,000 hospitals in the United States. However, some of these hospitals are not general medical surgical acute care hospitals, and the comparison of hospitals that service a specialized function such as orthopedic, psychiatric, or children's care may not be valid. For this reason, only those hospitals identified as general medical surgical acute care hospitals in the AHA database are included. The number of hospitals in the AHA database that are identified as general medical surgical acute care hospitals in the United States is 4,881. However, of these 4,881 hospitals, 224 are federally owned. Federally owned hospitals include the Veteran's Affairs Hospitals, Military Hospitals, and Public Health Indian Service Hospitals. These federally owned hospitals operate differently than non-federal hospitals with regard to their financing schemes and management structures and policies as well as their patient populations. For this reason, federally owned hospitals are excluded from the population leaving 4,657 non-federal acute care hospitals in the population. Of these 4,657 hospitals, 51 are located in U.S. territories such as Puerto Rico and are thus excluded from the study leaving 4,606 hospitals in the population. In an attempt to achieve superior external validity, the entire population of interest is included in this first portion of this study, which examines the organizational and environmental characteristics associated with EMR use. This entire population is also examined to determine organizational efficiency through the use of DEA. Of this population, 479 hospitals have fully automated EMRs in use in 2004. These 479 will be compared to the rest of the population of non-federal acute care hospitals, though no weightings based on organizational prevalence (sample size) are applied. The lack of weighting of observations based on prevalence in the population would not allow the logistic regression to take place as it would violate the assumptions of these analyses.

The sample size for comparing hospital quality and changes in efficiency is, however, smaller than the population. The reason for this is the availability of data, making the sample one of convenience. For the Windows Analysis, the sample only includes hospitals that used EMRs in both 2001 and 2004 and those hospitals that did not use EMRs in 2001 or 2004. The purpose of this analysis is to determine how efficiency changes for non-federal acute care hospitals over a period of three years of EMR use when compared to a non-equivalent group of hospitals that did not have EMRs in 2001 or 2004. The purpose of the non-equivalent comparison group is to control for efficiency changes that may have occurred in hospitals based on external events, which assumes that these events may have affected all hospitals the same with regard to efficiency. Two hundred and nine non-federal acute care hospitals have EMRs in 2001 and 2004, and nearly 4,000 did not have EMRs in 2001 or 2004 thus making the sample size for the Windows Analysis statistically powerful enough to detect differences as presented below. For the quality comparisons, the sample size consists of 2,891 hospitals. Again, this is due to data availability for quality measures. The data used to measure quality comes from the Centers for Medicare and Medicaid Services (CMS) and the Hospital Quality Alliance (HQA). These data contain stable performance measures for 3,558 hospitals in the year 2004. Six hundred and sixty seven of these hospitals are federal hospitals, specialty hospitals or clinics or are not located in the United States and are thus not included in the study. Although these data are available for more hospitals, 444 of the hospitals that submitted information are based on fewer than 25 patients, thus making these measures unstable (Jha, Li, Orav, Epstein 2005). This sampling scheme is illustrated in Figure 6.

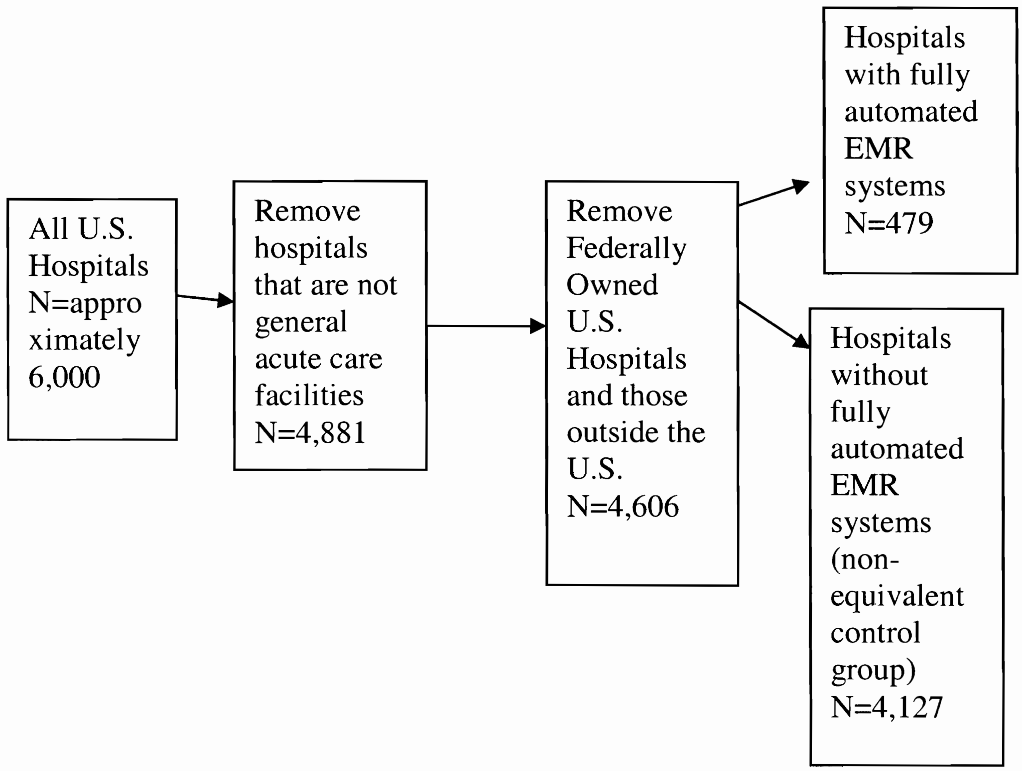

Figure 6: Sampling Method of Hospitals

When determining a sample size, it is essential to conduct a power analysis. Power is the ability to detect differences among variables. Power is a function of sample size, effect size, and the degrees of freedom. Larger sample sizes provide greater power and, thus greater accuracy. The formula to estimate power is:

$$Power = n^1 \frac{\sum(\mu_i - \mu_t)^{2/a}}{MSerror}$$

In this study, the sample size of 4,606 allows for power of .99 at alpha=.01. However, the power will be smaller in the quality and efficiency comparison sections since the hospitals will be grouped according to size. To ensure the reliability and validity of the findings of this study, the researcher will set the alpha to .05 to allow for adequate power in all comparisons. This .05 alpha value indicates the chance of a type 1 error, or the identification of a statistical relationship in a sample that does not actually exist. In other word, an alpha of .05 means that in 5 out of 100 sample sizes selected, a relationship or difference that is not really present in the population would be detected. According to Cohen et. al. an alpha value of .05 is, "widely used as a standard in the behavioral sciences" (2003, p. 15).

Data Sources

Several different data sources are consolidated to conduct this study. These sources include the HIMSS database, the AHA database, the Centers for Medicare and Medicaid (CMS) Minimum Cost Report database, the Area Resource File (ARF), and the Centers for Medicare and Medicaid (CMS) Health Quality Alliance (HQA) database. Since each of these is a secondary database collected annually by expert surveyors, the risk of reactive arrangement or linguistic or cultural bias is limited. The use of these data in previous research assists in providing validity to the data itself (Hillestad et. al. 2005).

The HIMSS database, formerly known as Dorenfest Data, will provide information regarding which hospitals are using EMR systems as well as how long they have used these systems. The HIMSS data have been used in previous studies to examine how HIT is used in hospitals. The HIMSS data contain information about approximately 6,000 hospitals in the United States, including their use of EMRs. According to Hillstad et. al., who also used these data to examine how EMRs can transform health care, the HIMSS dataset, "represents a broad canvassing of acute care hospitals, chronic care facilities, ambulatory practices on their adoption and plans to adopt various HIT components" (2004, p. 1104).

The HIMSS database defines an EMR as a computerized patient record. More specifically, an EMR is a:

> Comprehensive database system used to store and access patients' health care information electronically. The computer-based patient record replaces the paper medical record as the primary source of information for healthcare meeting all clinical, legal and administrative requirements. It is seen as a virtual compilation of non-redundant health data about a person across a lifetime, including facts, observations, interpretations, plans, actions and outcomes. The CPR is supported by a system that captures, stores, processes, communicates, secures, and presents information from multiple disparate locations as required (HIMSS 2004, p. 152).

According to the HIMSS data, hospital EMR use is categorized as automated, not automated, or contracted. Automated EMRs are with which, "software and hardware is used to automate a process" (HIMSS, 2004, p. 159). EMRs that are not automated include, "commercial or self-developed software (that) is not in use to support a specific business process. This includes when a facility is using general software to perform the function" (HIMSS 2004, p. 159). Contracted EMRs indicate that, "A software application that has been purchased and a contract signed, but have not been installed in the IHDS (integrated health delivery system)" (HIMSS 2004 p. 159). The HIMSS database includes all acute care hospitals in the United States and represents each with a field to indicate if EMRs are used, another field, which indicates if they are automated, not automated, or contracted, along with a date of implementation. While hospital EMR use may vary drastically by hospital through the possible use of other applications such as CPOE. Electronic prescribing, and electronic charge capture, this study only considers differences based on the HIMSS designated fully-automated EMR use for a number of reasons. First, the research questions of this study inquire only about EMR use, and an inclusion of other HIT features into this measure may dilute the presence of the feature of interest. Second, while there are some data regarding hospital HIT use, the creation of an index based on specific applications that may not be valid in that the presence of these applications does not necessarily mean that they are connected to EMR use. Finally, further specification of the intensity of EMR use may place hospitals into groups so small that the statistical power would not be adequate to detect any difference. The intended strength of this measure is based on the specificity of the HIMSS definition, which requires that hospitals that have fully automated EMRs must have completely replaced paper records with EMRs. This measure may, of course, prove to be weak and may provide an area for future research.

The AHA database is a compilation of descriptive and operational characteristics of more than 6,000 hospitals in the United States. Each year, the AHA surveys hospitals, both members and non-members, releasing the data approximately two years after the period of interest ends. To ensure that the data is appropriately matched, the HIMSS data will be merged with the AHA 2004 data, which is released in January or February of 2006. A great deal of previous health services research has relied on the AHA database for hospital information (Ozcan, Luke, and Haksever 1992, White and Ozcan 1996).

The Area Resource File (ARF) contains, "over 6,000 variables for each county in the US. ARF is used for health service research, health policy analysis, and other geographically based activities" (http://www.arfsys.com/main.htm). These county level data are connected to hospitals based on geographic location to provide information about the environment in which the hospital exists. In this analysis, the measure of per capita income, as an indicator of environmental munificence, and the measure of change in unemployment, an indicator or environmental uncertainty, will come from ARF. Previous health services research has relied heavily on the ARF data (Zinn, Proenca, and Rosko 1997, Clement and Grazier 2001, Balosky 2005).

The Centers for Medicaid and Medicare Services also provides hospital organizational, operational, and performance data as collected through the Medicare Cost Report Data. These data include financial performance and cost information for hospitals throughout the United States and are referred to as the CMS cost report data. These data are released every three months and contain descriptions of some 3,700 hospitals. Previous research utilizing these data is plentiful in areas relating to hospitals and other health care organizations (Ginn, Young, and Beekum 1995, Rosko 2004, and Mark 1999).

The hospital quality measures data come from the Center for Medicare and Medicaid Services (CMS) in conjunction with the Health Quality Alliance Program (HQA). These quality measures include, "ten indicators of the quality of care for acute myocardial infarction, congestive heart failure, and pneumonia" (Jha, Li, Orav, and Epstein 2005 p. 265). These data contain at least one stable measure for 3,558 hospitals and are collected and audited quarterly. These data have recently become publicly available through the efforts of CMS, the Joint Commission on Accreditation of Healthcare Organizations (JCAHO), and the Hospital Quality Alliance (HQA). The hospitals have voluntarily submitted these data as part of the Medicare Modernization Act, which provides financial incentives for hospital quality performance. The ten specific measures of hospital quality of three major clinical conditions have been selected by CMS based on their widely endorsed validity (Jha, Li, Orav, and Epstein 2005).

Measurement of Variables

This model includes a number of variables that are measured according to previous research (Ginn and Young 1992, Gresenz, Rogowski, and Escarce 2004). By using previous research measures as a guide, the measures themselves will be more reliable and valid through criterion related validity. The constructs in this study include organizational factors, environmental factors, EMR use, and hospital performance. The variables include hospital size, ownership, public payer mix, system affiliation, financial resources, teaching affiliation, competition, rurality, per capita income, change in unemployment rate, EMR use, efficiency and quality of care. The following section presents a description of each of the variables organized into organizational variables, environmental variables, and performance variables. The performance variables are further separated into an efficiency section of hospital inputs and outputs and a quality section.

Organizational Factors

Hospital factors are represented through six variables. These variables include bed size, ownership, public payer mix, teaching status, financial resources and system affiliation. Each of these variables is measured through information in the AHA database, with the exception of financial resources, which is measured through the CMS data. The hospital organizational variables are briefly discussed below:

Hospital bed size includes the number of beds in each hospital that are set up and staffed at the end of the reporting period and is represented by the variable bdtot. This variable exists in both a numeric form and also is categorized by the AHA. For the purposes of this study, the numeric value will be used in the logistic regression, and the categorization of this variable into small, medium, and large hospitals will be used to peer group the hospitals for analysis. In the logistic regression, bed size will measure hospital size, a factor that is hypothesized in this study to affect hospital EMR use. Previous studies have noted the influence of hospital size on organizational strategy and behavior (Ginn and Young 1992). For example, White, Cochran, and Patel claim that larger hospitals, measured by bed size, can be expected to offer more services (2002). Burgess, Carey, and Young also recognize the association between hospital bed size and hospital behavior as they include bed size in their analysis of hospital pricing behavior (2005).

Hospital Ownership includes public, non-profit, for-profit, federal and government owned. However, since federal hospitals operate quite differently than non-federal hospitals in terms of their patient populations, process of reimbursement and structure, they are not included in this study. The primary reason for their exclusion is the questionability of the validity of their comparison to non-federal hospitals. The influence of hospital ownership on organizational strategy, behavior, and performance has been studied extensively (Milcent 2005). Clement and Grazier report that the primary mission of public hospitals is, "assumed to be to serve the poor and medically indigent. In contrast, investor-owned hospitals must serve first the financial interest of their owner, thus indicating a rationale for a difference in organizational behavior (2001, p. 29). One study examines the extent to which for-profit ownership influences hospital strategy such as pricing (Burgess, Carey, and Young 2005). Alexander and Morrisey suggest that hospital ownership influences hospital contract management (1989). White, Cochran, and Patel also examined hospital strategy for end of life services while considering organizational ownership concluding that hospital ownership does in fact influence behavior (2002). Shen reports that hospitals that converted to government or for-profit ownership increased hospital profit margin and that conversion to for-profit ownership resulted in staff reductions (2003). It is possible that the influence of hospital ownership represents a hospital's mission, as some claim that for-profit hospitals are more motivated to improve efficiency and quality, while non-profit hospitals are more apt to provide a large amount of charity care and community service (Milcent 2005).

System affiliation indicates whether or not the hospital is a participant in a health system, meaning it is one of many hospitals sharing the same upper management structure or structures (AHA 2003). This variable is created with the use of a taxonomy system, which takes affiliations such as health systems and networks into account, as well as considering such relationship dimensions as centralization, differentiation, and integration (Bazzoli et. al. 1999). This particular taxonomy was created, in part, due to the rapid merging and acquisition of hospitals in the 1990s and provides a more descriptive representation of system affiliation while recognizing that not all hospital system affiliations are equal in terms of management structure, geographic dispersion, and size (Bazzoli et. al. 1999). A health system is a "corporate body that owns or manages health provider facilities or health-related subsidiaries and nonhealth-related facilities. It is a formal, permanent arrangement in which a common ownership exists in all or most of the components" (Lee, Alexander, and Bazzoli, 2003, p. 167). Since health systems, "relative to networks, are more formalized and exercise more control over hospital service and deliveries," only system affiliation is included in this analysis as a more formalized arrangement is likely more able to influence organizational structure than a more informal arrangement (Lee, Alexander, and Bazzoli 2003, p. 171). This measure is available in the AHA data Health System Cluster data field and allows for the identification of type of system, allowing the relationship between a particular category of system and EMR use to be determined. According to the AHA, "A health system is assigned to one of five categories based on how much they differentiate and centralize their hospital services, physician arrangements, and provider-based insurance products" (2003, p. 26). This data field indicates if a hospital is part of a classified type of system including a Centralized Health System, a Centralized Physician/Insurance Health System, a Moderately Centralized Health System, a Decentralized Health System, or an Independent Hospital System. Hospitals are grouped into these five distinct groups based on, "common strategic/structural features" (AHA 2003 p. 26). If this field is blank, it indicates the hospital is not part of a cluster, or data is not sufficient to identify a cluster assignment. The categories of health systems allow for an ordinal measurement of centralization based on descriptions of the data categories. The categories are described here in order from most centralized to least centralized: A Centralized Health System is one that, "centrally organizes individual hospital service delivery, physician arrangements, and insurance product development" with a moderate number of different products and/or services available (AHA 2003, p. 26). A Centralized Physician/Insurance Health System is a delivery system, "with highly centralized physician arrangements and insurance product development" and with "hospital services that are relatively decentralized with individual hospitals having discretion" over the moderate number of services they offer (AHA 2003, p. 26). A Moderately Centralized Health System, according to the AHA taxonomy, is one that "is distinguished by the presence of both centralized and decentralized activity for hospital services, physician arrangements, and insurance product development" (AHA 2003, p. 26). This Moderately Centralized Health System classification also implies a moderate number of services and products within the system. A Decentralized Health System is one with a, "high degree of decentralization of hospital services, physician arrangements, and insurance product development" and a lack of "overarching structure for coordination" and a high level of service and product differentiation" (AHA 2003, p. 26). Finally, an Independent Hospital System is "a delivery system with limited differentiation, hospital services, physician arrangements, and insurance product development" (AHA 2003, p. 26). Other health services research studies have indicated that system affiliation influences hospital behavior (Burgess, Carey, and Young 2005). Using AHA identified network affiliated private, general, urban hospitals, Rosko and Proenca report that system affiliated hospitals are more efficient than hospitals that, "did not use networks or systems for service provision" (2005, p. 69). The reason for increased efficiency for system-affiliated hospitals may be reduced transaction costs or increased economies of scope, but the influence of system affiliation in previous research is evident.

Additionally, Alexander reports that system-affiliation for a hospital influences the rate of organizational adaptation to environmental uncertainty (1991). Lee, Alexander, and Bazzoli used this AHA taxonomy of hospital system affiliation to examine hospital community responsiveness (2003).

Public payer mix is the percent of total Medicare and Medicaid inpatient days seen in a fiscal year compared to the total number of inpatient days. The calculation of this ratio will represent the percent of patients who seek services in the hospitals and are covered by Medicare and Medicaid. If this percentage is higher, it indicates that the hospital relies highly on CMS for reimbursement. If it is lower, the hospital may depend more on other sources of reimbursement. Additionally, hospitals that depend upon public payer groups for more than half of their reimbursement will be assigned a value of one for a dummy variable measure, with values of zero indicating hospitals that the hospital depends upon other payer groups such as commercial payers more than public payer groups. Both the percent payer mix ratio and the dummy variable coding groups will be used to assess the relationship between payer mix and hospital EMR use. Ginn and Young point out that hospitals, "that treat a high volume of patients who are insured under prospective reimbursement policies are less likely to have a proactive strategic orientation" (1992, p. 293). Jha, Li, Orav, and Epstein examine how quality of care varies from hospital to hospital in the United States, including Medicare payer mix as a variable (2005). Gresenz, Rogowski, and Escarce also examine the influence of Medicare payer mix on hospital competition (2004). Public payer mix represents the percent of patients who are covered by Medicare and Medicaid instead of private insurance companies. Hospitals that are highly dependent on the federal and state government for reimbursement may be less able to proactively make decisions for their respective hospitals as they must ensure continued Medicare and Medicaid reimbursement. As discussed in Chapters Two and Three, the federal government has indicated an interest in EMR use, thus causing speculation that EMR use may soon be a requirement for Medicare and Medicaid reimbursement. Medicare payer mix has also been used to control for the population in a hospital area since a most Medicare beneficiaries are 65 years of age or older, a group that uses a large amount of inpatient care (Burgess, Carey, and Young 2005). Zinn, Proenca, and Rosko used public payer mix in a model to examine determinants of hospital alliance (1997).

Teaching Status represents an additional role and responsibility of some of the hospitals of interest. Hospitals that hold teaching status also provide a great deal of training through residencies and other training and educational programs, as well as providing a complex services, research and a great deal of charity care. This variable is indicated through hospital membership with the Council of Teaching Hospital of the Association of the American Medical Colleges (COTH). This is a dichotomous variable, with a value of one indicating membership and a zero indicating no membership. Previous research has included teaching status in health services analyses and has measured this teaching status through membership in

COTH as indicated in the AHA database (Rosko 2004). In one such study, Rosko examined the performance of teaching hospitals in turbulent times (2004). Zinn, Proenca, and Rosko examined the association between organizational factors, including teaching status, and hospital alliance membership and contract management (1997). In this study, hospital teaching status is included as a control variable.

Financial Resources is a variable indicating the economic power of hospitals. This variable is measured using the hospital operating margin and represents a hospital's ability to invest in an EMR system. This operating margin indicates if a hospital has the financial resources beyond the expenses of running the facility. In other words, the operating margin is calculated by dividing the operating income by the net patient revenue and multiplying it by 100 (Clement and Grazier 2001). Rosko states that operating margin, "reflects the excess/shortage of revenues over expenses from the primary patient care operations of the hospital. It also indicates the amount of internally generated funds that might be used to acquire plant assets in the future" (2004, p. 39). Previous research has used operating margin as a measure of financial performance, an indication of monies that are available for hospital use or profit after all expenses are paid (Kelly 1999). Clement and Grazier used operating margin as a measure of financial performance in their analysis of the effects of HMO penetration on public hospitals (2001). Rosko used operating margin as a measure of teaching hospital performance (2004).

Environmental Factors

Hospital environmental variables are also believed, according to Resource Dependency Theory, to influence hospital behavior. For this model, environmental factors include rurality, competition, per capital income, and change in unemployment rate. Again, previous research has used the variables and measures in health services research, thus providing them with criterion related validity (Gresenz, Rogowski, and Escarce 2004, Ginn and Young 1992). The environmental variables are discussed here:

Rurality is measured as an index and is provided in the ARF database through the rural urban continuum code. This measure indicates the rural or urban nature of a hospital's environment based on the population surrounding the hospital. The range of these rural urban continuum codings is from one to nine, with one being the most urban area with over 1,000,000 in the population. The least urban classification is nine and represents areas that are rural and have fewer than 2,500 population in an area not adjacent to a metro area. This most rural group serves as the reference group in these analyses. Previous research has shown that there are differences in rural hospitals as compared to urban hospitals through their patient population and services, especially in their mortality rates (Glen and Jigon 1999). Furthermore, Menachemi et. al. examined the rate of health information technology use of rural hospitals in Florida, noting that rural hospitals may have a more difficult time implementing and using HIT practices. They found that system-affiliated rural hospitals were much more likely to use HIT practices than independent rural hospitals (2005).

Competition is measured using the Herfindahl-Hirschman Index (HHI), a measure of the, "market concentration that incorporates the size distribution of firms. It is found by summing the squares of the market shares of each firm" (Folland, Goodman, and Stano 2004 p. 563). Previous research has used the HHI as an indicator of environmental competition for hospitals (Gresenz, Rogowski, and Escarce 2004, Burgess, Carey, and Young 2005). For this study, the HHI will be calculated for hospital systems at the market level, recognizing that two hospitals in the same geographic area maintain greater market share through joint management than a single independent hospital in the same market.

Per capita income in the area surrounding the hospitals is likely an influential environmental factor. Per capita income represents the average household income in the hospital's market. The rationale for this variable selection is that the per capita income represents the financial resources available in the hospital's environment. Previous studies have included per capita income as a measure of environmental munificence for hospitals making strategic decisions (Zinn, Proenca, and Rosko 1997, Balosky 2005).

The change in unemployment rate for areas surrounding hospitals represents the degree of uncertainty that those hospitals face. In this study, the change in unemployment is the difference between the unemployment rate in 2001 and 2004 for the areas where hospitals exist. Because nearly 60% of private sector employees are enrolled in their employer's health plan, it is likely that a change in the unemployment rate affects the demand for health care services by restricting access for individuals that do not have health insurance coverage through an employer (www.cdc.gov/nchs/data/nehis/tab18.pdf). Using this measure, a greater change in unemployment represents a greater degree of uncertainty while less change in unemployment represents less environmental uncertainty. Previous research has noted the relationship between health care and unemployment rates (Bartley and Fagin 1990, Ginn and Young 1992). Hiotis et. al. state that breast cancer screening rates decrease with an increase in unemployment since many patients may depend upon employers for either health insurance or the financial resources to pay for health care services (2005).

Hospital Performance Measures

Hospital performance is measured by efficiency and quality. Efficiency is represented through a DEA score, which is computed for the purposes of this study. DEA is further explored later in this chapter, yet it is necessary to now explain the measures used to calculate the DEA score of efficiency. DEA is a technique that creates a relative efficiency frontier through the assessment of a combination of hospital inputs and outputs. Quality is measured through ten indicators relating to three clinical conditions. These quality measures are collected and audited each quarter by HQA and CMS. The two sections below provide more information about these specific constructs and their measures, which are expected to increase as the number of clinical conditions and respondents increases.

Efficiency Factors

In this study, as in many previous health services studies, hospital inputs for the DEA analysis include number of full time equivalent employees working at the hospital (FTEs), beds set up and staffed, capital assets and non-labor operating expenses. The number of full time equivalent (FTE) employees, and the non-labor operating expenses are input variables that come directly from the AHA database. For both of these variables, the number of nursing home employees and the nursing home operating expenses were subtracted when available in an effort to capture the true hospital input values. These variables quantify resources that are needed inputs for a hospital to function. The number of FTEs represents a labor or human resources input. The non-labor operating expenses represent the financial resources used as hospital inputs. The labor expenses are subtracted to control for pay differentials based on position and geographic location. However, capital assets are not as easy to operationalize. Previous research has indicated that an index based on the number and types of services offered in the hospital can be used to represent capital assets (Ozcan, Luke, and Haksever 1992). The rationale behind an index such as this is that hospitals with greater amounts of capital assets are more likely to offer more services and services that are more complex, thus requiring complex equipment. The correlation between number of services offered by a hospital and capital assets is strong (Ozcan, Luke, and Haksever 1992, and Chern and Wan 2000). The index for this study will include dichotomous variables to indicate if a hospital offers the service or not. Hospitals with higher scores on the index will be interpreted as having greater capital assets; hospitals with lower scores on the index will be assumed to have fewer capital assets. The hospital services included in the calculated index include: pediatric intensive care unit, neonatal intensive care unit, burn care, alcohol/drug dependency inpatient care, airborne infection isolation room, ambulance services, bariatric/weight control services, breast cancer screening/mammograms, hemodialysis services, cardiac catheterization, open heart surgery, chaplaincy/pastoral services, chemotherapy, community outreach, emergency department, certified trauma center, level one trauma services, palliative care program, gamma knife, HIV-AIDS services, neurological services, oncology services, outpatient services, , intensity-modulated radiation therapy, CT scanner, diagnostic radioisotope facility, electron beam computed tomography, magnetic resonance imaging (MRI), Positron emission Tomography (PET), Single photon emission computerized tomography (SPECT), Ultrasound, sleep center, bone marrow transplant services, solid organ transplant services, cardiac intensive care, and medical/surgical intensive care. These 36 services are used to create an index measure, which can range from zero to 36 for each hospital. Each of these 36 measures represents a service offered by the hospital. These variables are dichotomous, with a value of one indicating the hospital has the service and a value of zero if the hospital does offer the service. A score of thirty-six indicates that the hospital offers all of the services, thus representing a great deal of capital assets because of the equipment and personnel required to provide services. The number of beds set up and staffed represents the hospital's capacity for patients as well as serving as a classification scheme for hospitals based on size since DEA scores are calculated as relative values, and peer grouping allows for more stable DEA measurement. This classification scheme is further discussed later in this chapter.

Output variables include the total number of case mix adjusted admissions and the number of hospital outpatient visits. The number of case mix adjusted admissions represents the number of patients served while controlling for illness severity and case complexity. The number of hospital outpatient visits also represents the amount of care provided by quantifying the number of patients who receive this type of care. Output variables represent the productivity of the hospitals. Intuitively, hospitals that can produce more outputs with fewer inputs are more efficient than those that produce fewer outputs with more inputs. However, hospitals will be peer-grouped based on bed size since larger hospitals will likely produce more outputs than smaller hospitals and vice versa. Additionally, smaller hospitals may serve patients with less complex and severe conditions than larger hospitals, so the comparison of outputs between these may be invalid. To risk adjust for the patient population and to provide more stable measures, the hospitals will be peer grouped for the DEA analysis, and the number of admissions will be multiplied by the CMS case mix index. This peer grouping is further discussed later in this chapter.

Quality Measures

Finally, quality is another measure of hospital performance. Quality is a complex, multifaceted construct, which has been measured in many ways in health services research. Recent research has used quality indicators from the Hospital Quality Alliance Program and CMS (Jha et. al. 2005). These data consist of ten measures of hospital quality based on three common clinical conditions including acute myocardial infarction, congestive heart failure, and pneumonia. According to Jha et. al., these ten measures of quality of care, "have been widely endorsed and are considered valid and feasible for immediate public reporting" (2005, p. 266). Additionally, the three selected clinical conditions account for 15% of all Medicare admissions (Jha et. al. 2005). Previous research has used these same measures, indicating that there is great variation amongst quality performance of U.S. hospitals (Jha, Li, Orav, and Epstein 2005). The measures for quality of care for acute myocardial infarction include the use of aspirin within 24 of arrival at the hospital and at discharge, the use of beta-blockers within 24 hours of hospital admission or discharge, the use of angiotensin-coverting-enzymes for left ventricular systolic dysfunction. The measures of quality of care for congestive heart failure include an assessment of the left ventricular function and use of an angiotensin-converting-enzyme inhibitor. Finally, the three measures of quality of care relating to pneumonia include the time of antibiotic therapy, the availability of the pneumococcal vaccine, and the assessment of oxygenation. While more than 3,500 hospitals submitted quality measure data, not all of these hospitals submitted data for each of the ten measures. To calculate a quality score, the hospitals' scores are compared to the national average. It the hospital is performing at or above the national average, the hospital will receive a value of one for that measure, indicating a quality performance of at least average. If the hospital is performing below the national average, the hospital will receive a score of zero, indicating that the quality performance for that measure is below average. A total quality score will be calculated for each hospital based on the available quality measures data. The score will add all valid hospital measures of quality (one or zero) and divide them by the number of measures available for that hospital. In other words, a hospital that had two above average quality measures and one below average quality measure for a total of three indicators (1+1+0/3) would have a quality score of .667. These quality scores are rounded to the third decimal place. The reason for this index calculation is there is not a single measure that exists for all of the hospitals, and the data availability is limiting in this regard. Table 2 summarizes the operationalization of each of the variables used in this study.

Analysis Plan

First, descriptive statistics will be calculated to determine the specific prevalence of use of EMRs in acute care hospitals. These descriptive statistics will

Table 2: Variables Used in the Study

Variable	Measure	Source
Hospital Variables Organizational		
Size	Number of Beds Set Up and Staffed	AHA
System Affiliation	0=No identifiable affiliation 1=Centralized Health System 2= Centralized Physician/Insurance Health System 3=Moderately Centralized Health System 4=Decentralized Health System 5=Independent Health System	AHA
Ownership	Non-profit, For-profit, or Public	AHA
Public Payer Mix	Number of Medicare and Medicaid Inpatient Days/Total Number of Inpatient Days	AHA
Teaching Status (COTH Membership)	1=Yes 0=No	AHA
Hospital Financial Resources	Hospital Operating Margin=(operating income/net patient revenue)*100	CMS
Environmental Factors		
Competition in the Hospital Market	Herfindahl Index for systems and independent hospitals at the market level	Calculated
Rurality	Rural Urban Continuum Code Ranging from 1-9 based on population in the market surrounding the hospital	ARF
Per Capital Income	Average Household annual income in hospital market	ARF
Change in Unemployment Rate Over Time in Hospital Market	Change in unemployment rate from 2001 to 2004 in hospital market	ARF
DEA Variables Input Variables		

Table 2 Continued: Variables Used in the Study

Full time equivalent Employees (FTEs)	Total number of hospital employees, .5 for half-time employees minus the nursing home FTEs when given	AHA
Non-labor Expenses	Total hospital expenses- labor expenses- nursing home expenses (when available)	AHA
Capital Assets	Index measure calculated based on services offered (Value from 0 to 36)	AHA
Output Variables		
Total Hospital Outpatient Visits	Total number of Outpatient visits- nursing home outpatient visits (when available)	AHA
Case Mix Adjusted Admissions	Total number of hospital discharges times the case mix index score	AHA & CMS
Efficiency		
DEA score	Score between 0 and 1 based on multiple inputs and outputs converted to dichotomous value with efficient hospitals defined as those at or above the .75th percentile.	Calculated with DEA
Windows Analysis Score	Change in DEA score for hospitals that have EMRs in both 2001 and 2004. A positive score indicates an increase in quality. A negative score indicates a decrease in quality.	Calculated with DEA
Quality Variables		
Score of ten indicators of quality of care relating to acute myocardial infarction, congestive heart failure, and pneumonia	Score of average/above average (1) or below average (0) national average on each available measure per hospital divided by the number of indicators available for that hospital	CMS/HQA /AHRQ

include the total number of hospitals using EMR systems, the number of EMR systems that are automated, the number that are not automated, and the number that are contracted. Additionally, descriptive frequency statistics will inform the study as to when the EMR systems have been implemented. From this, it will be determined which year was the most common year of implementation. Descriptive statistics of the organizational and environmental characteristics of hospitals with EMRs will be compared to those without EMRs. These analyses will be completed with SPSS, a statistical software program for the social sciences.

Next, logistic regression will be used to determine organizational and environmental factors associated with EMR use. EMR use, in the automated sense, will be a dichotomous variable indicative of if a hospital is using this type of technology in 2004. From this, it is possible to determine characteristics; both organizational and environmental that are predictors of EMR use. Organizational factors of interest in this study include bed size, ownership, Public Payer mix, teaching status, financial resources, and system affiliation. Environmental factors of interest in this study include competition, per capita income and rurality. SPSS will also be used for the logistic regression analyses.

DEA will then be used to assess hospital efficiency through the development of a relative efficiency frontier. Hospitals will be grouped based on two factors: organizational size and EMR use. In other words, hospitals with EMRs will be measured for efficiency against only those other hospitals that also have EMRs while hospitals without EMRs will be measured for efficiency against those hospitals without EMRs. In addition to this grouping, the hospitals will be compared according to bed size. Previous research indicates that DEA efficiency scores are more stable when computed in relatively similar groupings according to bed size (Ozcan 1992-1993). To create an efficiency score using DEA, multiple inputs and outputs will be included in the model. However, since health care providers generally have more control over inputs than outputs, an input oriented model will be used. DEA also allows for a slack analysis, which identifies how inefficient DMUs must change their inputs or outputs to become efficient. This slack analysis will determine how hospitals with and without EMRs must change to perform as well as others in their size groupings. DEA Solver, a software package that functions with Excel, will be used for the DEA analyses.

A Windows Analysis Score will be computed to determine the difference in efficiency for hospitals that have used EMRs from at least 2001 to 2004. This technique will essentially take the first difference of efficiency for each of these hospitals to see if efficiency has improved or decreased over the period. The goal of this analysis is to detect how EMR use changes hospital efficiency as it is used over a longer period. Since a new system may take a period of adjustment for employees and the organization itself before differences are found, this analysis is important.

Logistic regression will be used to detect significant differences in performance for hospitals with and without EMRs. Hospital performance is measured through both efficiency and quality. In the efficiency analyses, hospitals will once again be peer grouped based on size, with the realization that smaller hospitals and larger hospitals operate quite differently and will likely not be comparable in efficiency measures. For the efficiency scores and the Windows Analysis Scores, comparisons for the efficient versus inefficient hospitals with EMRs and again for those without EMRs are conducted using logistic regression. These logistic regression analyses will allow for the comparison of hospitals by dichotomously coded quality and efficiency scores to determine the relationship with EMR use while controlling for other important variables such as system affiliation, teaching status, and ownership. For the quality comparisons, the case mix index will also be added as a control variable. High quality hospitals will be identified as those performing above the national mean. Low quality hospitals will be identified as those performing at or below the mean. Efficient hospitals will be those with a DEA score at or above the .75th percentile. All other hospitals will be coded as inefficient. For the Windows Analysis, hospitals with a positive score will be those that have improved their efficiency, and those with a negative score will be those that have decreased their efficiency.

A hospital performance classification scheme will also be employed. This classification system will identify hospitals that are high performers, mediocre performers, and poor performers. High performers are those that performed highest in efficiency and quality. Mediocre performers are those that performed high in quality and low in efficiency or low in quality and high in efficiency. Poor performers are hospitals that scored low in both quality and efficiency. From this classification system, the percent of hospitals in each category with EMRs will be noted, and three logistic regression equations will help determine the role of EMR use in hospital performance.

As mentioned earlier in this chapter, there is a chance that this conceptual model, though created using organizational theory and previous research and literature, may be at risk for endogeneity. This endogeneity relates to both the selection effect and reverse causality of the constructs of interest. Since EMR use was not randomly assigned to hospitals, rather they selected this strategy themselves, it is possible that the hospitals that adopted EMRs were already performing better than those that do not yet use EMRs. If this is the case, the higher hospital performance cannot be attributed to EMR use because it may have instead already existed and led to the adoption of EMRs. To ensure the validity of the results of this analysis, the Hausman specification test will be conducted to determine if the relationship is endogenous. The Hausman specification test examines the relationship between the error term and the potentially endogenous variable or variables by comparing the estimate of the endogenous explanatory variable in the original equation to the same equation with the residuals added as regressors (Wooldridge 2003). If the estimates are the same in both equations, there is no evidence of endogeneity; however, if the estimates are different, there is evidence of endogeneity and a solution must be applied. One possible solution to this potential problem is the use of instrumental variables in a refined regression model.

In the event endogeneity is found in this study, instrumental variables will be used to correct for this validity threat involving the quality and efficiency measure. An instrumental variable is a variable correlated with the endogenous variable and the dependent variable, but not with the error term (Wooldridge 2003). The mathematical reasoning for using an instrumental variable as an unbiased estimator of the endogenous variable x in $y_i = \beta_0 + \beta_1 x + \varepsilon_i$ is:

$$b_1^{IV} = \frac{Cov(y,z)}{Cov(x,z)} = \frac{Cov(\beta_0 + \beta_1 + \varepsilon, z)}{Cov(x,z)} = \frac{Cov(x,z)\beta_1 + Cov(\varepsilon, z)}{Cov(x,z)} = \frac{Cov(x,z)\beta_1}{Cov(x,z)} = \beta$$

(www.columbia.edu/~ag2319/teaching/G4075_Outline/node9.html 2006). The use of instrumental variables can correct the problem of endogeneity in the comparisons of hospitals with and without EMRs by providing unbiased estimates of their influence on performance.

Logistic Regression

Logistic regression is a multivariate method that is used when the outcome variable in the model is dichotomous. It is less stringent than OLS regression, in some ways, because it does not assume a linear relationship between the independent variables and the dependent variables, nor does it require a normal distribution or homoskedasticity. However, to apply logistic regression in a multivariate model with continuous independent variables as with this model, constant slope and linearity must be assumed.

Logistic regression does, however, allow for similar analyses to multivariate regression, though the difference lies in that logistic regression violates an assumption of multivariate regression since the residuals are not normally distributed. The overall fit of a model is determined with the Chi square statistic. The Chi-square indicates if the model is adequate in explaining the outcome variable. The Wald statistic is used to determine the significance of individual predictors, and the sign and strength of the coefficients will be used to assess the strength of the relationship of the variables, if they are statistically significant. These statistics will be used to assess the strength of the model and the individual predictors. The explained variance of the predictors is assessed through a post hoc analysis using either Cox and Snell or Nagelkerke. This variance is further explored through deviance, a measure of how the data varies from what the model predicted, similar to the sum of squares for multivariate regression.

Logistic regression also allows for the development of confidence intervals based on the coefficient estimates. The development of these confidence intervals allows a researcher to examine individual cases based on the variables included in the model. Logistic regression also allows the assessment of relative risk or determination of group membership. Relative risk is the likelihood that an individual unit will have a value for the discrete outcome variable. Logistic regression will also offer a look at classification tables, which provide information about probabilities, odds, and odds ratios. Each of these is a different variation of one another, but each is useful to examine the analysis of interest. The probability can range from 0.0 to 1.0 and is the predicted chance of group membership. The odds are, "the ratio of the predicted probability of being a case p to the predicted probability of not being a case (1-p)" (Cohen et. al. 2003, p. 490). The odds ratio is, "the ratio of the odds of being a case for one value of the predictor X divided by the odds of being a case for a value of X one point lower than the value of X in the numerator" or "by what amount the odds of being in the case group are multiplied when the predictor is incremented by a value of one unit" (Cohen et. al. 2003, p. 492).

In this research study, the outcome variable, whether or not the hospital has EMRs, is dichotomous. The hospital characteristics of interest in this study include size, Medicare Payer mix, ownership, system affiliation, teaching status, financial position, competition, rurality, change in unemployment rate, and per capita income. Although, according to the HIMSS database, different levels of EMR use are possible including not automated, contracted, and fully automated, this study will only consider those hospitals that are fully automated with EMRs to be categorized as using EMRs. The justification for this is that optimal performance of EMRs is expected when they are incorporated into all functions including clinical, administrative, and fiscal realms. Additionally, when projections are made to encourage health care providers to adopt EMRs within ten years, it is expected that these EMRs will be fully automated. Finally, the interest of this study is to determine the impact of fully automated EMR use on hospital performance and the factors associated with automated EMR use. To determine what factors are associated with hospital EMR use, the following equation will be used:

EMR use=f(size+ownership+system affiliation+ Public Payer mix+teaching status + financial position +competition+rurality + per capital income+change in unemployment rate)

The above equation identifies factors of interest in this model. Logistic regression is based on the below rationale for a model with one variable:

$$\pi(x) = \frac{e^{\beta_0 + \beta_1 x}}{1 + e^{\beta_0 + \beta_1 x}}$$

The logit transformation of this equation is:

$$g(x) = \ln\left[\frac{\pi(x)}{1 - \pi(x)}\right] = \beta_0 + \beta_1 x$$

The estimated Logit Equation for this model is:

$$\begin{aligned} G(x) &= \beta_0 + \beta_1 Size + \beta_2 Ownership + \beta_3 SystemAffiliation + \beta_4 Competition + \\ &\beta_5 TeachingStatus + \beta_6 FinancialPosition + \beta_7 PublicPayermix + \beta_8 Rurality + \\ &\beta_9 PerCapitaIncome + \beta_{10} ChangeinUnemploymentRate \end{aligned}$$

Logistic regression will predict EMR use. This includes whether or not the hospital, based on the characteristics in the equation, uses an EMR system. A classification table will indicate how good the model is at predictions, and the odds ratio will represent the relative risk of having EMRs. The Wald statistics are used to indicate the significance of the individual predictors, and the model chi-square will provide information about the overall significance of the model. Each of the variables with a significant Wald statistic is a significant predictor of the use of an EMR system. If, for example, size is a significant predictor, the relationship is indicated through the coefficient and the Wald Statistic. This indicates that there is a difference in efficiency for hospitals with and without EMRs. These coefficients can further be used to determine the nature of the relationship. If the coefficient for size is negative, an inverse relationship between size and EMR use is indicated.

Organizational Efficiency

Organizational efficiency has been studied for many decades and in many different ways (Cooper, Seiford, and Tone 2000). Researchers have struggled with how to best measure and compare organizational efficiency, and several strategies have been used. Efficiency is an important component of organizational performance, and if it cannot be measured, it is difficult to say if it has changed or improved. Because of the attention of the cost containment efforts in health care, coupled with the quality improvement in this same industry, efficiency may be the answer to improved hospital performance. Shortell and Kaluzny claim that higher organizational efficiency is associated with information and feedback, interdepartmental coordination and resource sharing, and concentration of staff work and activity (2000). Of course, it is easy to see how each of these work structure characteristics could be achieved with EMR use.

Efficiency is defined in many different ways and exists in several forms. According to Webster's Student Dictionary, efficiency is, "the ratio of the output energy of an organism or machine to input energy," and efficient is defined as, "Acting or operating effectively with little waste of energy, effort, or material" (1996). Efficiency, in its rawest form, is the ratio of outputs to inputs (Cooper, Sieford, and Tone 2000). Efficiency is also defined as, "the cost per unit of output" (Shortell and Kaluzny 2000 p.459). A distinction is between at least four types of efficiency: allocative efficiency, distributive efficiency, managerial efficiency, and technical efficiency (Long and Harrison 1985). Allocative efficiency represents the optimal combination of inputs and outputs given input prices and technology. Distributive efficiency considers both the structure of the organization and equity of resources. Managerial efficiency is concerned with the internal organizational performance. Technical efficiency is the maximization of outputs for a given amount of inputs. Ultimately, efficiency means that input resources are used in such a way that there is no waste and the outputs are maximized in terms of quality, cost, and production. With such efficiency, fewer resources are required based on processes and structures that are in place to allow for such organizational performance. There is no doubt that increased efficiency can lead to cost savings, and thus increased or improved efficiency is often the goal of organizations.

Previous measures of efficiency in organizational performance include partial productivity ratios, total factor productivity, multiple regression, and stochastic frontiers. While some of these measures are very simple to use, most do not allow for the measurement of multiple inputs and outputs while measuring efficiency to examine the optimal combination of resources and production. Other measures, such as total productivity ratios, assume that all firms are efficient, when this is clearly not the case. Several of the measures also required price information for efficiency analysis, and this data is not always available. Finally, these more traditional methods of efficiency did not provide the identification of sources of inefficiency, making them more descriptive than prescriptive.

Data Envelopment Analysis

Data Envelopment Analysis (DEA) is a prominent method for measuring organizational efficiency using a non-parametric statistical technique. DEA has been used to measure efficiency in industries such as airlines, banks, libraries, engineering, and fast food stores (Chern and Wan 2000, Cooper, Seiford, and Tone 2000). This approach has also been used to measure efficiency in health care. Efficiency is an important performance measure in health care since recent rising costs have caused concern among consumers, providers, policy makers, and payer groups. Improved efficiency may be part of the answer to the cost containment movement that currently challenges the health care field. Developed by Charles, Cooper and Rhodes in 1978, DEA uses non-parametric techniques, assumes that not all firms are efficient, and allows for each subject of interest to have multiple inputs and outputs. Data envelopment analysis (DEA) examines technical efficiency through the development of a production possibilities frontier. Total efficiency of an organization is made up of technical efficiency and allocative efficiency. Technical efficiency refers to the way in which an organization maximizes outputs based on the amount of inputs. Allocative efficiency refers to an organization producing the optimal mix of inputs and outputs, based on equipment, technology, and prices or costs. DEA measures total efficiency as well as allocative, technical, and scale efficiency.

The literature that has used DEA to successfully measure efficiency in hospitals has accumulated over a number of years. One study allows for the analysis of efficiency in hospitals with regard to ownership (Ozcan, Luke, and Haksever 1992). In this study, the authors peer-grouped hospitals to control for market characteristics that may affect performance, thus creating a more stable efficiency frontier. Hospital inputs for this study include capital, including service complexity and number of hospital beds, labor, including the number of nonphysician full time equivalent staff members and a weighted number of part time staff, and supply, including the operational expenses. Hospital outputs include adjusted discharges, outpatient visits, and training. Once the efficiency scores were calculated through

DEA software, pair-wise comparisons were conducted to identify statistically significant differences among the ownership types for hospitals. Overall, the authors found that 43% of hospitals were efficient, and a slack analysis identified that government hospitals may "underproduce discharges" (Ozcan, Luke, and Haksever 1992, p. 790).

Another study compared hospital efficiency between Norway and Finland using DEA (Linna, Hakkinen, and Magnussen 2005). In this study, the authors sought to compare internationally two health systems to determine patterns of efficiency for policy makers. The input measure in this study is operating costs, including all production costs of the hospital, both direct and indirect. The output measures include DRG-weighted admissions, weighted outpatient visits, day care, and impatient days. Linna, Hakkinen, and Magnussen conclude that hospitals in Norway and Finland have, "marked differences in cost efficiency, both for the within country and across country comparisons" (2005 p. 10). The authors attribute these differences to variation in price inputs and health care practices such as length of stay.

Another study uses DEA to measure the technical efficiency of hospitals in Ghana (Osei et. al. 2005). The inputs in this examination of hospital efficiency include number of medial and technical officers (staff), support of subordinate staff, and the number of hospital beds. The output measures include the number of maternal and childcare, the number of child deliveries, and the number of patient discharges. Using a constant returns to scale model (CRS), and increasing returns to scale model (IRS) and a decreasing returns to scale model (DRS), the authors report that approximately half of all of the hospitals were inefficient (47% technically inefficient, 59% scale inefficient). This study also directed these inefficient hospitals in specific ways to achieve efficiency, such as “reduce their current number of medical officers/dentist by 44%, technical staff by 22%, and subordinate staff by 28%, and beds by 29% while holding the output constant” (Osei et. al. 2005, p. 12). It is, in part, this prescriptive nature that makes DEA a valuable tool for hospitals that wish to become efficient.

DEA provides an analysis of relative efficiency between appropriately grouped units of analysis, referred to as Decision Making Units (DMUs). Previous research in many different health related DMU areas exists. DMUs have included hospitals, hospitals based on ownership type, physicians in hospitals, substance abuse treatment units, dialysis centers, and many others (Ozcan, Luke and Haksever 1992, Chilingerian 1995, Alexander et. al. 1998, Ozgen and Ozcan 2002). DMUs are the unit of analysis. In this study, DMUs will be hospitals, as DEA is used to study hospital efficiency.

DEA allows for multiple inputs and outputs, and their relationship to one another results in an efficiency score ranging from zero to one, with one indicating efficiency and less than one indicating inefficiency. Inputs in DEA studies with the hospital as the unit of analysis include assets, non-physician full time employees, service mix, beds, and non-labor/capital operating expenses (Ozcan 1992-1993 and Harris, Ozgen and Ozcan 2000). Previous research indicates that hospital outputs can include outpatient visits, adjusted discharges, training full time employees, Medicare patient days, and training hours (Ozcan 1992-1993). DEA can be used to assess efficiency through inputs and outputs and finds the optimal combination they produce to achieve superior organizational performance. DEA measures efficiency relative to the organizations that are included in the analysis, meaning that it is able to very explicitly identify efficient and inefficient DMUs, however, these are not absolute efficiencies since it is possible that none of the DMUs is absolutely efficient. In other words, a performance that is not yet realized may be perfectly efficient, but it will not influence the DMUs included in the analysis.

DEA is an appropriate method for benchmarking hospitals and identifying best performing providers. DEA also provides prescriptive information about how inefficient organizations may move closer to the efficiency frontier by analyzing the slacks that inefficient DMUs use. DEA is not generally conducted by hand, and instead, is completed using software such as DEA solver. However, the rationale behind DEA is herein discussed. According to Ozcan, Luke, and Haksever, using DEA for peer-grouped hospitals (j=1,...n) with inputs (Y_{rj}, r=1,...s) and inputs (x_{ij}, i=1, ...m), the following fractional formulation is used:

$$\text{Maximize } E_o = \frac{\sum_{r=1}^{s} u_r y_{ro}}{\sum_{i=1}^{s} v_i x_{io}}$$

Subject to:

$$\frac{\sum_{r=1}^{s} u_r y_{ro}}{\sum_{i=1}^{s} v_i x_{io}} \leq 1$$

$$u_r \geq 0; \quad v_i \geq 0$$

where

E_o = efficiency score for each facility in the set of o = 1...s facilities,

y_{ro} = selected output "r" produced by each facility in the set "o",

x_{io} = selected input "i" used by each facility in the set "o",

y_{rj} = selected output "r" produced by facility "j",

x_{ij} = selected input "i" used by facility "j" (Ozcan, Luke, Haksever 1992, p. 784).

In this formulation, u_r and v_i are the weights assigned respectively to output "r" and input "i", both obtained from DEA.

The above formula indicates that the inputs and outputs are maximized for each individual DMU or hospital in order to obtain an efficiency score. When all DMU efficiency scores are calculated using the multiple inputs and outputs, an efficiency frontier is created. Neither u nor v can be zero nor less than zero values since doing so would cause the cancellation of the numerator or denominator or would cause a negative efficiency score.

In the analysis of performance of acute care hospitals, an input oriented model is appropriate. Because health care organizations do not have much control over their outputs, an input oriented model is generally employed (White and Ozcan 1996, Ozgen and Ozcan 2004, and Harris, Ozgen and Ozcan 2000, Chern and Wan 2000). The rationale for this is that health care planners and policy makers will have more control over what resources go into their organization than those that go out, such as discharges or outpatient visits, based on the complex nature of health care services. For example, hospital administrators, who may be trying to measure or improve efficiency, likely have more control over inputs, such as labor, capital, and expenses than they do over outputs such as patient discharges. This approach is common in previous health care related DEA literature and thus will be used in this study. The value of this type of model is that is can also be used in the determination of organizational slacks.

DEA allows for either a CRS or a VRS model. A VRS model, or variable returns to scale, assumes that the relationship between changes in input and output does not necessarily create a straight line relationship; rather changes in inputs will produce varying changes in outputs. The CRS model, or constant returns to scale model, assumes that there is a linear, proportional change in outputs for changes in inputs. However, the CRS model will also allow the determination of whether the returns to scale are increasing or decreasing (Cooper, Seiford, and Tone 2000). Further, a DMU that is named efficient through the CRS model will also be efficient in the less stringent VRS model (Cooper, Seiford, and Tone 2000). The CRS model is appropriate if the DMUs are grouped by size, as is the case in this study. Using

DEA will allow for the determination of organizational efficiency and its relationship to the use of EMRs. Figure 7 illustrates an input oriented, CRS model graphical representation of a DEA efficiency frontier. In this graph, DMUs are hospitals in a model of two inputs and one output. The two inputs include non-labor operational expenses and non-physician FTEs, and the output includes discharges. For the sake of example, this chart represents the non-labor operational expenses in thousands of dollars and non-physician FTEs used for one discharge from a hospital. The dots on the line represent efficient DMUs on the efficiency frontier. The dots above the line represent inefficient DMUs or hospitals.

This input oriented CRS model will assess the relationship between inputs and outputs. Inputs will include labor, capital, and expenses. The number of full time employees measures Labor. This number is divided into physicians and non-

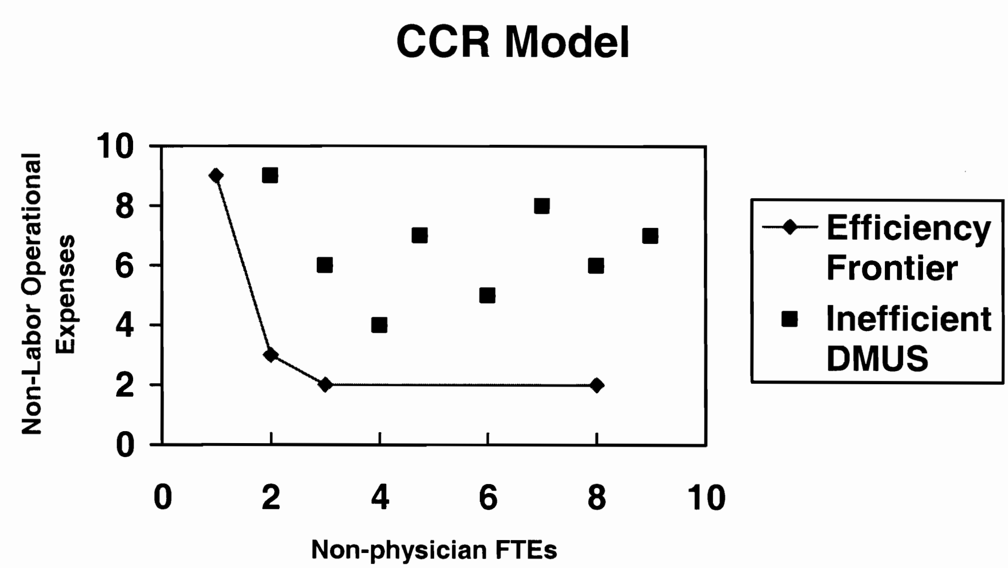

Figure 7: CCR Model

physicians, since non-physician labor is generally less expensive than physician labor, thus making comparisons inaccurate. Capital is measured by hospital size and service complexity (White and Ozcan 1996). Expenses include operational expenses, not including payroll, capital, or depreciation (Ozcan 1992-1993). Outputs include adjusted discharges (adjusted by the case- mix index for risk adjustment) and training hours for employees. The use of the CRS model implies that there is a linear (straight line) relationship between inputs and outputs. In other words, if each hospital unit is expected to produce three discharges per day, an increase in inputs by one hospital unit would equate to an increase in outputs by three discharges.

DEA also offers several other features to examine efficiency. The CRS model measures both technical efficiency and scale efficiency. Scale efficiency is calculated to determine the difference between the CRS and VRS scores and is found by dividing the CRS score by the VRS score. A difference in the two scores indicates scale inefficiency. After calculating efficiency scores through DEA, one can identify efficient and inefficient DMUs. Once the efficient DMUs are identified, it is possible to conduct a slack analysis to determine which inputs and outputs need to be changed in order to improve the efficiency of inefficient DMUs. The returns to scale indicate the source of the inefficiency and can describe how an inefficient DMU must change, through inputs and/or outputs, to become more efficient. These specific numeric values lead administrators to make changes to lead to improved performance through rates of return and are found through $\sum\lambda$ (sigma lambda). If sigma lambda is less than one, it indicates increasing returns to scale, and if sigma lambda is greater than one it indicates decreasing returns to scale. If sigma lambda is less that one, it shows increasing returns to scale, and the DMU must increase outputs to become efficient. If sigma lambda is greater than one, it indicates decreasing returns to scale, and the DMU must decrease its inputs to become scale efficient. These increases or decreases of outputs are referred to as slacks. According to Chern and Wan, "slacks analysis indicates by what amount (i.e. slack values) hospitals can decrease the inputs and/or increase the outputs to reduce the discrepancy of efficiency scores as compared to the efficiency frontier" (2000 p. 166). The slacks for inputs are referred to as "excesses" and the slacks for the outputs are defined as "shortages." Figure 8 displays the distance between the inefficient DMUs and the efficiency frontier. Again, this figure represents a two-input, one output CRS model of hospitals. The two inputs are non-labor operational expenses, in thousands of dollars, and non-physician FTEs. The output is discharges in this model. The distance between the inefficient DMUs and the line, which represents the efficiency frontier, is the amount of change, in terms of inputs per one discharge (output) that must occur in order for the inefficient DMUs to become efficient. For example, the lines that start at the inefficient DMU (3,4) and cross the efficiency frontier show the amount of change needed in inputs per one output to achieve efficiency. It is clear to see that efficient hospitals use fewer non-labor operational expenses and non- physician FTEs per discharge than inefficient

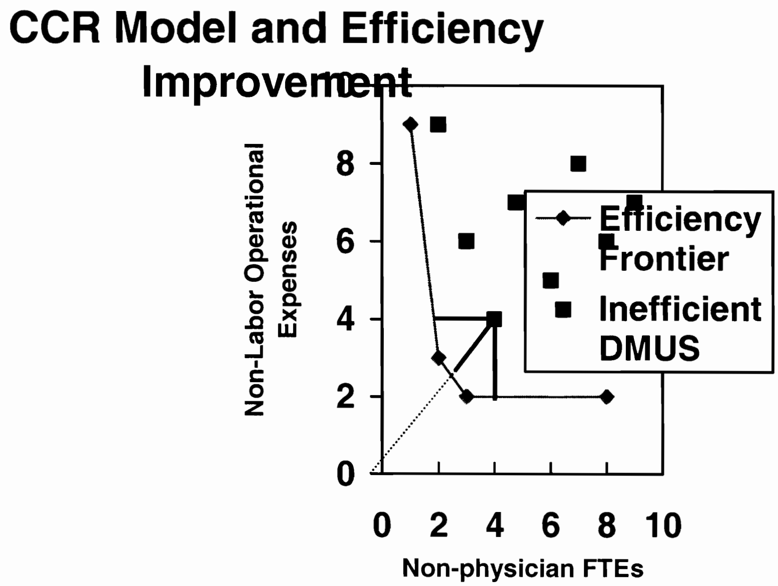

Figure 8: CCR Model and Efficiency Improvement

hospitals. The inefficient hospital with the lines must either decrease the number of non-physician FTEs by slightly more than two or decrease the non-labor operational expense by two units in order to achieve efficiency. A third option for this particular DMU to achieve efficiency is to decrease non-labor operational expenses by 1.5 while also decreasing the number of non-physician FTEs by 1.5.

As mentioned in chapters two and three, it is possible that the implementation period for EMRs in a hospital may not be a time of optimal performance. As with any new organizational practice, it may take time to adjust to the new equipment and policies. For this reason, this study will employ a Windows Analysis Approach to assess efficiency changes over time for hospitals. This approach, though associated with DEA, is discussed in the next section of this chapter as it presents a slightly modified approach.

To employ a model with stricter standards for efficiency, a VRS model with weight restrictions can account for environmental factors or other influences. A model of this type would allow for the restriction of certain inputs or the production of certain outputs (Ozcan 1992-1993). In the case of the hospitals, administrators may wish to limit the input of FTEs by limiting the use of physicians in an effort to increase efficiency. To accomplish this, the weights would be used to determine base weight ratios to identify substitutions and how they should be restricted. This may be accomplished using price, for example. They can then be restricted to the median, or some other standard. In the instance of hospitals, administrators could restrict physician hours, while encouraging nurse of technician hours instead. The discrepancy between the DMUs with and without the weight restriction can be compared. However, based on the research questions and the broad scope of this study, it is important to first examine the hospitals' efficiency without weighted inputs. Additionally, these weights are generally based on first hand supervisor limits and price information, which is not included in this study as it may vary or is otherwise unknown. Based on the findings of this project, though, it is a potential area for future research.

DEA does, however, have some weaknesses. First, DEA is completely relational in analysis, so the identified best performers may only be so because of the group to which they are compared. Additionally, DEA does not account for random noise in analyses, which may be better handled by a stochastic frontier approach. Finally, DEA cannot alone test hypotheses, but these scores of efficiency can be compared using other parametric or non-parametric techniques.

Windows Analysis of Efficiency

Another benefit of DEA is its ability to measure changes in efficiency over time. There are two techniques that allow for the observation of changes to efficiency over time. Using a technique called Window Analysis, a DMU in each period is treated as if it were a different DMU to contrast a DMU's efficiency from one time period to another. Another method for observing the change in efficiency over time is the Malmquist Index. The Malmquist Index has been used to measure how hospital efficiency changes from one period to the next. Linna used a Malmquist Index to study efficiency changes in hospitals in Finland over time (1998). The primary purpose of this study was to assess the Malmquist model compared to a stochastic cost frontier model, but the study also aims to assess the efficiency of Finnish hospitals, which are under governmental cost containment pressure. The study concludes that the models do not produce varying results and that hospitals in Finland improved in efficiency over the period of interest (1988-1994) through both the "rate of technical change and to the effect of time-varying cost efficiency" (Linna 1998 p. 425). Another study uses the Malmquist Index to measure the changes in efficiency in Dialysis Markets. Ozgen and Ozcan examine free-standing dialysis facilities to assess performance and detect improvements in efficiency (2004). Using data from each year from 1994 until 2000, this study includes both multiple inputs and multiple outputs. Output variables include outpatient dialysis, dialysis training, and home dialysis treatments. Input variables include physicians, registered nurses, other medical staff, and the total number of dialysis machines. This study concludes, through the Malmquist Index, that the dialysis facilities did not improve based on technological change, rather many of the facilities decreased in efficiency.

The Malmquist Index is especially useful for examining technical efficiency, and differs from Windows Analysis in how it measures the change in efficiency. The Malmquist Index considers two distinct periods to calculate the change in efficiency while the Windows Analysis approach places treats each period as a separate DMU in the same relative efficiency frontier analysis. Additionally, the Malmquist Index is used to assess dynamic efficiency assuming CRS technology by measuring productivity change (Ozgen and Ozcan 2004). While both approaches have strengths, the interest in this study is in over all change in efficiency instead of technical efficiency. Thus, the Windows Analysis CRS approach is used.

Previous researcher has reported findings using Window Analysis including examining the effects of organizational merger on hospital performance (Harris, Ozgen and Ozcan 2000). In this study, researchers conducted a windows analysis to allow for the lag time in hospitals that may require a period to adjust to the new management based on the merger, observing hospitals before a merger, and one and two years after a merger respectively, showing that changes in efficiency occurred from the time of the merger to the first year after the merger, and again two years after the merger, though none of these relationships were statistically significant. Some of these hospitals had decreased efficiency the first year after the merger, which then increased two years after the merger. These trends indicate that the first year after an organizational change, such as merger or implementation of a new practice such as EMR use, efficiency may decrease before performance improves.

Windows Analysis subjects each hospital period to the same standards of relative efficiency by including the two periods as distinct DMUs (Cooper, Seiford, and Tone 2000). This approach, like other DEA techniques, generally uses cross-sectional data and does not assume that all firms are efficient. It also does not assume than any of the firms are efficient in that it measures efficiency using a relative efficiency frontier. The strength of this type of approach is that the Windows Analysis essentially uses an econometric technique called first differencing, which considers only the change in performance for the DMUs. By only examining the change in efficiency, the validity issues relating to endogeneity, confounding factors, non-equivalent comparison groups, and selection effect are decreased. In other words, with the Windows Analysis, it does not matter if one group of hospitals is more efficient in 2001 than the other group because the only change in efficiency from 2001 to 2004 is examined. Then, logistic regression is used.

Test of Endogeneity

Hausman Specification Test

As previously mentioned, there is a chance of endogeneity in this model based on possible reverse causality. To test for endogeneity, a regression model must be utilized at this point to ensure the validity of the upcoming planned comparisons. To allow for the testing of efficiency and quality as endogenous variables, the following equations will be used for the Hausman Specification Test:

$$EMRUse = \beta_0 + \beta_1 Quality$$

$$EMRUse = \beta_0 + \beta_1 Efficiency$$

If according to the Hausman Specification Test, quality or efficiency is found to be endogenous, an appropriate instrumental variable will be found for the respective variable. If endogeneity is not found for either variable, the analysis will proceed as planned.

Testing the Relationship Between EMR Use and Performance

Quality

To determine the relationship between hospital EMR use and quality, a logistic regression analysis is conducted to control for other possible factors including hospital teaching status, ownership, system membership, case mix index, and size. Each of these variables come from the AHA data and was presented in the first logistic regression analysis of correlates of EMR use. The quality measure values will be transformed to allow for greater variance and distribution among the scores. The transformation will recode the scores into a dichotomous outcome variable with high quality hospitals performing above the 50^{th} percentile of quality scores. When the logistic regression analysis is complete, a significant p-value for the EMR variable will indicate a relationship between EMR use and quality. Further, the odds ratio will determine the strength and direction of this relationship.

Efficiency

A similar approach is taken to assess the relationship between hospital EMR use and efficiency and change in efficiency over time. For these analyses, six separate logistic regression analysis will be conducted to control for confounding factors. Again, the hospitals will be grouped according to bed size. The groups will be small, medium, and large. The hospitals in the small size category will have less than 100 beds. The hospitals in the medium size category will have between 101 to 349 beds. Finally, hospitals that have 350 or more beds will make up the large size category. Similar size groupings have been used in previous research to provide more stable estimates of efficiency using this technique (Ozcan, Luke, and Haksever 1992, Chern and Wan 2000). The hospitals will be grouped in this manner according to size for both the DEA analysis and for the efficiency logistic regression analyses. The reason for the grouping is that small hospitals may operate differently, have different resources, and have different patient case mixes than medium or large hospitals. A more stable and accurate comparison will exist if hospitals are compared to others of a similar bed size because of the operational differences associated with hospitals based on bed size. The size groupings used in this study are summarized in Table 3.

Table 3: Hospital Groupings by Bed Size

Category	Number of Beds
Small	0-100
Medium	101-349
Large	350 or more

The six logistic regression analyses used to examine the relationship between hospital EMR use and efficiency will also control for other potentially confounding factors by including them in the equation. In the first three equations, the DEA efficiency scores will be transformed into dichotomous outcome variables with efficient hospitals defined as those performing at or above the 75^{th} percentile. The control variables included in these three equations are: teaching status, ownership, system membership, and size. These measures all come from the AHA database and were presented in the first analysis. A significant relationship, as reported by the p-value, between the dichotomous efficiency value and the EMR use variable will signify a relationship between these two factors. The odds ratio will report the strength and direction of this relationship.

For the analysis considering the relationship between hospital EMR use and the change in efficiency over time, three separate, peer size grouped analysis will be conducted. Only the hospitals that were consistent in EMR use in both 2001 and

2004 will be included in this analysis. In the Windows Analysis, the difference must be found between two periods for each DMU. The 2001 efficiency score will be subtracted from the 2004 efficiency score. A negative value will represent a decrease in efficiency while a positive value will represent an increase in efficiency. Once the difference in efficiency is calculated, these scores will be recoded into a dichotomous outcome variable with increased efficiency being recoded to a value of one and decreased efficiency being recoded into a value of zero. These three separate logistic regression equations will control for ownership, bed size, system membership, and case mix index. A p-value of less than .05 between the EMR use variable and the dichotomous outcome variable will determine that there is a relationship between hospital EMR use and the change in efficiency over time. The strength and direction of this relationship will be determined using the odds ratio value.

Total Hospital Performance Classification Scheme

To further explore the relationship between hospital EMR use and total performance, a classification scheme will be used to examine the combination of quality and efficiency for hospitals. Hospitals will be classified into one of three groups. These groups will include the high performers, the middle ground performers, and the poor performers. The high performers are those that scored high in both efficiency and quality. The middle ground performers are those that scored high in efficiency and low in quality or low in efficiency and high in quality. The poor performers are those that scored low in quality and low in efficiency. The numbers and percentages of hospitals with and without EMRs in each group will be reported.

Hospitals with EMRs will also be grouped based on the number of years of EMR use to determine if there is a relationship between length of EMR use and total performance using the performance classification scheme that considering both quality and efficiency. The hospitals will be assigned to six groups based on years of EMR use and will include: 1 year or less, 2 to 5 years, 6 to 9 years, and 10 or more years. The years of use are determined from the HIMSS data, which indicates the year of implementation of the fully automated EMR system. These hospital groupings will be used for logistic regression analyses comparing these hospitals in efficiency and quality. The relationship between total performance and length of time of hospital EMR use will be examined using three separate logistic regression equations while controlling for ownership, system membership, and size. The outcome variables in these equations will be dichotomous design variables for high performance, middle ground performance, and poor performance. The p-value and odds ratios of the length of time of EMR use groups will determine if a relationship exists while also providing information about the strength and direction of the relationship. It is expected that hospitals that have used EMRs for longer lengths of time will be more accustomed to the systems. The length of time of EMR use groupings are summarized in Table 4.

Table 4: Hospital Groupings by Length of Time of EMR Use

Number of Years of EMR Use
1 or less years of use
2 to 5 years of use
6 to 9 years of use
10 or more years of use

Study Weaknesses

This study does have acknowledged weaknesses. First, the cross-sectional design in research design A puts the model at risk for endogeneity and selection effect bias. This occurs because a single observation does not allow the researcher to determine the order of events regarding performance and EMR adoption. In other words, the comparisons of hospitals with EMRs to those without EMRs does not ensure that the hospitals with EMRs were not already performing better than those without EMRs before adoption. This issue is addressed with the Hausman Specification Test and the possible use of instrumental variables.

Second, there is a great deal of variability with EMR use in hospitals. In other words, EMRs are used in different ways and with different systems and software making it difficult to isolate and identify hospitals with EMRs. The measure of hospital EMR use may prove to be a weak one, and few previous studies have examined this issue to provide guidance.

Finally, health care organizational performance is difficult to measure. In this analysis, performance is measured through efficiency and quality, and both of these constructs have weaknesses. The efficiency measure is created through DEA, which only allows for relative measures of efficiency. In other words, efficient organizations may not actually be efficient, but they may appear to be based on the other organizations with similar inputs and outputs. For quality, it is difficult to find an available measure that incorporates all aspects of this complex construct. The measures selected have been used in previous research, though they do not include components of long-term health outcomes or patient satisfaction, thus making them somewhat incomplete. Additionally the quality measures are not available for each hospital of interest, thus limiting the sample in this part of the analysis.

Chapter Summary

This chapter describes the methodology planned in this study to assess EMR use in acute care hospitals. This methodology includes a plan for analysis, a description of the sample size, a description of the sources of data, the operationalization of the constructs into variables, DEA, and logistic regression information, as well as a test and solution for the possible endogeneity of the model. A classification scheme to consider the relationship between hospital performance and length of time of EMR use is also described. It is the hope that the careful planning and description in this chapter will allow for a valid and reliable study, yet the weaknesses of the plan are discussed as well.

CHAPTER 5: RESULTS

The purpose of this chapter is to present the results of the statistical analyses of this study. The first part of this chapter provides the descriptive analysis of the variables included. The remaining parts of this chapter present the statistical analyses of the research questions including the logistic regression results, DEA analysis, quality comparisons, and assessment of change in efficiency over time. Each of the results provides information about EMR use in hospitals.

Descriptive Statistics

Descriptive statistics were calculated using frequencies, means, cross-tabulations, percentages, and standard deviations. Descriptive statistics are provided for all dichotomous, continuous, and categorical variables. Descriptive statistics present the frequency and/or means of variables' values for the total group of hospitals as well as the values for hospitals with EMRs and without EMRs. Table 5 repoprts hospital ownership; Table 6 displays teaching status; Table 7 provides information about the regional distribution of hospitals; Table 8 displays the location of hospitals by state and EMR use; Table 9 describes the frequency of hospitals and EMR use along the rural urban continuum code; Table 10 reports hospital system membership; Table 11 displays the type of health system affiliation; Table 12

Table 5: EMR Use By Hospital Ownership

		No EMRs	EMRs	Total
Ownership	Public	1053 (94.8%)	58 (5.2%)	1111 (100.0%)
	Non-profit	2434 (87.4%)	352 (73.50%)	2786 (100.0%)
	For Profit	640 (90.3%)	69 (14.40%)	709 (100.0%)
Total	Total	4127 (89.6%)	479 (10.4%)	4606 (100.00%)
Chi-square (2df)=47.26 (p<.001)				

Table 6: Hospital Teaching Status and EMR Use

Teaching Status	No EMRs	EMRs	Total
Teaching Hospital	226 (80.4%)	55 (19.6%)	281 (100.0%)
Non-teaching	3901 (90.2%)	424 (9.8%)	4325 (100.0%)
Total	4127 (89.6%)	479 (10.4%)	4606 (100.00%)
Chi-square (1df)=27.03 (p<.001)			

Table 7: Hospital Divisions and EMR Use

Region	No EMRs	EMRs	Total
New England	167 (91.8%)	15 (8.2%)	182 (100.0%)
Mid Atlantic	389 (89.2%)	47 (10.8%)	436 (100.0%)
South Atlantic	606 (87.3%)	88 (12.7%)	694 (100.0%)
East North Central	622 (89.5%)	73 (10.5%)	695 (100.0%)
East South Central	347 (84.8%)	62 (15.2%)	409 (100.0%)
West North Central	622 (94.8%)	34 (5.2%)	656 (100.0%)
West South Central	608 (91.0%)	60 (9.0%)	668 (100.0%)
Mountain	299 (87.9%)	41 (12.1%)	340 (100.0%)
Pacific	467 (88.8%)	59 (11.2%)	526 (100.0%)
Total	4127 (89.6%)	479 (10.4%)	4606 (100.00%)
Chi-square(8df)=36.78 (p<.001)			

Table 8: Hospital State Location and EMR Use

State Name	No EMRs	% No EMRs	EMRs	% EMRs	Total	% Total
Alabama	79	79.8%	20	20.2%	99	100.0%
Alaska	17	94.4%	1	5.6%	18	100.0%
Arizona	48	84.2%	9	15.8%	57	100.0%
Arkansas	70	88.6%	9	11.4%	79	100.0%
California	306	87.7%	43	12.3%	349	100.0%
Colorado	63	95.5%	3	4.5%	66	100.0%
Connecticut	30	100.0%	0	0.0%	30	100.0%
Delaware	5	100.0%	0	0.0%	5	100.0%
D.C.	6	75.0%	2	25.0%	8	100.0%
Florida	158	83.2%	32	16.8%	190	100.0%
Georgia	128	90.1%	14	9.9%	142	100.0%
Hawaii	19	95.0%	1	5.0%	20	100.0%
Idaho	34	91.9%	3	8.1%	37	100.0%
Illinois	158	84.9%	28	15.1%	186	100.0%
Indiana	101	97.1%	3	2.9%	104	100.0%
Iowa	111	96.5%	4	3.5%	115	100.0%
Kansas	126	98.4%	2	1.6%	128	100.0%
Kentucky	86	86.0%	14	14.0%	100	100.0%
Louisiana	108	88.5%	14	11.5%	122	100.0%
Maine	35	97.2%	1	2.8%	36	100.0%
Maryland	34	73.9%	12	26.1%	46	100.0%
Massachusetts	56	84.8%	10	15.2%	66	100.0%
Michigan	114	86.4%	18	13.6%	132	100.0%
Minnesota	122	94.6%	7	5.4%	129	100.0%
Mississippi	80	87.0%	12	13.0%	92	100.0%
Missouri	101	91.0%	10	9.0%	111	100.0%
Montana	53	100.0%	0	0.0%	53	100.0%
Nebraska	78	96.3%	3	3.7%	81	100.0%
Nevada	28	100.0%	0	0.0%	28	100.0%
NewHampshire	24	92.3%	2	7.7%	26	100.0%
New Jersey	68	93.2%	5	6.8%	73	100.0%
New Mexico	27	77.1%	8	22.9%	35	100.0%
New York	161	84.7%	29	15.3%	190	100.0%
North Carolina	104	92.9%	8	7.1%	112	100.0%
North Dakota	36	85.7%	6	14.3%	42	100.0%
Ohio	140	92.1%	12	7.9%	152	100.0%
Oklahoma	94	94.0%	6	6.0%	100	100.0%

Table 8 Continued: Hospital EMR Use by State

Oregon	47	82.5%	10	17.5%	57	100.0%
Pennsylvania	160	92.5%	13	7.5%	173	100.0%
Rhode Island	8	80.0%	2	20.0%	10	100.0%
South Carolina	52	88.1%	7	11.9%	59	100.0%
South Dakota	48	96.0%	2	4.0%	50	100.0%
Tennessee	102	84.6%	16	13.5%	118	100.0%
Texas	336	91.6%	31	8.4%	367	100.0%
Utah	22	56.4%	17	43.6%	39	100.0%
Vermont	14	100.0%	0	0.00%	14	100.0%
Virginia	68	86.1%	11	13.9%	79	100.0%
Washington	78	95.1%	4	4.9%	82	100.0%
West Virginia	51	96.2%	2	3.8%	53	100.0%
Wisconsin	109	90.1%	12	9.9%	121	100.0%
Wyoming	24	96.0%	1	4.0%	25	100.0%
Total	4127	89.6%	479	10.4%	4606	100.0%

Table 9: Rural Urban Continuum Code and EMR Use

	No EMRs	EMRs	Total
Metro 1	1233 (86.0%)	201 (14.0%)	1434 (100.0%)
Urban 2	609 (89.3%)	73 (10.7%)	682 (100.0%)
3	426 (87.5%)	61 (12.5%)	487 (100.0%)
4	306 (90.3%)	33 (9.7%)	339 (100.0%)
5	142 (92.8%)	11 (7.2%)	153 (100.0%)
6	603 (92.6%)	48 (7.4%)	651 (100.0%)
7	447 (92.4%)	37 (7.6%)	484 (100.0%)
8	121 (92.4%)	10 (7.6%)	131 (100.0%)
Rural 9	240 (98.1%)	5 (2.0%)	245 (100.0%)
Total	4127 (89.6%)	479 (10.4)%)	4606 (100.0%)
Chi-square (8df)=54.21 (p<.001)			

Table 10: System Membership and EMR Use

System Membership	No EMRs	EMRs	Total
Non-system member	2130 (98.2%)	40 (1.8%)	2170 (100.0%)
System Member	1997 (82.0%)	439 (18.0%)	2436 (100.0%)
Total	4127 (89.6%)	479 (10.4%)	4606 (100.0%)
Chi-square (1df)= 322.36 (p<.001)			

Table 11: EMR Use and Type of System Cluster Code

Health Cluster Code	No EMRs	EMRs	Total
No Identified System Type	2132 (98.2%)	40 (1.8%)	2172 (100.0%)
Centralized Health System	145 (67.1%)	71 (32.9%)	216 (100.0%)
Centralized Physician/Insurance Health System	117 (72.2%)	45 (27.8%)	162 (100.0%)
Moderately Centralized Health System	567 (77.4%)	166 (22.6%)	733 (100.0%)
Decentralized Health System	939 (90.4%)	100 (9.6%)	1039 (100.0%)
Independent Hospital System	167 (80.3%)	41 (19.7%)	208 (100.0%)
No Cluster Assignment	60 (78.9%)	16 (21.1%)	76 (100.0%)
Total	4127 (89.6%)	479 (10.4%)	4606 (100.00%)
Chi-square(6df)=487.55 (p<.001)			

Table 12a: Variables In Hospital Correlates Analysis Descriptive Information

EMR Use		Beds Set Up and Staffed	Public Payer Mix	Per Capita Income	Change in Unemployment	Herfindahl Index	Operating Margin
No EMR	N	4127	4127	4127	4127	4127	4127
	Mean	160.9	0.696%	26718.40	1.55%	0.457	-0.055%
	Std. Dev	173.791	0.14106	8298.22	1.137	0.410	0.877
EMR	N	479	479	479	479	479	479
	Mean	229.02	0.684%	28369.23	1.82%	0.334	-0.023%
	Std. Dev	218.725	0.12753	10107.97	1.314	0.402	0.194
Total	N	4606	4606	4606	4606	4606	4606
	Mean	167.98	0.695%	26890.08	1.576	0.446	-0.052%
	Std. Dev	180.167	0.13975	8518.05	1.159	0.411	0.829

Table 12b: Significant Difference of Means of Continuous Variables by EMR Use

Variable	F(1d.f.)
Beds set up and staffed	62.17***
Public Payer Mix	3.20
Per Capita Income	16.17***
Change in Unemployment	24.45***
Herfindahl Index	39.05***
Operating Margin	.629
*p<.05, **p<.01, ***p<.001	

displays the mean, frequency and standard deviation of the continuous variables included in the first logistic regression analysis; Table 13 provides the frequency, mean, and standard deviation of all input and output variables for the DEA analysis; Table 14 provides information about the year of adoption of hospitals with EMRs.

Table 13a: Descriptive Statistics for DEA Input and Output Variables

		Input Variables				Output Variables	
EMR Use		Beds set up and staffed	Non-labor Expenses	Capital Assets	FTEs	Case mix Adjusted Admission	Outpatient Visits
No EMR	N	4127	4127	4127	4127	4127	4127
	Mean	160.9	45087554.83	9.34	794.92	10270.49	115018.38
	Std. Dev	173.791	73546760.7	5.94	1115.20	14630.16	171893.56
EMR	N	479	479	479	479	479	479
	Mean	229.02	72294760.22	10.67	1224.96	16722.54	151344.12
	Std. Dev	218.725	94344690.83	6.33	1462.85	19824.96	172249.93
Total	N	4606	4606	4606	4606	4606	4606
	Mean	167.98	47916962.43	9.48	839.64	10941.47	118796.06
	Std. Dev	180.167	76415902.4	5.99	1163.47	15377.06	172269.25

Table 13b: Statistical Differences of Means for DEA Variables

Variable	F (1d.f.)
Beds Set Up and Staffed	62.17***
Non-labor expenses	55.04***
Capital Assets	21.15***
FTEs	59.38***
Case Mix Adjusted Admissions	76.80***
Outpatient Visits	19.16***
*p<.05, **p<.01, ***p<.001	

Table 14: Year of EMR Contract/Implementation

EMR Implementation	EMRs	% Total
1983	2	0.55%
1986	5	1.39%
1989	3	0.83%
1991	1	0.28%
1992	25	6.93%
1993	15	4.16%
1994	14	3.88%
1995	15	4.16%
1996	12	3.32%
1997	24	6.65%
1998	66	18.28%
1999	12	3.32%
2000	16	4.43%
2001	57	15.79%
2002	67	18.56%
2003	24	6.65%
2004	3	0.83%
Total Included	361	100.00%

EMR Use in Hospitals

To describe the use of EMRs in hospitals, each of the variables is described for the total group of hospitals and those hospitals with EMRs as compared to those without. The ownership categories of hospitals included in this analysis are non-profit, for profit, and public. Table 5 provides a description of the hospital ownership prevalence. For the total group, the majority of hospitals are owned by non-profit entities (n=2,786), with nearly one quarter owned by public entities (n=1,111), and only

640 hospitals owned by for profit entities. Consistent with ownership trends for the total group of hospitals, the majority of hospitals with EMRs report non-profit ownership. Nearly three quarters of the hospitals with EMRs (n=352) report non-profit ownership, but more for profit hospitals than public hospitals report using EMRs, a trend inconsistent with the frequency of this type of ownership by profit status in the total hospital population. According to chi-square statistic for this table, the difference is significant at p<.001. This indicates that there is a significant difference in ownership for hospital EMR use when considering ownership. In other words, hospitals vary in EMR use in relationship to their type of ownership. Table 6 summarizes the teaching status of hospitals included in the study. Teaching status is defined as membership in COTH. Only 281 of the hospitals in this study are COTH members. Relative to this, they are more likely to have EMRs than other hospitals (n=55). Because the chi-square statistic is significant, the null hypothesis, that there is no difference in EMR use for hospitals relating to teaching status, is rejected.

This project also describes the location of hospitals in this study. Location includes both geographic region and state location. Hospitals in the South Atlantic division comprise the largest number of EMR users (n=88, 18.37%) followed by the East North Central (n=73, 15.24%). This is consistent with the largest total number of hospitals also existing in these areas. The smallest numbers of hospitals that use EMRs are in New England (n=15, 3.13%) and West North Central (n=34, 7.10%).

To consider that these differences may be due to the total number of hospitals in the region, the percentages are also included.

Table 7 describes the percentage of hospitals in each division that use EMRs. The highest percentage of hospitals in a region that use EMRs are in the East South Central (15.2%), the South Atlantic (12.7%), and the Mountain Region (12.1%). The smallest percentage of hospitals using EMRs in a region are West North Central (5.2%), New England (8.2%) and West South Central (9.00%). The average number of hospitals in a region using EMRs is 10.40%. According to the chi-square statistic, there is a significant difference between regions in the practice of hospital EMR use.

Table 8 displays hospital EMR use by state in the United States. By state, the largest number of hospitals with EMRs is California (n=43) followed by Texas (n=31), New York (n=29), and Illinios (n=28). Five states report no hospital EMR use. These states include Vermont, Connecticut, Delaware, Montana, and Nevada. Hawaii, Alaska, Maine and Wyoming each report one hospital that uses EMRs. The average for percent hospital EMR use in all states in 10.40%. Utah reports the greatest percentage of hospital EMR use with 43.6% of all hospitals reporting EMR use. Maryland, the District of Columbia, and New Mexico also report that greater than 20% of hospitals in their state use EMRs (26.1%, 25.0%, and 22.9% respectively). Excluding the five states that report no hospital EMR use, the states with the smallest percentage of hospital EMR use include Maine (2.78%) and Indiana (2.88%). Each of these statistics reveals geographic variation in EMR use.

Table 9 provides information regarding how EMRs are used in hospitals in areas of varying urban-ness. Hospitals in more urban areas report greater hospital EMR use. Hospitals in metro areas account for more than 40% of all hospital EMR use (n=201) while hospitals in rural areas account for only 1% of hospital EMR use (n=5). In metro areas, 14.0% of hospitals in use EMRs, while in rural areas, only 2.0% of hospitals report EMR use. On the continuum from most urban to most rural, the percent of hospitals using EMRs declines in most instances; however, there are a higher percentage of hospitals using EMRs in category 3 than category 2. Category 3 represents metro areas of fewer than 250,000 population while category 2 represents counties in metro areas of 250,000 to 1 million population (http://www.ers.usda.gov/Briefing/Rurality/RuralUrbCon). According to the chi-square statistic, there is a significant difference in hospital EMR use and urban-ness at the $p<.001$ level.

Tables 10 and 11 describe hospital EMR use and its relationship to hospital system affiliation. Table 10 displays system affiliation as a dichotomous measure. According to Table 10, 439 of the 479 hospitals with EMRs are system affiliated, thus indicating that only 40 hospitals with EMRs are not system affiliated. The chi-square statistic of this relationship is significant, indicating that there is a statistically significant difference. In non-system affiliated hospitals, only 1.88% report EMR use while 21.98% of system affiliated hospitals report EMR use. Because there is variation in the types of system, health system cluster codes allow for closer examination of hospital system affiliation and EMR use. According to Table 11, only 1.84% of hospitals with no identified system use EMRs. In centralized health systems, 32.87% of hospitals report EMR use. The smallest percentage of hospital EMR use by type of system for system-affiliated hospitals is in decentralized health systems (9.62%), which allow for greater management at the hospital level. The relationship between hospital EMR use and type of system affiliation is highly significant according to the chi-square statistic at the $p<.001$ level. Table 12 describes the continuous variables analyzing the determinants of EMR use. This analysis used logistic regression to examine the organizational and environmental factors associated with hospital EMR use. Table 12a provides the frequency, mean, and standard deviation of each variable for the total group as well as for the hospitals with and without EMRs. The mean bed size for the total group is 167.98, but the mean bed size for hospitals with EMRs is 229.02, and the mean bed size for hospitals without EMRs is 160.9. The public payer mix variable describes the amount of dependency a hospital has on public funds including Medicare and Medicaid. This variable is the number of Medicare and Medicaid inpatient days divided by the total number of inpatient days. Thus, the higher the number is, the greater a hospital's dependency on these public funds. For the total group of hospitals, the mean Public Payer Mix is 69.49%. The mean Public Payer Mix for hospitals without EMRs is 69.61%, and the mean Public Payer Mix for hospitals with EMRs is 68.41%. The mean per capita income in the market for all hospitals is $26,890.08. Hospitals without EMRs report a mean per capita income in the market of $26,718.40, and hospitals with EMRs report a mean per capita income in the market of $28,369.23. The mean change in unemployment from 2000 to 2004 for all hospitals is 1.58%. The mean change in unemployment from 2000 to 2004 for hospitals without EMRs is 1.55%. The mean change in unemployment from 2000 to 2004 for hospitals with EMRs is 1.82%. For all hospitals, the mean Herfindahl Index is .44. For hospitals without EMRs, the mean Herfindahl Index is .46. Hospitals with EMRs report a mean Herfindahl Index of .33. Finally, the mean operating margin ratio for all hospitals is -5%. Hospitals without EMRs have a mean operating margin ratio of -5%. Hospitals with EMRs have a mean operating margin ratio of -2%. To assess the statistical significance of the difference in means for the continuous variables included in this analysis, a one-way ANOVA was performed. The results of this analysis are presented in Table 12b. According to this F-statistics in this table, a statistically significant difference of means exists for the following variables: number of beds set up and staffed, per capita income, change in unemployment, and the Herfindahl Index. No statistically significant difference was detected in operating margin and public payer mix.

Table 13 describes the frequency, mean and standard deviation of the variables included in the DEA analysis. The input variables include the beds set up and staffed, non-labor expenses, capital assets, and full time equivalent (FTE) employees. Outputs include Case Mix Adjusted Admissions and Outpatient Visits.

The description of bed size was discussed in the previous chapter and thus will not be presented here. The mean non-labor expenses for the total group of hospitals are $47,916,962.40. The mean non-labor expenses for hospitals with and without EMRs are $72,294,760.20 and $45,087,554.80 respectively. For all hospitals, the mean index of capital assets is 9.48 out of a possible 36 total points on the capital asset index presented in Chapter 4. A higher capital asset score indicates that the hospital offers more of the included services and thus has more capital assets. Hospitals without EMRs have a mean capital asset index of 9.38 and hospitals with EMRs have a mean index of capitals assets of 10.67. The mean number of FTEs for all hospitals is 839.64 while the mean number of FTEs for hospitals without EMRs is 794.92 and the mean number of FTEs for hospitals with EMRs is 1224.96. The mean number of case mix adjusted admissions for all hospitals is 10,941.47. Hospitals without EMRs have a mean case mix adjusted admissions of 10,270.49. Hospitals with EMRs have a mean case mix adjusted admissions of 16,722.54. The case mix index is described in Table 13. Values range from .45 to 2.63 with a mean value of 1.27. Admissions are also described in Table 13. The mean number of outpatient visits for all hospitals is 118,796.06. The mean number of outpatient visits for hospitals without EMRs is 115,018.38 while the mean number of outpatient visits for hospitals with EMRs is 151,344.12. To determine the statistical significance of the relationship in these variables between the group of hospitals with EMRs and the group of hospitals without EMRs, a one-way ANOVA was performed. The results of this analysis are presented in Table 13. According to the F statistic, each of the DEA input and output variables has a statistically significant difference in means for hospitals with and without EMRs at the p<..001 level.

Table 14 describes the year of EMR adoption for hospitals that use EMRs. This information comes from the HIMSS database, but in some instances, these values are missing. Three hundred and sixty one hospitals have reported their contract year. The years range from 1983 to 2004. The most frequent year given for EMR contract is 2002, when 67 hospitals contracted EMRs. 2002 is followed by 1998 and 2001 as the most frequently given years of EMR contract with 66 and 57 hospitals, respectively, reporting these as their dates of EMR contract. Since it is unlikely that only 3 hospitals began using EMRs in 2004, it is possible that the hospitals that have implemented at this time have not yet reported their EMR use in these data. Or, it may be the case that the hospitals that did not report a year of EMR implementation have implemented EMRs in recent years (2003 or 2004).

Missing Values

There were some missing values in the data used in this study. The variables with missing data include year of EMR contract, case mix index, and operating margin ratio. Because there is no reliable way to estimate year of EMR contract, the cases that had missing values for this variable were excluded from the analyses in part two (Windows Analysis of change in efficiency over time). This excluded 118 hospitals from the analysis. Since 1,226 hospitals were missing values for case mix index, several regression equations were attempted without success to estimate the missing values. The reason that this approach did not work is that there was not a strong enough model or correlation with any of the variables to allow for an accurate prediction of values. Because of this, the missing case mix index values were substituted with the average CMI value for all hospitals with exactly the same number of beds. For operating margin ratio, 2,809 hospitals had not yet submitted their CMS financial data from 2004, so the value they reported for 2003 was used as a substitute. For the remaining hospitals, a regression was attempted to use total expenses, capital assets, rurality, and size as predictors, but none of these variables was strongly correlated with operating margin to provide a reliable estimation. Three hundred hospitals did not have values in 2003 or in 2004. These 300 hospitals' missing values were replaced with the mean value of similar hospitals stratified by ownership and number of beds.

Correlation Analysis

Bivariate correlation analyses were performed to test for possible multicollinearity in the independent variables. The table providing these correlations is available in Appendix A. This analysis revealed overall low and moderate correlations between the independent variables. Four variables have correlations greater than +- .60. The correlation between non-profit and public ownership is .698 ($p<.01$). These two variables represent a design variable coding scheme that distinguishes hospital ownership into three categories: public, non-profit, and for-profit. Since the for-profit group serves as the reference group, and the three categories are mutually exclusive, it is expected that they may be moderately correlated. The other two variables that are correlated greater than .60 are the Herfindahl Index and the Urban 1 group, which represents the most urban hospital surroundings. Again, this correlation is not surprising since areas that are densely populated according to the rural urban continuum code are also likely to be areas of greater competition since there will be more resources (patients, payers) available in such an environment. Since neither of these correlations is greater than .70, they were left in the model to test for the corresponding hypotheses. Each of the other correlations among the independent variables is less than .60.

Logistic Regression

The first analysis of hospital correlates examines the organizational and environmental factors associated with hospital EMR use in 2004. The dichotomous outcome variable is EMR use. According to the HIMSS data and definition used in this analysis, 479 of the 4,606 hospitals included in this analysis use EMRs. Logistic regression was performed to determine the relationship between EMR use and the independent variables. Logistic regression also provides information about the model's ability to predict the correct outcome variable value for hospitals based on the predictors in the model in the classification tables.

According to the logistic regression, fourteen variables had significant p values. Overall the model was significant with a chi-square statistic of 467.87

(p<.001). The -2 log likelihood is 2606.847. Table 15 shows the classification rate and reveals that the model is correctly predicts hospital EMR use in 89.6% of cases.

Table 15: Determinants of EMR Use

	B	Exp(B)	95.0% C.I. for EXP(B)	
Variables			Lower	Upper
Bed Size	0.001*	1.001	1.000	1.001
Teaching Status	-0.160	0.852	0.562	1.291
Public Payer Mix	-0.045	0.956	0.420	2.176
Per Capita Income	0	1	1	1
Unemployment Change 2000-2004	0.106*	1.111	1.020	1.211
Operating Margin Ratio	0.030	1.03	0.860	1.233
Non-profit	0.134	1.143	0.829	1.576
Public	-0.090	0.913	0.603	1.383
Centralized System	2.791***	16.302	10.803	24.599
Centralized Physician System	2.553***	12.84	8.177	20.162
Moderately Centralized System	2.328***	10.256	7.356	14.299
Decentralized System	1.428***	4.171	2.907	5.983
Independent System	2.309***	10.065	6.441	15.728
Herfindahl Index	0.129	1.138	0.731	1.771
URBAN 1	1.092*	2.98	1.067	8.323
URBAN 2	1.017*	2.766	1.003	7.629
URBAN 3	1.371**	3.938	1.470	10.548
URBAN 4	1.157*	3.18	1.177	8.589
URBAN 5	0.887	2.429	0.793	7.437
URBAN 6	1.079*	2.941	1.126	7.686
URBAN 7	1.298**	3.661	1.381	9.700
URBAN 8	1.233*	3.431	1.103	10.678
Constant	-4.661***	0.009		
-2 Log-Likelihood = 2606.85 Goodness of Fit Statistics Chi-Square (22 df) = 467.87 (p=0.00) Correct Classification Rate = 89.6%				

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

Five variables in this analysis are significant at the p<..001 level. Each of these variables represented a different type of system affiliation and included: centralized health system, centralized physician insurance system, moderately centralized health system, decentralized health system, and independent system. Each of these variables is a design variable representing type of health system affiliation and providing a comparison against the reference group of hospitals with no identified system affiliation. The odds ratio for these variables support, in all categories except for independent systems, the hypothesis that as health system centralization increases, so does the likelihood of EMR use. As Table 15 shows, hospitals in centralized health systems are more than sixteen times as likely as hospitals not in systems to use EMRs. The only exception to the hypothesis is that hospitals in decentralized systems are not more likely than hospitals in independent systems to use EMRs.

At the p<.05 level, nine variables are significant predictors of hospital EMR use: bed size, change in unemployment (environmental uncertainty), and urban-ness. Bed size is a significant predictor (p=.032) and supports the hypothesis that larger hospitals are more likely to use EMRs. As revealed by in Table 15, larger hospitals are slightly more likely than smaller hospitals to use EMRs (Beta=.001, p<.05). Change in unemployment from 2000 to 2004 represents environmental uncertainty and is a significant predictor of hospital EMR use (p<.05). As the amount of change in unemployment rates increases, the likelihood of hospital EMR use also increases supporting the hypothesis that an increase in environmental uncertainty also increases the likelihood of hospital EMR use. According to the odds ratio in Table 15, hospitals with each unit increase of change in unemployment are 1.11 times more likely to use EMRs. Urban-ness is also a significant predictor of EMR use. In this analysis, the most rural group serves as the reference group, and urban 1 is the most urban group with a continuum of levels of urban-ness between these groups. According to the p-values, each of the levels of urban-ness is significantly different than the most rural group except for urban 5. However, as the odds ratio displays, the most urban are more likely than the most rural groups to use EMRs in hospitals, but they are not more likely to use EMRs than some of the other more rural groups such as urban 3, urban 4, urban 7 and urban 8 when compared to the most rural group. For example, the most urban group is almost three times more likely than the most rural group to have hospitals using EMRs (2.9), but hospitals in Urban 3 areas are 3.9 times more likely than the most rural hospitals to use EMRs. Teaching status, public payer mix, per capita income, operating margin, non-profit or public ownership, and competition, as measured through the Herfindahl Index were not significant predictors of hospital EMR use. However, since the model itself is significant, the non-significant variables were included in the analysis as control variables. These control variables serve as measures of factors that could indirectly affect the hospitals' behavior, thus also reducing the chance of a confounding influence.

Quality Analysis

Hospital quality scores are calculated by coding ten different measures dichotomously to represent hospitals that performed at or above the national average on each measure with a 1 and hospitals that performed below the national average as a 0. Since hospitals varied in the number of measures reported, each of theses values was added together and divided by the number of measures for which the hospital reported scores. The mean of these quality scores is .69; thus, hospitals that scored at or above this mean were coded as high quality while those hospitals scoring below .69 were coded as performing with low quality. From this point, these dichotomous values to serve as the outcome variable of a logistic regression equation. The purpose of dichotomizing the quality measure is to allow for the clear identification of hospitals as high and low quality performers. Additionally, these measures of quality are new and did not prove to be as sensitive to this analysis as expected when included in an OLS regression. The dichotomization of this variable allows for the relationship to be better examined with this measure, and future sets of these data contain more responses and measures, which may increase the sensitivity of the measures. The selection of logistic regression for this analysis is the result of a lack of sensitivity in the data, which allows this study to examine the relationship between EMR use and quality. The mean, frequency, and standard deviation of the hospital quality scores are presented in Table 16. According to these descriptive statistics, 2,543 hospitals do not have electronic medical records and report a mean

Table 16: Raw Quality Score Frequency and Mean

EMR Use	N	Mean Quality Score	Standard Deviation	% of Total N
No EMRs	2543	.68	.26	88.0%
EMRs	348	.74	.23	12.0%
Total	2891	.69	.26	100.0%
Chi-square(32d.f.)=57.86 (p<.01)				

quality score of .68 compared with the 348 hospitals that do use EMRs and report a mean quality score of .74. Combined, these hospitals report a mean quality score of 0.69. According to the chi-square statistic in this analysis, there is a significant difference between means at the p<.01 level. Table 17 shows that 1,194 hospitals perform below the 50th percentile in quality. One hundred nine of these lower performers in quality have EMRs. 1,697 hospitals perform above the 50th percentile in the area of quality; of these 239 use EMRs. This analysis reveals a chi-square statistic that is significant at the p<.001 level, indicating that there is a difference in mean quality performance of hospitals based on EMR use. Additional information about the range and frequency of the raw quality scores is provided in Appendix B.

Table 17: Coded Quality Score Frequency

	No EMRs	EMRs	Total
Low Quality	1085 (42.67%)	109 (31.32%)	1194 (41.30%)
High Quality	1458 (57.33%)	239 (68.68%)	1697 (58.70%)
Total	2543 (100.0%)	348 (100.00%)	2891 (100.0%)
Chi-square(1d.f.)=16.25 (p<.001)			

The results of this logistic regression are presented in Table 18. Logistic regression was used to determine the direct relationship between EMR use and high and low quality performance parsimoniously. By coding the quality variable to identify hospitals as high or low performers, the model allows for the identification of an association between EMR use and quality performance in a simple way as there are no middle ground performers. The model is significant at the p<.001 level. The -2 log likelihood is 3601.85. The model correctly predicts high or low performance in quality 64.3% of the time. The purpose of this logistic regression is

Table 18: Predictors of Quality

	B	Exp(B)	95.0% C.I. for EXP(B)	
Variables			Lower	Upper
EMR Use	0.334*	1.397	1.072	1.819
System Member	0.110	1.116	0.934	1.334
Case Mix Index	1.649***	5.202	3.243	8.345
Non-profit Ownership	0.781***	2.183	1.724	2.764
Public Ownership	0.518**	1.679	1.248	2.259
Teaching Status	-0.472*	0.624	0.417	0.932
Per Capita Income/100	.003***	1.003	1.001	1.004
Change in Unemployment	.067	1.070	0.997	1.148
Herfindahl Index	0.074	1.077	0.849	1.367
Beds Set up and Staffed/100	-0.005	0.995	0.932	1.062
Public Payer Mix	-.865**	0.421	0.223	0.796
Constant	-1.847**	0.158		
-2 Log Likelihood =3601.85 *Goodness of Fit Statistics* *Chi-Square (11 df) = 317.97 (p=0.00)* *Correct Classification Rate = 64.30%*				

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

to determine if hospitals with EMRs provide better quality care than hospitals without EMRs while also controlling for other potentially confounding factors such as bed size, case mix index, system affiliation, ownership, competition, environmental uncertainty, and teaching status. In the first run of this model, the coefficient values for bed size and per capita income were zero, which is difficult to interpret and is likely the result of a large range of values in this measure, relative to the values of the dependent variable. To prevent the coefficient value of zero for bed size and per capita income based on a large range of values for these measures, the number of beds and per capita income was divided by 100 to allow for a more meaningful analysis. Several other models were attempted to also control for other hospital characteristics including operating margin ratio, type of system affiliation, and rurality, but these variables were statistically insignificant and the inclusion of these additional variables led to a weaker model. Thus, the model presented here was used. Seven variables in this equation are significantly correlated with the outcome measure of high or low quality performance at the $p<.05$ level. Significant predictors of hospital quality include EMR Use, teaching status, ownership, per capita income, public payer mix, and case mix index. Because the odds ratio for EMR use is 1.397, hospitals with EMRs are 1.397 times more likely to have quality performance scores in the high range than hospitals without EMRs. The results of this analysis therefore support the hypothesis that hospital EMR use is associated with high quality performance. As Table 18 shows, the odds ratio for teaching status is 0.624 revealing that teaching hospitals are less likely to provide high quality care than non-teaching hospitals ($p<.01$). Ownership is also a significant predictor of quality. Both public and non-profit hospitals are more likely than for-profit hospitals to be high quality performers. Non-profit hospitals are more than two times as likely to be high quality performers as for-profit hospitals (Exp(B)=2.183, $p<.001$), and public hospitals are more than one and a half times more likely to be high quality performers than for-profit hospitals (Exp(B)=1.679, $p<.01$). Case mix index is one of the strongest predictors of hospital quality performance ($p<.001$). Hospitals with higher case mix indexes are more likely to be high quality performing hospitals according to this analysis. Per capita income increases the likelihood of hospital quality performance, and a higher public payer mix decreases the likelihood of hospital quality performance. The bed size variable, while included to control for hospital size, is insignificant. System membership is also not a significant predictor of quality for hospitals, despite the strong correlation between hospital EMR use and type of system affiliation. Environmental uncertainty and competition, measured through the change in unemployment from 2000 to 2004 and the Herfindahl index, respectively, are not significant predictors of hospital quality.

Efficiency Analysis

DEA scores were calculated using an input-oriented, constant returns to scale model and measure hospital efficiency. As mentioned previously in this chapter, the descriptive information about the input variables and output variables are summarized in Table 19. The DEA efficiency analysis involved three groups created based on bed size. The groups include small, medium, and large hospitals as size grouped DEA scores tend to be more stable. As presented in Chapter 4, small hospitals are those with 0-100 beds. Medium hospitals are those with 101-349 beds. Large hospitals are those with 350 or more beds. The DEA scores represent hospital efficiency levels, with a one being a score of perfect relative efficiency. The mean, frequency, and standard deviation of efficiency scores for hospitals by size group are summarized in Table 19. According to this table, large hospitals have a higher mean efficiency score, followed by medium hospitals and then small hospitals.

Table 19: Mean Efficiency Scores by Hospital Size and EMR Use

No EMRs	N	Mean DEA Score	Std. Deviation
Small (0-100 beds)	2044	0.25472	0.148560
Medium (101-349 beds)	1608	0.55423	0.159573
Large (>350 beds)	475	0.59307	0.138954
Total	4127	0.41036	0.216733
EMRs			
Small	157	0.29623	0.170739
Medium	229	0.59437	0.149934
Large	93	0.60598	0.144150
Total	479	0.49890	0.210533
Total			
Small	2201	0.25769	0.150587
Medium	1837	0.55923	0.158919
Large	568	0.59518	0.139770
Total	4606	0.41957	0.217758
F(1d.f.)=961.98 p<.001			

The DEA scores were then transformed into dichotomous values representing efficient hospitals and inefficient hospitals. Efficient hospitals were identified by having a DEA score at the 75th percentile for the corresponding size group. Since a score of one indicates efficiency, these hospitals are perfectly relatively efficient; however, very few hospitals received a perfect DEA score, thus not allowing for adequate statistical power to examine the relationship between EMR use and efficiency. For this reason, hospitals in the top one quarter of efficiency scores were identified as efficiency since they were the closest to the efficiency frontier and were the top relative performers in efficiency. The 75th percentile DEA scores are .29 for the small sized hospitals, .65 for the medium hospitals, and .66 for the large hospitals. An ANOVA analysis revealed a significant difference in the groups by size and EMR use with an F statistic of 961.98. This analysis resulted in 550 efficient hospitals and 1,651 inefficient hospitals in the small group, 459 efficient hospitals and 1,378 inefficient hospitals in the medium group, and 299 efficient hospitals and 269 inefficient hospitals in the large group. These coding of efficiency performance and their frequency can be found in Table 20. In this table, the percentage of hospitals with and without EMRs in each category are presented. For small hospitals, 33.80% of the hospitals with EMRs are efficient, compared with only 24.30% of hospitals without EMRs. Likewise, in medium hospitals, a higher percentage with EMRs (34.10%) are efficient than the corresponding percentage of efficient hospitals without EMRs (23.70%). Finally, the same is true for large

Table 20: Frequency of Efficient/Inefficient Performance by Hospital Size and EMR Use

Small Size	Inefficient	Efficient	Total
No EMRs	1547 (75.70%)	497 (24.30%)	2044 (100.00%)
% of Total	70.30%	22.60%	92.90%
EMRs	104 (66.20%)	53 (33.80%)	157 (100.00%)
% of Total	4.70%	2.40%	7.10%
Total	1651	550	2201
% of Total	75.00%	25.00%	100.00%
Chi-square(1 d.f.)=6.94 (p<.01)			

Medium Size	Inefficient	Efficient	Total
No EMR	1227 (76.30%)	381 (23.70%)	1608 (100.00%)
% of Total	66.80%	20.70%	87.50%
EMRs	151 (65.90%)	78 (34.10%)	229 (100.00%)
% of Total	8.20%	4.20%	12.50%
Total	1378	459	1837
% of Total	75.00%	25.00%	100.00%
Chi-square(1d.f.)=11.49 (p<.01)			

Large Size	Inefficient	Efficient	Total
No EMRs	227 (47.80%)	248 (52.20%)	475 (100.00%)
% of Total	40.00%	43.70%	83.60%
EMRs	42 (45.20%)	51 (54.80%)	93 (100.00%)
% of Total	7.40%	9.00%	16.40%
Total	269	299	568
% of Total	47.40%	52.60%	100.00%
Chi-square(1d.f.)=.215 (p>.05)			

hospitals, but without as much of a difference. Nearly 55% of large hospitals with EMRs (54.80%) are efficient while 52.20% of large hospitals without EMR are efficient. In each size group, a larger percentage of hospitals with EMRs are efficient compared to hospitals without EMRs. The chi-square statistics for these analyses reveal a significant difference in efficiency and EMR use for small and medium size hospitals (chi-square=6.94 and 11.49 respectively), but no difference in efficiency and EMR use was detected for the large hospitals (chi-square=.215). The results of the corresponding logistic regression analyses are summarized in Tables 21, 22, and 23. Each of these logistic regression analyses predicts whether a hospital is efficient or not to determine the relationship between EMR use and efficiency while controlling for other variables including teaching status, ownership, system membership, and the number of beds set up and staffed. The analyses include three different sizes of hospitals for the stability of the estimates associated with DEA, a relative efficiency technique.

Table 21: Determinants of Efficiency for Small Sized Hospitals

	B	Exp(B)	95.0% C.I. for EXP(B)	
Variables			Lower	Upper
EMR Use	0.546**	1.727	1.200	2.486
Teaching Status	-1.148	0.317	0.020	5.127
Non Profit Ownership	-0.048	0.954	0.708	1.285
Public Ownership	-0.003	0.997	0.719	1.382
System Membership	-0.04	0.961	0.774	1.193
Beds Set up and staffed	-0.007***	0.993	0.989	0.997
Constant	1.543	4.678		
-2 Log Likelihood = 2542.95 *Goodness of Fit Statistic* *Chi-Square (6 df) = 21.90 (p=.001)* *Correct Classification Rate = 75.1%*				

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

Table 22: Determinants of Efficiency for Medium Sized Hospitals

	B	Exp(B)	95.0% C.I. for EXP(B)	
Variables			Lower	Upper
EMR Use	0.290	1.336	0.977	1.828
Teaching Status	-0.361	0.697	0.392	1.240
Non Profit Ownership	0.113	1.120	0.840	1.492
Public Ownership	-0.493*	0.611	0.391	0.954
System Membership	0.443**	1.558	1.213	2
Beds Set Up and Staffed	0.004***	1.004	1.002	1.005
Constant	-1.478*	0.228		
-2 Log-Likelihood = 1997.65 *Goodness of Fit Statistics* *Chi-Square (6 df) = 67.82 (p=0.00)* *Correct Classification Rate = 75.1%*				

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

Table 23: Determinants of Efficiency for Large Sized Hospitals

	B	Exp(B)	95.0% C.I. for EXP(B)	
Variables			Lower	Upper
EMR Use	0.132	1.141	0.709	1.835
Teaching Status	-0.152	0.859	0.595	1.239
Non Profit Ownership	-1.034**	0.356	0.172	0.734
Public Ownership	-1.583***	0.205	0.086	0.493
System Membership	0.155	1.167	0.797	1.711
Beds Set up and Staffed	0	1	0.999	1.001
Constant	1.239*	3.452		
-2 Log-Likelihood = 767.85 *Goodness of Fit Statistics* *Chi-Square (6 df) = 17.98 (p=0.006)* *Correct Classification Rate =57.0%*				

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

The analysis of the small hospitals is summarized in Table 21. The model is significant at the p<.001 level. The -2 log likelihood is 2,453.95. The model correctly predicts efficient performance in 75.1% of hospitals. Two variables are significantly correlated with hospital efficiency in the small group: EMR use (p<.01) and the number of beds set up and staffed (p<.001). The odds ratio of the EMR use variable indicate that hospitals with EMRs are 1.727 times more likely to be efficient than those hospitals without EMRs.

The analysis of medium hospitals is summarized in Table 22. This model is significant at the p<.001 level. The -2 log likelihood is 1997.65, and the model accurately predicts efficiency performance in 75.1% of hospitals. Three variables are significantly related to efficiency including public ownership, system membership, and the number of beds set up and staffed. The odds ratio of the public ownership variable indicate that hospitals that are publicly owned medium hospitals are less likely to be efficient than medium hospitals that are for profit (odds ratio=.611). System members of the medium hospital are more likely to be efficient than medium size non-system members (odds ratio=1.558).

Finally, the analysis of large hospitals' efficiency is presented in Table 23. This model is significant (p<.001), and the -2 log likelihood is 767.85. The model accurately predicts large hospital efficiency performance 57% of the time. Two variables are statistically significant: non-profit ownership and public ownership.

Non-profit large hospitals and public large hospitals are less likely than for-profit large hospitals to be efficient (odds ratio=.356 and .205 respectively). EMR use is not a statistically significant predictor of efficiency for large hospitals (p=.588). Teaching status, bed size, and system membership do not appear to influence large hospital efficiency as displayed in this analysis.

Change in Efficiency Over Time

Windows Analysis

Windows analysis is one DEA strategy used in this study to examine the relationship between hospital EMR use and the change in efficiency over time. Windows analysis involves the calculation of DEA scores for DMUs in two or more periods while combining the two periods to create one efficiency frontier. In this study, the two periods included are 2001 and 2004. Only hospitals that existed in both years and were consistent in EMR use in 2001 and 2004 are included, yielding a sample of 4,167. Again the DEA analyses were conducted to three separate size groups of hospitals. Once the DEA scores were calculated for 2001 and 2004, the change in efficiency was calculated by subtracting the 2001 efficiency score from the 2004 efficiency score. The descriptive information of mean and standard deviation of these scores by size groups are in Table 24. According to this table, in small hospitals without EMRs, the mean change in efficiency is negative indicating a decrease in efficiency. Medium hospitals without EMRs increased efficiency slightly (.01), and large hospitals without EMRs remained relatively the same in

Table 24: Descriptive Analysis of Efficiency by Hospital Size and Time Window

No EMRs		2001 Score	2004 Score	Change in Efficiency (Windows Score)
Small	N	1922	1922	1922
	Mean	0.3761	0.3752	-0.0009
	Std. Deviation	0.15502	0.16373	0.15406
Medium	N	1574	1574	1574
	Mean	0.4938	0.5097	0.0159
	Std. Deviation	0.14797	0.16213	0.21514
Large	N	462	462	462
	Mean	0.5612	0.5631	0.0019
	Std. Deviation	0.12624	0.1329	0.10918
Total	N	3958	3958	3958
	Mean	0.4445	0.4506	0.0061
	Std. Deviation	0.16449	0.17651	0.17713
EMRs		2001 Score	2004 Score	Change in Ef
Small	N	70	70	70
	Mean	0.442	0.4515	0.0095
	Std. Deviation	0.15614	0.17035	0.16594
Medium	N	98	98	98
	Mean	0.5081	0.5317	0.0236
	Std. Deviation	0.1441	0.14524	0.18329
Large	N	41	41	41
	Mean	0.5648	0.5596	-0.0053
	Std. Deviation	0.12481	0.11987	0.12301
Total	N	209	209	209
	Mean	0.4971	0.5103	0.0132
	Std. Deviation	0.15083	0.15519	0.16683
F(5d.f.)=1.86 (p>.05)				

efficiency with a windows score of .0019. For all hospitals without EMRs, the mean difference between the 2004 and 2001 efficiency indicates only a very slight change in efficiency (.0061). An ANOVA was performed to determine the statistical significance among the hospital groups based on EMR use and size, but no relationship was found (F(5d.f)=1.86). For hospitals with EMRs, a larger change in efficiency is present; Table 25 indicates that hospitals with EMRs increased in efficiency (.0132). Small hospitals with EMRs did not change very much inefficiency. Medium hospitals with EMRs increased in efficiency by .0236. Large hospitals with EMRs decreased slightly in efficiency from 2001 to 2004 (-.0053). Once the change in efficiency scores were calculated, these values were transformed into a design variable using the zero as a threshold since hospitals that have increased in efficiency would have a positive score, and hospitals that decreased in efficiency would have a negative score. The frequency of increased and decreased efficiency by time and by size group are provided in Table 25. In small size group, 54.30% of hospitals with EMRs increased in efficiency compared with 46.00% of hospitals without EMRs. In the medium size group, only half of the hospitals with EMRs (50.00%) increased in efficiency while 53.20% of hospitals without EMRs increased in efficiency. In the large size group, 56.10% of hospitals with EMRs increased in efficiency compared to 49.40% of hospitals without EMRs. However, the chi-square statistics for each of these size-based groups did not reveal any significant relationship in change in efficiency over time.

Table 25: Frequency of Increased/Decreased Efficiency by Hospital Size in Time

Small Size	Decreased Efficiency	Increased Efficiency	Total
No EMRs	1038 (54.00%)	884 (46.00%)	1922 (100.00%)
% of Total	52.10%	44.40%	96.50%
EMRs	32 (45.70%)	38 (54.30%)	70 (100.00%)
% of Total	1.60%	1.90%	3.50%
Total	1070	922	1992
% of Total	53.70%	46.30%	100.00%
Chi-square(1d.f.)=1.868 (p>.05)			
Medium Size	Decreased Efficiency	Increased Efficiency	Total
No EMRs	737 (46.80%)	837 (53.20%)	1574 (100.00%0
% of Total	44.08%	50.06%	94.14%
EMRs	49 (50.00%)	49 (50.00%)	98 (100.00%)
% of Total	2.90%	2.90%	5.90%
Total	786	886	1672
% Total	47.00%	53.00%	100.00%
Chi-square(1d.f.)=.374 (p>.05)			
Large Size	Decreased Efficiency	Increased Efficiency	Total
No EMRs	234 (50.60%)	228 (49.40%)	462 (100.00%)
% of Total	46.50%	45.30%	91.80%
EMRs	18 (43.90%)	23 (56.10%)	41 (100.00%)
% of Total	3.60%	4.60%	8.20%
Count	252	251	503
% of Total	50.10%	49.90%	100.00%
Chi-square(1 d.f.)=.686 (p>.05)			

To determine if a relationship exists between change in efficiency over time and hospital EMR use, a logistic regression equation was used to control for hospital bed size, ownership, case mix index, teaching status, and system affiliation. The dependent variable in this analysis is the dichotomously coded windows score, which represents the first difference or change in efficiency for hospitals that were consistent in their EMR use in 2001 and 2004.

Three separate logistic regressions were run to control for the fact that the DEA scores were run in groups based on hospital bed size. The groups include small, medium, and large sized hospitals. While each of the models was significant, EMR use was not a statistically significant predictor of change in efficiency for any of the groups. The results of these logistic regression models indicate significant predicates of change in efficiency over time and are presented below in Tables 26, 27, and 28. It is interesting to note that the classification rates for each of these three models is poor; the small size model correctly predicts only 45.6% of the hospitals' change in efficiency while the medium and large size groups predict slightly more hospitals' change in efficiency performance correctly (58.3% and 55.1% respectively). The hypothesis 13, which predicts that hospitals that used EMRs in 2001 and 2004 will increase their efficiency over time more than hospitals that did not use EMRs in either 2001 nor in 2004, is not supported. Essentially, hospital EMR Use did not improve efficiency over time for hospitals any more than the hospitals that did not have EMRs during this period. Unlike in the preliminary efficiency analysis, which found small hospitals with EMRs to be more efficient than those without EMRs, no such differences were found here. Possible explanations for the lack of support for this hypothesis are presented in Chapter 6 along with discussion.

Table 26: Predicates of Change in Efficiency for Small Size Hospitals

	B	Exp(B)	95.0% C.I. for EXP(B)	
Variables			Lower	Upper
Non-profit	0.279	1.322	0.983	1.777
Public	0.247	1.281	0.929	1.765
EMR Use	0.383	1.467	0.892	2.415
Bed Size	-0.004*	0.996	0.992	1
System Membership	0.065	1.067	0.877	1.298
Case Mix Index	2.169***	8.752	3.839	19.952
Constant	-2.612***	0.073		
-2 Log Likelihood = 2715.39 *Goodness of Fit Statistic* *Chi-Square (6 df) = 35.10 (p=0.00)* *Correct Classification Rate = 45.6%*				

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

Table 27: Predicates of Change in Efficiency for Medium Size Hospitals

	B	Exp(B)	95.0% C.I. for EXP(B)	
Variables			Lower	Upper
Non-profit	-0.016	0.984	0.753	1.286
Public	0.138	1.148	0.795	1.657
EMR Use	-0.052	0.95	0.621	1.452
Bed Size	0.001	1.001	0.999	1.003
System Membership	-0.287*	0.75	0.601	0.937
Case Mix Index	-2.002***	0.135	0.075	0.243
Constant	2.809***	16.599		
-2 Log Likelihood = 2236.91 *Goodness of Fit Statistics* *Chi-Square (6 df)=74.00 (p=0.00)* *Correct Classification Rate = 58.3%*				

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

Table 28: Predicates of Change in Efficiency for Large Size Hospitals

	B	Exp(B)	95.0% C.I. for EXP(B)	
Variables			Lower	Upper
Non-profit	-0.202	0.817	0.417	1.600
Public	0.152	1.165	0.502	2.702
EMR Use	0.211	1.235	0.626	2.437
Bed Size	0	1	0.999	1.001
System Membership	0.181	1.199	0.804	1.787
Case Mix Index	1.555***	4.737	1.973	11.369
Constant	-2.402**	0.091		

-2 Log Likelihood = 680.98
Goodness of Fit Statistic
Chi-Square (6 df) = 16.32 (p=0.012)
Correct Classification Rate = 55.1%

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

Endogeneity Analysis

To test for possible endogeneity between EMR use and quality and efficiency, the Hausman Specification Test was performed. To complete this test, instrumental variables that are correlated with the independent variable and the dependent variable, but not the error term are required. For this reason, the following variables were used: Number of outpatient surgical operations, number of Medicaid inpatient days, and number of operating rooms. Each of these variables is strongly correlated (p<.001) with the respective potentially endogenous variable to avoid the use of weak instruments. However, even with a weaker instrumental variable, estimation can still be precise with large samples (www.columbia.edu/~aj2319/teaching/G4075_Outline/node 9.html). The number of outpatient surgical operations is correlated with hospital EMR use and with quality and is thus used to test for endogeneity relating to quality and EMR use. It is likely that in hospitals where the surgical procedures are performed frequently, the quality may be better because the staff is more experienced. For this reason, the error term would likely not be correlated with the number of procedures since the relationship between number of procedures and quality is likely the result of frequency of procedure. For small hospital efficiency, the number of Medicaid inpatient days is used as an instrumental variable and is correlated with small hospital efficiency and EMR use. It was selected because hospitals that have a greater number of Medicaid inpatient days are likely more efficient since they are reimbursed at an amount less than other payers and must be efficient in order to accommodate for this. The number of operating rooms is used as an instrument for both medium and large hospital efficiency, but the endogeneity of these relationships are tested in two separate equations. The number of operating rooms is correlated with EMR use and the efficiency of both medium and large hospitals. This relationship likely exists because efficiency is a relationship between inputs and outputs; the number of operating rooms represents an input and is related to efficiency because hospitals that have more operating rooms can likely also produce more outputs than hospitals that have fewer operating rooms. Table 29 provides a list of the instrumental variables used and the correlations that exist to qualify these variables as instruments.

Table 29: Instrumental Variables for Endogeneity Testing

Instrumental Variable	Potentially Endogenous Variable	Correlation with Endogenous Variable	Significance	Correlation with EMR Use	Significance
Number of Surgical Operations (Outpatient)	Quality	0.222	0.00	0.96	0.00
Number of Medicaid Inpatient Days	Small Group Efficiency Score	0.164	0.00	0.075	0.00
Number of Operating Rooms	Medium Group Efficiency Score	0.262	0.00	0.133	0.00
Number of Operating Rooms	Large Group Efficiency Score	0.167	0.00	0.133	0.00

Each of the variables in Table 29 was regressed against the potentially endogenous variable and then the residuals of that regression were added to the logistic regression equation to determine if the relationship was endogenous. If the residual variable was significant and not equal to zero, the relationship was determined to be endogenous. The following equations were used:

EMR Use = quality + residual value of regressing number of outpatient surgical operations on quality

EMR Use = Small Group DEA Score + residual value of correlation between small group DEA score on the number of Medicaid Inpatient Days

EMR Use = Medium Group DEA Score + residual value of correlation between medium group DEA score and the number of operating rooms

EMR Use = Large Group DEA Score + residual value of correlation between large group DEA score and the number of operating rooms

In each of these individual analyses, the significance of the instrumental variable residual was not significant at p>.05, thus indicating that there is no difference in the estimates when regressed with the residuals. Thus, it is possible to conclude that these relationships are not endogenous. The results of this analysis are presented in Table 30.

Table 30: Results of Hausman Specification Test for Endogeneity

Instrumental Variable Residual	Coefficient with EMR Use	Significance
Number of Outpatient Surgical Operations	0.8411	0.190
Number of Medicaid Inpatient Days	1.041	0.762
Number of Operating Rooms	1.048	0.479
Number of Operating Rooms	1.022	0.867

Classification of Hospital Performance and EMR Use

Beyond the hypothesis testing of this study, the opportunity exists to examine hospital EMR use and performance further. This portion of the study is an additional exploratory analysis examining EMR use and performance, considering both efficiency and quality. Furthermore, this analysis is related to the conceptual model because Donabedian's structure, process, outcome framework emphasizes the interrelationship between hospital structure, process, and outcome. However, because EMR use is a fairly new area of research, and the quality measures used in this study are also new, there is little previous research to guide the specific development of hypotheses relating to this classification scheme. For this reason, it is an ad hoc exploratory analysis.

To determine the high and low performing hospitals, four categories were created using the quality scores and efficiency scores. High performing hospitals are those that scored in the highest range for both efficiency and quality. Middle ground performers are those that are high in either efficiency or quality. Low performing hospitals are those that are performing low in both efficiency and quality. Table 31 provides a description of the frequency of hospitals in each of the performance categories. Table 32 provides information about the frequency of EMR use in each hospital performance category and reveals a significant difference according to the chi-square at the $p<.001$ level.

Table 31: Hospital Performance Categories

Efficiency	Quality	
	Low	High
High	305 total hospitals (10.5%)	578 total hospitals (20.0%)
Low	889 total hospitals (30.8%)	1,119 total hospitals (38.7%)

Table 32: Hospital Performance Categories and EMR Use

Efficiency	Quality	
	Low	High
High	270 hospitals without EMRs (10.6%), 35 hospitals with EMRs (10.17%)	485 hospitals without EMRs (20.0%),93 hospitals with EMRs (26.7%)
Low	815 hospitals without EMRs (32.0%), 74 hospitals with EMRs (21.3%)	973 hospitals without EMRs (348.3%), 146 hospitals with EMRs (42.0%)
Chi-square(3 d.f.)=21.71 (p<.001)		

Table 33 provides information about the size of hospitals in each category. The mean number of beds for the total group is 207.93 (192.65 standard deviation). Table 34 presents information about hospital system affiliation in each of the performance categories. These tables are further discussed after they are presented.

Table 33: Mean (Standard Deviation) Hospital Bed Size in Each Performance Category

	Quality	
Efficiency	Low	High
High	178.66 (204.74)	306.80 (230.61)
Low	155.82 (127.73)	206.24 (191.54)

Table 34: System Membership in Each Performance Category

	Quality	
Efficiency	Low	High
High	176 system members (10.7%), 129 non-system members (10.3%)	384 system members (23.4%), 194 non-system members (15.5%)
Low	457 system members (27.9%), 432 non-system members (34.5%)	623 system members (38.0%), 496 non-system members (39.6%)
Chi-square(3d.f.)=31.64 (p>.001)		

This performance classification system reveals that more than half of all hospitals with EMRs perform at a high quality level, and a higher percentage of hospitals with EMRs are in the highest performing group (26.7%) compared to hospitals without EMRs in the same group (19.1%). Also, a smaller percentage of hospitals with EMRs are in the lowest performing group (21.3%) compared to hospitals without EMRs (32.0%). Table 34 shows that there is a statistically significant difference, according to the chi-square at the $p<.001$ level. This classification scheme is further discussed in Chapter 6.

This classification scheme also reveals that hospitals in the highest performance category are larger overall than the other classification groups. The highest performing group has a mean bed size of 306.80 while the lowest performing hospitals have a mean bed size of 155.82. There is also a difference in bed size between the two groups of mid level performance. Hospitals that are efficient but not high quality have a lower mean bed size (178.66) than hospitals that provide high quality but are not efficient (206.24).

The performance classification scheme is also useful for considering hospital system affiliation, which is strongly associated with hospital EMR use as reported in the first logistic regression analysis. According to Table 34, a higher percentage of the hospitals that are system affiliated are in the highest performance category (23.4%) as compared to the percentage of independent hospitals that are in this performance category (115.5%). Likewise, a smaller percent of system-affiliated hospitals are classified in the lowest performance group (27.9%) as compared to independent hospitals (34.5%). More than half of all system-affiliated hospitals are classified with high quality care, while just fewer than one half of independent hospitals are classified as providing high quality care. This relationship is significant according to the chi-square statistic at the p<..001 level.

To explore the relationship between hospital performance and EMR use further, the performance categorization system was recoded to allow for three dichotomous design variables identifying high performing hospitals, middle ground performing hospitals and low performing hospitals. High performing hospitals are those that are performing high in quality and efficiency. Middle ground performing hospitals are those that are performing either high in efficiency and low in quality or low in efficiency and high in quality. The poor hospital performance group is the hospitals that are performing low in both quality and efficiency. These three dichotomous design variables then served as the outcome variables in three separate logistic regression analyses to determine the relationship between hospital quality and efficiency performance and length of time of EMR use while controlling for size, ownership, and system membership. When these analyses were run, the models were not significant. For this reason, the models were redone to analyze the relationship between total performance and hospital EMR use instead of length of time of EMR use. These new models were significant and were thus analyzed instead of the models that considered length of time of EMR use. The results of these analyses are presented in Tables 35, 36, and 37.

Table 35: Correlates of Poor Hospital Performance

	B	Exp(B)	95.0% C.I.for EXP(B)	
Variables			Lower	Upper
Large	-1.177***	0.308	0.229	0.415
Small	0.115	1.122	0.942	1.337
EMRs	-0.373**	0.689	0.518	0.916
System Member	-0.263**	0.769	0.642	0.921
Non-profit	-0.577***	0.562	0.444	0.710
Public	-0.259	0.772	0.578	1.095
Constant	-0.906	0.909		
-2 Log Likelihood = 3411.43 *Goodness of Fit Statistic* *Chi-Square (6 df) = 156.59 (p<.001)* *Correct Classification Rate = 69.4%*				

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

Hospitals in the poor hospital performance category have a statistically significant relationship with hospital EMR use. Hospitals with EMRs are 0.689 times less likely to be in the poor performing group (p<.01). According to this analysis, hospitals that are large, system members, and non-profit are less likely to be in the poor performing group. These results are presented in Table 35.

Table 36: Correlates of Middle Ground Hospital Performance

	B	Exp(B)	95.0% C.I.for EXP(B)	
Variables			Lower	Upper
Large	-0.224*	0.799	0.647	0.987
Small	0.129	1.138	0.965	1.343
EMRs	0.153	1.165	0.922	1.473
System Member	-0.013	0.987	0.838	1.162
Non-profit	0.250*	1.124	1.028	1.605
Public	0.198	1.128	0.924	1.606
Constant	-2.53*	0.777		

-2 Log Likelihood = 2663.89
Goodness of Fit Statistic
Chi-Square (6 df) = 15.21 (p<.05)
Correct Classification Rate =53.3%

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

Table 37: Correlates of High Hospital Performance

	B	Exp(B)	95.0% C.I.for EXP(B)	
Variables			Lower	Upper
Large	1.187***	3.276	2.605	4.121
Small	-.0.503***	0.605	0.474	0.772
EMRs	0.167	1.182	0.893	1.564
System Member	0.386***	1.472	1.187	1.825
Non-profit	0.422**	1.524	1.124	2.068
Public	-0.018	0.922	0.659	1.463
Constant	-2.063***	0.127		

-2 Log Likelihood = 2663.89
Goodness of Fit Statistic
Chi-Square (6 df) =228.88 (p<.001)
Correct Classification Rate = 80.2%

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

For hospitals in the middle ground and high performing groups, there is no statistically significant relationship with EMR use. While both of these models are significant, the EMR variable is not statistically significant. These results are in tables 36 and 37. According to these analyses, non-profit hospitals are more likely to be in the mediocre performing group than medium hospitals and for-profit hospitals while large hospitals are less likely to be in this performance group. Small size is not a significant predictor of middle ground hospital performance. Likewise, system membership is not a significant predictor of Middle Ground Hospital Performance. Large, system affiliated, and non-profit hospitals are more likely than medium, independent, and for profit hospitals to be in the highest performing group. Small sized hospitals are less likely than medium sized hospitals to be in the high performance group. Public ownership is not significant in either equation. These findings are further discussed in Chapter 6.

Hypotheses in the Study

Through the analyses described in this chapter, it is possible to now consider the hypotheses made using the conceptual model. Table 38 provides a list of the hypotheses in this study as well as an indication of whether the analyses support them or not. Five hypotheses from the conceptual model were supported by these analyses. Hospital EMR use is associated with environmental uncertainty, bed size, system affiliation and centralization, and rurality. Hospitals with EMRs perform services with higher quality. For efficiency, EMRs only influence small

Table 38: Confirmation of Study Hypotheses

Hypothesis	Significant	Supported
H1: Hospitals with greater financial resources are more likely to use EMRs.		No
H2: Hospitals with a higher percentage of public reimbursement are more likely to use EMRs.		No
H3: As environmental competition increases, the likelihood of hospital EMR use increases.		No
H4: Rural hospitals are less likely than urban hospitals to use EMRs.	*	Yes
H5: Larger hospitals are more likely to use EMRs.	*	Yes
H6: For-profit hospitals are more likely than public or non-profit hospitals to use EMRs.		No
H7: As a hospital's relationship to a system moves along a continuum from no affiliation to highly centralized systems, the likelihood of ERM use increases.	*	Yes
H8: Teaching hospitals are more likely to use EMRs.		No
H9: Hospitals in environments of more uncertainty are more likely to use EMRs.	*	Yes
H10: Hospitals in areas of more munificence are more likely to use EMRs.		No
H11: Hospitals with EMRs are more efficient than those without EMRs.	*	Small Hospitals
H12: Hospitals with EMRs will increase their efficiency over time.		No
H13: Hospitals with EMRs will report greater quality than those without EMRs.	*	Yes

hospitals' performance. These hypotheses are further discussed in Chapter 6 along with possible reasons for the findings and the implications of these results. A return to the theoretical model is also imposed.

Chapter Summary

This chapter presents the statistical descriptions and analyses conducted in this study. The analyses include descriptive summaries, logistic regression analyses, power analyses, tests for endogeneity, and a categorization of hospitals based on quality and efficiency performance. The descriptive analyses provide information about how where EMRs are used in hospitals. Of the 4,606 hospitals included in this study, 479 currently use fully automated EMRs.

In the first analysis, the logistic regression reveals that there are several factors significantly associated with EMR use. These factors include rurality, system affiliation, environmental uncertainty, and bed size. Another logistic regression equation examines the relationship between hospital EMR use and quality performance. A statistically significant relationship is found between quality and EMR use. Three separate logistic regression equations examine the relationship between hospital EMR use and efficiency. These three equations separate hospitals into three groups based on bed size and statistically significant relationships are found between hospital EMR use and efficiency in small and medium sized hospitals. No statistically significant relationship was found between hospital EMR use and efficiency in large hospitals.

DEA Windows Analysis was used to assess the change in efficiency from 2001 to 2004 for all hospitals that were consistent in their EMR use during this period. According to the Windows Analysis, hospital EMR use is not a significant predictor of hospital change in efficiency.

Finally, to examine overall hospital performance, hospitals were assigned a code of performance that combined their quality scores and efficiency scores. These values provide information about hospital performance overall as well as its relationship to EMR use. Hospitals with EMRs are less likely than those without EMRs to be in the poor performing group, but no other statistically significant relationships were found between EMR use and middle ground performance or high performance. In the last section of this chapter, the hypotheses are reviewed and supported or rejected. In the final chapter, the conclusions and implications of these results are explored and summarized.

CHAPTER 6: CONCLUSIONS AND IMPLICATIONS

The purpose of this chapter is to discuss the conclusions and implications of the results of this study. This chapter summarizes the key findings of this study and presents implications and conclusions of hospital EMR use. The implications relate to policy, practice, and theory as well as contribute to the body of knowledge. This study also discusses the limitations of this study and the opportunities for future research.

Summary of Key Results

The purpose of this study is to examine hospital EMR use. The model was created using Resource Dependence Theory and Donabedian's Structure, Process, Outcome Model, which were joined sequentially. Specifically, the organizational and environmental factors associated with EMR use and the relationship between hospital EMR use and performance is examined. A single logistic regression model was used to test the first ten hypotheses, which examine the organizational and environmental factors associated with hospital EMR use. Another single logistic regression model examined the relationship between hospital EMR use and quality. Six separate peer-sized logistic regression equations were used to examine the relationship between hospital EMR use and efficiency and change in efficiency over time.

Results of Tests of Hypotheses

The results of the hypotheses tests are presented here with discussion. Table 38 also presents these hypotheses along with indication of their statistical significance and support.

H1: Hospitals with greater financial resources are more likely to use EMRs.

The logistic regression analysis found no statistically significant relationship between hospital EMR use and operating margin ratio. Because of the expense of EMR purchase and implementation, the model predicted that a greater operating margin would increase the likelihood of EMR use. One possible reason for this finding may be that hospitals that used their financial resources to purchase EMRs have less of a positive operating margin ratio than those that did not spend a large portion of their earnings on an EMR system. Additionally, it may take more data to determine a relationship between hospital behavior and financial resources as hospitals may create their strategic plans based on the current operating margin, but it may require several years for the strategic plans to be implemented. In other words, a hospital that had a positive operating margin in 2004 may only now be deciding to implement EMRs, which may not take place until 2007. For this reason, it may be valuable to study the relationship between lagged operating margin and EMR use. Hospitals with greater operating margins in 2000 may only now be distinguishable by practices that were implemented based on financial information. Another possible explanation is that many of these hospitals have been using EMRs for more than one year; in other words, a hospital's operating margin in 2004 may be the result of EMR purchase and use instead of a predictor of use. Hospital operating margin ratios from 2004 may predict future EMR use.

H2: Hospitals with a higher percentage of public reimbursement are more likely to use EMRs.

The logistic regression analysis also did not find any significance or support for this relationship. According to the model, it was predicted that higher dependence on public reimbursement would be associated with EMR use. This hypothesis is based on the action of the federal government, which promotes EMR use. The discussion about the government's support of EMR use is presented in Chapter 2. One possible reason for the lack of support for this hypothesis is that Medicare sometimes and Medicaid often reimburse for services at rates below private payers. In other words, a hospital that depends highly on public payers may have fewer financial resources to use to purchase and implement EMRs.

H3: As environmental competition increases, the likelihood of hospital EMR use increases.

No statistical significance or support was found for the relationship between hospital EMR use and environmental competition. As the Resource Dependency predicts, organizations in areas of greater competition are more likely to act or strategize to enhance their likelihood of survival. One of the ways organizations, namely hospitals, do this is by distinguishing themselves from competitors in an effort to secure demand for their services. It is possible, however, that hospitals realize that many patients seek a hospital based on their relationship with a physician; in other words, hospital selection occurs because a patient's physician has a relationship with the hospital. If this is the case, and many physicians are opposed to EMR use, hospital administrators may realize that in areas of competition, they must appeal to physicians, not patients, in order to secure demand. If physicians determine the hospitals where their patients seek care and they are opposed or indifferent to EMR use, EMR use may not serve as a useful way for hospitals to secure their relationships with physicians and patients. If this is the case, the conceptual model using resource dependence theory would look quite different as EMRs may be seen as a method for decreasing demand from the environment instead of a possible strategy to increase the likelihood of organizational survival. It is also possible that hospitals in areas of greater competition are using different methods or strategies, such as advertising, to survive intense competition.

H4: Rural hospitals are less likely than urban hospitals to use EMRs.

The analysis does support the model hypothesis that there is a relationship between hospital urbanness and EMR use. Using the rural urban continuum code with the most rural group as the reference group, hospitals in nearly every other type of urbanness were more likely to use EMRs than hospitals in the most rural areas. The urban 5 category is the only type of surrounding that is not associated with a greater likelihood of hospital EMR use. Hospitals in more urban areas, except for those in urban 5 areas, are between two and four times more likely to use EMRs than hospitals in the most rural areas. Hospitals in the most rural areas are likely to only hospital in close proximity, thus limiting their competition. Additionally, these rural hospitals offer fewer and less complex services than other hospitals (Williams 2005). Finally, hospitals in the most rural areas may not exist in environments where information technology products and services are readily available, thus also reducing the likelihood of EMR use.

H5: Larger hospitals are more likely to use EMRs.

The logistic regression analysis did support this hypothesis. While a statistically significant relationship between EMR use and hospital bed size is present, the coefficient reveal that this relationship is not very strong. Larger hospitals are only slightly more likely to use EMRs than smaller hospitals. The reason for this may be the role of system affiliation. The relationship between hospital EMR use and type of system affiliation was quite strong. This may indicate that hospitals are acquiring and using EMR applications as part of their system affiliation instead of as a result of their size. In other words, larger hospitals may be slightly more likely to use EMRs, but smaller hospitals that are system members may also be using EMRs due to their purchasing power as members in a system.

H6: For-profit hospitals are more likely than public or non-profit hospitals to use EMRs.

No statistically significant relationship between hospital EMR use and ownership was revealed in this analysis. It was predicted through the model that for-profit hospitals would be more likely than public or non-profit hospitals to use EMRs because for-profit hospitals have different missions and often seek to maximize financial gain for investors. Since EMRs were believed to improve efficiency while also serving as an additional service to secure patient demand, it was hypothesized that EMRs would be more likely to be used in for-profit hospitals. Since this study failed to show that hospital EMR use is associated with greater efficiency in all hospitals, it is possible that for-profit hospitals are not more likely to use EMRs because these hospitals will not implement a new and expensive service that has not been shown to increase efficiency and financial gain.

H7: As a hospital's relationship to a system moves along a continuum from no affiliation to highly centralized systems, the likelihood of EMR use increases.

The relationship between type of system affiliation and hospital EMR use was strongly supported by this analysis. Because system affiliated hospitals have more resources to attain EMR systems, the model predicted that more highly centralized systems would be more likely to use EMRs. Using non-system affiliated hospitals as the reference group, hospitals in each of the types of systems was shown to be significantly more likely to use EMRs. Along the continuum, each of the hospital classifications except for decentralized systems were more likely than the previous type of system to use EMRs when compared to the reference group. This result may reveal a characteristic of decentralized systems; they may function by allowing hospitals to make individual decisions about hospital practices. In centralized systems, hospital practice decisions are likely made at the system level. In decentralized systems, the affiliation may serve hospitals through the power of size, such as bargaining power for purchasing, without combining hospital management structures. In other words, decentralized systems may leave more of the hospitals' operating practices and decisions up to the individual hospitals than more centralized systems. The benefits of these less centralized systems may be greater pooled resources and market power, while still allowing for individual hospitals to function more independently that more centralized systems. If this is the case, it would be likely that decentralized systems would use their group power to share the price of an EMR system, but implementation and use would be at the discretion of the hospitals themselves. These hospitals are still more likely than non-system affiliated hospitals to use EMRs, but they are not as likely as the other types of systems to use EMRs.

H8: Teaching hospitals are more likely to use EMRs.

This analysis did not reveal that there is a significant relationship between hospital teaching status and EMR use. The model predicted that teaching hospitals, which often provide many very complex services, were more likely to use EMRs. However, it may be the case that teaching hospitals do not have the financial resources to implement and use EMRs. Teaching hospitals are often less efficient and have higher costs than non-teaching hospitals because of the training that occurs in these facilities. For this reason, their operating margins tend to be lower than non-teaching hospitals. If this is the case, it is possible that teaching hospitals do not have the financial means to buy EMR systems.

H9: Hospitals in environments of more uncertainty are more likely to use EMRs.

The logistic regression analysis does reveal a significant relationship between environmental uncertainty and hospital EMR use. Using the change in unemployment rate from 2000 to 2004, hospitals in areas of greater environmental uncertainty are more likely to use EMR systems. This is consistent with Resource Dependence theory in that uncertainty leads to hospital action and strategy as these organizations attempt to ensure survival by responding to change (Hatch 1997).

H10: Hospitals in areas of more munificence are more likely to use EMRs.

The logistic regression analysis revealed no support or significance in the relationship between hospital EMR use and munificence. The theory predicts that organizations in environments of more abundant resources will be more likely to act to secure these resources, but no relationship between per capita income in the area surrounding a hospital and hospital EMR use was present. One possible reason for the lack of support of this hypothesis is the measure used in this study may be improved. It is possible that this measure does not adequately represent munificence, and a better measure may exist such as percent of the population covered by health insurance. It is also possible that hospitals are competing for these funds on more of a national level. According to resource dependence theory, organizations work to acquire resources. Since the government is the largest payer of health care services in the United States, the hospitals may instead be competing for funds outside of the immediate surroundings, thus making this measure weak.

To examine the relationship between hospital EMR use and efficiency, six separate logistic regressions were done to control for the tendency for hospitals to function differently based on bed size. The first three analyses examined hospital efficiency in 2004 and EMR use. The second three analyses examined the change in efficiency from 2001 to 2004 and hospital EMR use. These results and hypotheses are discussed below:

H11: Hospitals with EMRs are more efficient than those without EMRs.

This hypothesis was partially supported. While the theoretical model predicted that EMR use would increase efficiency through the relationship between structure and process, this is only true for small hospitals. This analysis found no significant relationship between efficiency and EMR use for large or medium hospitals. Interestingly, the first analysis also showed that small hospitals are less likely than large hospitals to use EMRs. This finding along with the failure to reject hypothesis 5 may present an especially important characteristic of hospital EMR use: Small hospitals are less likely than large hospitals to use EMRs, but they are more likely to see a relationship between the practice and performance outcomes in efficiency.

H12: Hospitals with EMRs will increase their efficiency over time more than hospitals without EMRs.

This analysis found no relationship between hospital EMR use and change in efficiency over time. Since EMR implementation and use may initially reduce efficiency as staff adjust to new practices associated with EMR use, the model predicted that hospitals with EMRs would increase in efficiency more than hospitals without EMRs as the efficiency gains associated with EMRs were realized. To test this hypothesis, a model was attempted to examine the relationship between change in efficiency and length of time of EMR use. However, this model was statistically insignificant, so a model examining the relationship between EMR use and change in efficiency over time was used. Three separate logistic regression equations were run, which revealed no significant relationship between hospital EMR use and change in efficiency over time. The three groups included small, medium, and large hospitals because previous research has declared peer group sized efficiency analyses to be more stable (Ozcan 1992-1993). However, because of the variance of bed size still included in these three groups, bed size was included in each analysis as a control variable. It is possible that hospitals with EMRs did not display significantly greater improvement in efficiency between 2001 and 2004 because all hospitals, with and without EMRs, are under intense pressure to increase efficiency in order to survive under the current reimbursement schemes. The strongest predictor of hospital change in efficiency during this period for each of the size groups is case mix index. This may indicate that changes in hospital efficiency relate more to the type of patient that is served than the structures and processes of care.

H13: Hospital with EMRs will report greater quality than those without EMRs.

The hypothesis derived from the conceptual model was supported, revealing that hospitals with EMRs perform better in the area of quality than hospitals without EMRs. A single logistic regression equation was used to examine the relationship between quality and hospital EMR use. This equation controlled for hospital teaching status, ownership, system membership, size, and case mix index, which were included in the initial model presented in chapter 3 with the analysis of organizational and environmental factors associated with EMR use. This is likely the result of the relationship between EMR automation and patient safety. Because EMRs may reduce patient care errors such as drug interactions while increasing the standardization to care, they may increase the likelihood that patients receive the right care in the right way at the right time. This automated standardization would likely be the result of the relationship between structure (EMRs), process (automated, standardized), and outcome (quality).

Performance Classification

While there are no hypotheses directly related to this analysis, the opportunity exists to examine hospital EMR use and performance further with an exploratory performance analysis. This performance analysis, combining efficiency and quality, was presented in Chapter 5 and is discussed here. This analysis does, however, relate to the conceptual model presented in Chapter 3 because Donabedian's structure, process, and outcome framework emphasizes that structures, processes, and outcomes are interdependent. Additionally, there is a significant correlation between quality and efficiency in this analysis. This performance classification allows the exploration of the relationship among these constructs as presented in Chapter 5. Because the last several years have been characterized by a push for both increased quality and decreased costs associated with health care, top performing hospitals are those that provide efficient, effective care with good outcomes. In chapter five, the total count of hospitals in each of four performance categories are provided.

In addition, these performance categories reveal information about hospital EMR use and performance. More hospitals with EMRs, relative in frequency to hospitals without EMRs are high performers. Of hospitals with EMRs, 26.7% are in the highest performance category while only 19.1% of hospitals without EMRs are in the highest performance category. Likewise, a smaller proportion of hospitals with EMRs (21.3%) is in the lowest performance category compared to hospitals without EMRs (32.00%). In other words, only approximately one quarter of hospitals with EMRs are in the lowest performance category while more than one third of hospitals without EMRs are in the lowest performance category. Also supporting the analysis reported in chapter 5 is the fact that more than half (n=236) of hospitals with EMRs included in this part of the analysis perform with high quality.

This analysis and classification scheme also reveals relationships among hospitals by performance category. Hospitals in the highest performance group have a higher mean bed size than hospitals in the lowest performance group or any other performance group. As previously stated, hospital EMR use is also more likely in larger hospitals. Larger hospitals are also more likely to perform procedures more frequently and have more services, personnel and resources than small hospitals. Because of this, it is likely that overall high hospital performance may be a function of both EMR use and of the many resources and frequency of procedures performed at larger hospitals. This analysis also reveals that system affiliated hospitals are classified more often in the highest performance group and less often in the lowest performance group. Additionally, more than half of these system-affiliated hospitals are providing high quality care, which is more than the percentage of independent hospitals. This finding is interesting because hospital EMR use is highly correlated with type of system affiliation and quality. If system affiliated hospitals are more likely to use EMRs and perform higher quality care, policy makers and practitioners may wish to find ways to encourage system affiliations and EMR use to increase the quality of care. Finally, the logistic regression analyses using the hospital performance variables as outcome variables have shown that hospitals with EMRs are less likely than those without EMRs to be in the poor hospital performance group. This is important because hospitals that are not providing efficient or high quality care must make changes to perform better. One interpretation of this analysis is that EMR use may not guarantee high performance in all areas, but it may prevent the likelihood poor performance.

Practice and Policy Implications

If certain hospitals are more likely than others based on environmental and organizational characteristics to use EMRs, it is possible that these significant predictors represent barriers to EMR implementation and use for some hospitals. According to this analysis, hospitals that are small, non-system affiliated, and rural are less likely to use EMRs. Previous research has determined that physician resistance, cost of EMR implementation and maintenance, and concern over the security of electronic information are barriers to hospital EMR use. Small, independent hospitals in rural areas are unlikely to have the financial or human resource means to implement and use and EMR system. Additionally, it is possible that a smaller, more rural community may not have the human resources available to run such a system. If this is the case, these smaller, independent, rural hospitals may need to join a health system or form a coalition together to investigate the feasibility of a group purchase and implementation of EMRs. Because EMRs are expensive, and larger and system affiliated groups have begun using EMRs more often, it is possible that without greater economies of scale for implementation, EMRs are too costly for the smaller hospitals. However, because this research has shown that

EMR use is related to performance in quality and efficiency in small hospitals, EMR use may be especially important to this population. Hospitals must take the necessary action to use EMRs because of their potential impact on performance, especially in the area of quality. Policymakers should take steps to encourage hospital EMR use. These steps could include programs that aid hospitals in implementing and using EMRs with EMR hardware and software as well as training and personnel to help with implementation. These programs will be especially important to smaller hospitals in rural areas. Policymakers may also, at some point, offer greater financial reimbursement for hospitals that use EMRs as a way to encourage hospital use. Additionally, more regulations from payer groups and policymakers can ensure that hospital EMR use is practiced. These regulations may be in the form of requirements for certification, endorsements, or accreditation.

This study shows that high quality performance is associated with hospital EMR use. This may possibly be the most important finding in this analysis. Chapter 2 presented information about the impact of poorer quality health care. Not only does it affect the patient and his or her outcomes, it can also drive up the cost of health care. Increasingly, patients, payer groups, and policymakers have been interested in determining and improving the quality of health care. If EMRs provide a tool to improve hospital quality, it is likely that their prevalence will increase as hospitals attempt to distinguish themselves as top performers. Hospitals that wish to improve their quality should consider EMR use because of its potential relationship to better quality performance. Policymakers should especially consider this finding as they encourage hospitals to use EMRs.

Finally, small hospitals, which have been shown to benefit in the area of efficiency through EMR use should especially consider using them. However, smaller hospitals are less likely than larger hospitals to use EMRs according to this analysis. Larger hospitals that have not demonstrated higher efficiency through EMR use may wish to examine why or if the lack of change in efficiency with EMR use is instead related to higher quality performance. A positive correlation between quality and efficiency ($B=.126$, $p<.01$) reveals that medium and large size hospitals may be producing higher quality outcomes with less efficiency. In other words, quality may be improving at the price of efficiency. If possible, while maintaining quality, adjustments to the EMR system that will allow for greater efficiency should be utilized. It is important, though, that the increased efficiency not happen at the cost of quality. Additionally, research may be done to investigate if one type of EMR system is more efficient than others. If one particular system is found to be more associated with efficiency, policymakers may wish to consider adopting the system as the universal, interoperable EMR system for the United States. It is also possible that the efficiency of EMRs may only be realized through the use of a standardized interoperable EMR system, which would allow hospitals and other health care providers to rapidly share the medical histories of their patients with one another. In other words, the efficiency increases may not be observed until EMR use is widespread enough to allow most, if not all, providers to share the medical records of their patients, thus negating the need of new providers to take extensive medical histories from patients.

Theoretical Implications

According to resource dependence theory, environmental uncertainty is a strong predictor of organizational strategy and behavior. This tenet was supported in this analysis as the greater relative change in unemployment, the greater the likelihood of hospital EMR use. If, according to resource dependence theory, environmental uncertainty is a motivator of organizational action, then organizational power provides the means to achieve such action. Power, according to this theory, is associated with size. This particular tenet is especially supported in this analysis. Both bed size and centralization of health system are positively correlated with EMR use. Larger hospitals and health systems are more likely to have the financial and human resources needed to acquire and use EMR systems, and their economies of scale are likely more beneficial with EMR use than a smaller hospital.

While this study supported four hypotheses derived from the resource dependence perspective, six hypotheses from this theory were not supported. For this reason, the use of resource dependence theory to examine hospital EMR use is questioned. One other theory option includes diffusion theory. Diffusion theory would have likely examined EMR adoption and years of use to distinguish early adopters from later and non-adopters, but, as this study shows, the relationship between years of EMR use and efficiency was not significant. In addition, diffusion theory has been criticized for assuming environmental stability and considering only a limited number of environmental actors, who generally already exist (Renshaw, Kimberly, and Schwartz 1990). Since hospitals have recently faced tumultuous times as discussed in Chapter 2, this theory would likely not examine the full picture of EMR use. With regard to environmental actors, new organizations have emerged in response to interest in EMR use; private companies are now offering the sale of EMR systems to hospitals and patients directly. For these reasons, it is possible that while resource dependence cannot explain the entire phenomenon of hospital EMR use, it is the best choice of the theories available.

Using Donabedian's structure, process, outcome model, it was predicted that EMR use would lead to increased efficiency, which would lead to increased quality. This relationship was not supported in this analysis. While hospital efficiency does appear to be related to EMR use in small hospitals, this is not the case in medium or large hospitals. Additionally, the model predicted an increase in efficiency over time as EMRs were used in hospitals. This hypothesis also was not supported. However, EMR use is positively and significantly related to hospital quality. One of the important concepts of Donabedian's framework is that there is a relationship among quality, efficiency, and structure. It is possible that instead of improving efficiency, EMRs makes the process more complete and standardized, which leads to greater quality. In other words, it is possible that the lack of increase in efficiency allows clinicians in hospitals to be more thorough, and thus provide greater quality care. Donabedian's model does not necessarily predict that both an improvement in process and an improvement in outcome would be required in support of the framework; rather, it states that one influences the other. While the efficiency of hospitals may not have been influenced as a process as expected, it may still have ultimately led to the outcome of greater hospital quality as was found to be associated with EMR use. To explore this, the hospital performance classification scheme examined a combined score of hospitals' efficiency and quality. More than half of all hospitals with EMRs were providing high quality care, but a smaller percentage of these hospitals were providing efficient care. Since this relationship is significant at the $p<.001$, it may indicate that the high quality performance of hospitals with EMRs occurs at the cost of efficiency. One reason for the weakness of the model in predicting outcomes and the relationship between quality and efficiency may relate to Donabedian's structure, process, outcome model. Since, as stated in Chapter 3, Donabedian's framework does not provide information about the direction of relationships relating to structure, process, and outcome, this model was inadequate for addressing the relationship between hospital EMR use and outcomes more specifically.

Finally, the more hospital EMR use is associated with high quality health care, the more likely it will become a hospital organizational strategy for survival.

Hospitals, as presented in the first chapter, have faced tumultuous times in recent decades. Many are looking for practices that will make their services more appealing to patients and payers. The hospitals that are currently using EMRs may be classified, at some point, as early adopters of this practice. As time continues and the clear benefits of hospital EMR use are found and disseminated, hospital EMR use may gain more prestige and accepted value. Hospitals that use EMRs may be viewed as having greater legitimacy, thus encouraging hospitals that do not use EMRs to implement such systems. The application of other theories including institutional theory and contingency theory to hospital EMR use is clear, and future research may wish to apply a different framework to this issue. Institutional theorists could examine the increase in legitimacy and corresponding prevalence of EMR use in hospitals. Contingency theorists may wish to examine which hospitals perform the best with EMRs while considering various organizational factors.

Contribution to Health Services Research

The study provides an important contribution to the body of knowledge in that it explores a relatively new and promising practice. Many entities, including the federal government, payer groups, Leap Frog, and hospitals systems, have emphasized and encouraged hospital EMR use to make patient care follow a more documented and automated standard. Yet, EMR implementation is expensive. Without clear benefits associated with its use, there is no justification for continuing to pursue the practice. While several studies have examined anecdotally and qualitatively hospital EMR use, no other study has examined hospital EMR use throughout the United States with rigorous methods. Additionally, while this study does show benefits in the area of quality, it also shows that EMRs are not necessarily making care more efficient. This is important because the practice of EMR use may be revisited to allow for hospital performance gains in both efficiency and quality before more implementation is completed. It is also possible that the cost of EMR implementation and use in hospitals is so great that the increased efficiencies will never be realized. If this is the case, the gains associated with EMRs will most likely be more in the realms of standardization of processes and quality of care rather than increased efficiency or decreased cost. It may be too early yet in the evolution of EMRs to determine all of the costs and benefits for organizations, patients, providers, policymakers, and payers. For this reason that EMRs should be continually studied in hospitals and other health care settings.

Another importance of this study is in the identification of organizational and environmental factors associated with hospital EMR use. Without this analysis, certain hospitals may be left behind the wave of EMR implementation. Because of the identification of organizational and environmental factors associated with EMR use, it is possible to identify those which are at risk of not using. Once these hospitals are identified, programs and policies that assist them in using EMRs may be developed. These programs and policies can be developed by the government as well as by private payer groups.

Limitations

One weakness of this study is the identification of hospitals that use EMRs. Although the HIMSS data provide a strong definition of hospital EMR use, there is likely still considerable variability in how EMRs are used in hospitals. This variability may be present in the level of adoption or use of EMRs (hospital wide versus departmental use), staff buy-in of EMRs, and the components, such as CPOE and electronic prescribing that may work along with the EMR system. Additionally, there is currently no standardized, universal EMR system. The EMRs that are used in hospitals are varied in features and manufacturers. It is also likely that the level of information technology support for clinical staff using the EMRs is varied from one hospital to the next. Relating to this same issue, another issue is the weakness of the HIMSS data in identifying when EMRs were implemented at hospitals. More than 100 hospitals with EMRs did not provide a date of implementation or contract. Because of this, these hospitals were excluded from the Windows analysis to examine the change in efficiency over time.

Another limitation in this study is the possible selection bias. While the researcher attempts to control for this by including the entire population in the study and by testing for endogeneity, hospital EMR use is not randomly selected. Hospitals and health systems have decided to use EMRs or not, and other factors likely influenced these decisions. This study also attempts to control for this by identifying organizational and environmental factors associated with EMR use in the first logistic regression analysis. However, in the event that hospitals are implementing EMRs because of an unobserved variable or a factor not included in the model, this study does not reveal the true relationship among hospital EMR use and performance, thus reducing the validity of the findings. Several steps, including testing for endogeneity, using theory to guide the conceptual model, and the use of previous research to guide measures and analyses, have been taken to validate the results of this study.

While this study does reveal a relationship between hospital EMR use and quality performance, little is known about how EMR use affects quality. This study does not determine if the automated nature of EMRs or the increase in patient safety and monitoring is influencing the increased quality. This is an area for future research.

Also relating to quality is the weakness of the measure of quality itself. While the Hospital Quality Alliance data represent many practices associated with greater quality outcomes, they do not account for all conditions and all dimensions of quality. These data also do not include a measure of patient satisfaction, an important element of hospital quality. The measures are also not as sensitive as this analysis may require, thus requiring the transformation described in Chapter 5. This sensitivity may improve as the HQA has since added additional respondents and measures of quality in more recent years of data collection. Additionally, these measures are voluntarily reported by the hospitals, which may chose to report only "good" scores or design procedures to achieve "good" scores. Future researchers may also wish to examine new ways to risk adjust these measures of quality, which focus primarily on provider behavior rather than patient outcomes.

While DEA presents an effective methodology for measuring efficiency, the efficiency scores do not represent absolute efficiency. Rather, they represent relative efficiency. For this reason, the entire population was included in this analysis, with the hospitals peer grouped by bed size for stability. However, it is possible that a level of efficiency that does not currently exist in any hospital is what must be achieved in order to reduce health care costs while maintaining or increasing quality. In other words, DEA is able to identify the best performers, but it does this relative to all DMUs included in the analysis. If all of the DMUs are performing poorly in the area of efficiency, the highest performers will still be identified as efficient, even though a higher level of efficiency performance may be possible. DEA relies on a relative efficiency frontier to identify efficient organizations.

Areas of Future Research

Because hospital EMR use is still in the early stages, there is much to be explored. Analyses similar to this one could be done to examine EMR use in outpatient clinics, physicians' offices, or long term care facilities. Future researchers may also wish to consider a similar analysis to determine the correlates and outcomes associated with other HIT applications such as CPOE, electronic prescribing, or standardized clinical pathways as these applications may or may not be used in conjunction with hospital EMR use.

At the time this study was completed, the HQA data used to construct the quality measure was newly reported. Since this time, these data have grown in the number of hospitals participating and the number of measures collected. For this reason, the richness and validity of these quality measures will likely increase. Examining the relationship between hospital EMR use and change in quality over time through a first differencing technique with two points of observation may be possible in the near future due to the availability of these data.

The classification scheme of hospital performance provides a rich ground for future research. While hospital performance is a complex concept, incorporating efficiency and quality into the measure may provide a more complete picture of hospital outcomes. Future researchers may wish to refine this measure or add to it. It may also be a useful outcome measure for studying other hospital structures of interest.

Conclusions

Hospital EMR use is in the early stages of development and practice. Because of this, little research has been done in this area. According to this study, hospital EMR use is associated with certain environmental and organizational characteristics as well as with high quality care. In small hospitals, EMR use is associated with higher efficiency, but no relationship was found between hospital

EMR use and efficiency in the medium and large size hospitals. It is possible that as hospital EMR use continues to evolve, the EMR systems will become more developed. This study provides an important contribution to the body of knowledge because it explores a new area of health services research. Hospital EMR use is predicted to increase, but the justification for this increase has not yet been empirically shown. This study shows the benefits of EMR use, especially in the area of quality performance.

Because so little is yet known about hospital EMR use, there is a great deal of room for contribution in the area of future research. Studies considering why hospitals adopt EMRs and how their use influences performance should continue to be investigated. Additionally, as more hospitals begin to use EMRs, the results of these findings may change as the practice becomes more developed and widespread.

REFERENCES

REFERENCES

"A Giant Step Forward: A Specialty Practice Goes Entirely Paperless by Combining Electronic Document Management Technology with its Existing EMR." 2002. *Health Management Technology.* 23(10).

Al Farsi, M., and West, D. (2006). "Use of Electronic Medical Records inOman and Physician Satisfaction." *Journal of Medical Systems.* 30(1).

Alexander, J., and Morrisey, M. (1989). "A Resource-dependence Model of Hospital Contract Management." *Health Services Research.* 24(2).

Anderson, G. (2004). "Preventive Medicine and the Electronic Health Record." *Medscape Public Health and Prevention.* 2(2).

Ash, J., and Bates, D. (2004). "Factors and Forces Affecting E HR System Adoption: Report on a 2004 ACMI Discussion." *Journal of the American Medical Informatics Association.* 12.

Asch, S., McGlynn, E., Hogan, M., Hayward, R., Rubentstein, L, Keesey, J., Adams, J., And Kerr, E. (2004). "Comparison of Quality of Care for Patients in the Veterans Health Administration and Patients in a National Sample." *Annals of Internal Medicine.* 141(12).

Balosky, E. (2005). "Is it Resources, Habit, or Both: Interpreting Twenty Years of Hospital Strategic Response to Prospective Payment." *Health Care Management Review.* 30(4).

Baron, R., Fabens, E., Schiffman, M., and Wolf, E. (2005). "Electronic Health Records: Just Around the Corner? Or Over the Cliff?"

Bartley, M., and Fagin, L. (1990). "Hospital Admissions Before and After Shipyard Closure." *British Journal of Psychiatry.* 156.

Bates, D. (2002). "The Quality Case for Information Technology in Healthcare." *BMC Medical Informatics and Decision Making.* 2(7).

Bates, D., Ebell, M., Gotlieb, E., Zapp, F., and Mullins, H. (2003). "A Proposal for Electronic Medical Records in U.S. Primary Care." *Journal of the American Medical Informatics Association.* 10.

Bates, D., Kuperman, G., Rittenberg, E., Teich, J., Fiskio, J., Ma'luf, N., Onderdonk, A., Wybenga, D., Winkelman, J., Brennan, T., Komaroff, A., and Tanasijevic, M. (1999). "A Randomized Trial of a Computer-based Intervention to Reduce Utilization of Redundant Laboratory Tests." *The American Journal of Medicine.* 106(2).

Baucus, M., and Fowler, E. (2002). "Geographic Variation in Medicare Spending and The Real Focus of Medicare Reform." *Health Affairs Web Exclusive.*

Bazzoli, G., Shortell, S., Dubbs, N., Chan, C., and Kravolec, P. (1999). "A Taxonomy Of Health Networks and Systems: Bringing Order Out of Chaos." *Health Services Research.* 33(6).

Berner, E., Detmer, D., and Simborg, D. (2004). "Will the Wave Finally Break? A Brief View of the Adoption of Electronic Medical Records in the United States." *Journal of the American Medical Informatics Association.* 12.

Brailer, D. (2005). "Interoperability: the Key To The Future Health Care System Interoperability Will Bind Together A Wide Network of Real-time, Life-Critical Data that Not Only Transform But Become Health Care." *Health Affairs WebExclusive.*

Burgess, J., Carey, K., and Young, G. (2005). "The Effect of Network Arrangements On Hospital Pricing Behavior." *Journal of Health Economics.* 24(2).

Burt, C., and Hing, E. (2005). "Use of Computerized Clinical Support Systems in Medical Settings: United States, 2001-2003." *Advance Data From Vital and Health Statistics of the CDC.* 353.

Chern, J., and Wan, T. (2000). "The Impact of the Prospective Payment System on the Technical Efficiency of Hospitals." *Journal of Medical Systems.* 24(3).

Clement, J., and Grazier, K. (2001). "HMO Penetration: Has it Hurt Public Hospitals?" *Journal of Health Care Finance.* 28(1).

Cohen, J., Cohen, P., West, S., and Aiken, L. (2003). *Applied Multiple Regression/ Correlation Analysis for the Behavioral Sciences Third Edition*. Lawrence

Erlbaum Associates Publishers.

Cooper, W., Seiford, L., and Tone, K. (2000). *Data Envelopment Analysis A Comprehensive Text with Models, Applications, References, and DEA-Solver Software.* Kluwer Academic Publishers.

"Crossing the Quality Chasm: A New Health System for the 21st Century." (2001).

Cushman, R., (1997). "Serious Technology Assessment for Health Care Information Technology." *Journal of the American Medical Informatics Association.* 4.

Deeks, J., Dinnes, J., D'Amico, R., Sowden, A., Sakarovtich, C., Song, F., Petticrew, M., And Altman, D. (2003). "Evaluating Non-Randomized Intervention Studies." *Health Technology Assessment.* 7(27).

Delpierre, C., Cuzin, L, Fillaux, J., Alvarez, M., Massip, P., and Lang, T. (2004). "A Systematic Review of Computer-based Patient Record Systems and Quality of Care: More Randomized Clinical Trials or a Broader Approach?" *International Journal for Quality in Health Care.* 16(5).

Demiris, G., Patrick, T., and Boren, S. (2004). "Assessing Patient Safety Awareness And Needs in Rural Hospitals in One U.S. State." *Informatics in Primary Care.* 12.

Dess, G., and Beard, D. (1984). "Dimensions of Organizational Task Environments." *Administrative Science Quarterly.* 29.

Diero, L., Rotich, J., Bii, J., Mamlin, B., Einterz, R., Kalamai, I., and Tierney, W. (2006). "A Computer-based Medical Record System and Personal Digital Assistants to Assess and Follow Patients With Respiratory Tract Infections Visiting a Rural Kenyan Health Center." *BMC Medical Informatics and Decision Making.* 6(21).

Dobbing, C. (2001). "Paperless Practice- Electronic Medical Records at Island Health." *Computer Methods and Programs in Biomedicine.* 64(3).

Donabedian, A. (1980). *Explorations in Quality Assessment and Monitoring Volume I The Definition of Quality and Approaches to Its Assessment.* Ann Arbor: Health Administration Press.

Dubois, R., Batchlor, E., and Wade, S. (2002). "Geographic Variation in the Use of Medications: Is Uniformity Good News or Bad?" *Health Affairs.* 21(1).

Dubbs, N., Bazzoli, G., Shortell, S., Kravolec, P. (2004). "Reexamining Organizational Configurations: An Update, Validation, and Expansion of the Taxonomy of Health Networks and Systems." *Health Services Research.* 39(1).

England, I. and Stewart, D. (2003). "Health: IT Leader or Laggard? A ComparativeAssessment of IT Maturity." *Autralian Health Review.* 26(2).

Fernandopulle, R., Ferris, T., Epstein, T., McNeil, B., Newhouse, J., Pisano, G., and Blumenthal, D. (2003). "A Research Agenda For Bridging the 'Quality Chasm' Bridging the Quality Chasm Requires a Marriage Between Research and Action." *Health Affairs.* 22(2).

Fletcher, R., Dayhoff, R., Wu, C., Graves, A., and Jones, R. (2001). "Computerized Medical Records in the Department of Veterans Affairs." *Cancer.* 91(S8).

Garrido, T., Jamieson, L., Zhou, Y., Wiesenthal, A., and Liang, L. (2005). "Effect of Electronic Health Records in Ambulatory Care: A Retrospective, Serial, Cross Sectional Study." *BJM.* 330.

Ginn, G., and Young, G. (1992). "Organizational and Environmental Determinants Of Hospital Strategy." *Hospital and Health Services Administration.* 37(3).

Ginn, G., Young, G., and Beekum, R. (1995). "Business Strategy and Financial Structure: An Empirical Analysis of Acute Care Hospitals." *Hospital and Health Services Administration.* 40(2).

Gresenz, C., Rogowski, J., and Escarce, J. (2004). "Updated Variable-Radius Measures Of Hospital Competition." *Health Services Research.* 39(2).

Hannan, T. (1999). "Variation in Health Care- The Roles of the Electronic Medical Record." *International Journal of Medical Informatics.* 54(2).

Harrison, J., and Sexton, C. (2004). "The Paradox of the Not-for-Profit Hospital." *The Health Care Manager.* 23(3).

Hillman, J. and Given, R. (2005). "Hospital Implementation of Computerized Provider Order Entry Systems: Resulrs from the 2003 Leapfrog Group Quality and Safety Survey." *Journal of Healthcare Information Management.* 19(4).

Hiotis, K., Ye, W., Sposto, R., Goldberg, J., Mukhi, V., and Skinner, K.(2005). "The Importance of Location in Determining Breast Conservation Rates." *American Journal of Surgery.* 190(1).

Hosmer, D. and Lemeshow, S. (2000). *Applied Logistic Regression.* John Wiley and Sons.

Hospital Quality Alliance Overview Summary. (2006). www.cms.hhs.gov/HospitalQualityInits/

James, B. (2005). "E-Health: Steps on the Road To Interoperability A Large Integrated Delivery System Takes Action on Improving Health Care Information Exchange." *Health Affairs Web Exclusive.*

Jha, A., Kuperman, G., Rittenberg, E., Teich, J., Bates, D. (2001). "Identifying Hospital Admissions Due to Adverse Drug Events Using a Computer-Based Monitor." *Pharmacoepidemiology and Drug Safety.* 10(2).

Jha, A., Li, Z., Orav, J., and Epstein, A. (2005). "Care in U.S. Hospitals –The Hospital Quality Alliance Program." *The New England Journal of Medicine.* 353(3).

Korst, L., Eusebio-Angeja, A., Chamorro, T., Aydin, C., and Gregory, K. (2003). "Nursing Documentation Time During Implementation of an Electronic Medical Record." *Journal of Nursing Administration.* 33(1).

Kranhold, K. (2005). "Switching to Electronic Medical Records is Necessary But Costly." *The Wall Street Journal.* www.post-gazette.com/pg/05171/525309.stm

Lee, S., and Alexander, J. (1999). "Managing Hospitals in Turbulent Times: Do Organizational Changes Improve Hospital Survival?" Health Services Research. 34(4).

Lee, S., Alexander, J., and Bazzoli, G. (2003). "Whom Do They Serve?: Community Responsiveness Among Hospitals Affiliated with Health Systems and Networks. *Medical Care.* 41(1).

Linnas, M. (1998). "Measuring Hospital Cost Efficiency With Panel Data Models." *Health Economics.* 7.

Linna, M., Hakkeinen, U., and Magnussen, J. (2005). "Comparing Hospital Cost

Efficiency Between Norway and Finland." *Health Policy.* 7.

Long, A. and Harrison, S. 1985. Health Services Performance. Effectiveness and Efficiency. Croom Helm.

Lucas, J., Avi-Itshak, T., Robinson, J., Morris, C., Koren, M., and Reinhard, S., (2005). "Continuous Quality Improvement as an Innovation: Which Nursing Facilities Adopt It?" *The Gerontologist.* 45.

Mark, T. (1999). "Analysis of the Rationale For and Consequences of, Nonprofit And For-Profit Ownership Conversions." *Health Services Research.* 34(1).

McKay, N., Deily, M., and Dorner, F. (2002-2003). "Ownership and Changes in Hospital Inefficiency, 1986-1991." *Inquiry.* 39(4).

Menachemi, N., Burke, D., Clawson, A., and Brooks, R. (2005). "Information Technologies in Florida's Rural Hospitals: Does System Affiliation Matter?" *Journal of Rural Health.* 21(3).

Mick, S. (1990). *Innovations in Health Care Deliver: Insights for Organizational Theory.*_San Francisco: Jossey-Bass Publishers.

Mick, S. and Wyttenback, M. (2003). Advances in Health Care Organization Theory. San Francisco: Jossey-Bass. John Wiley and Sons.

Middleton, B., Hammond, W., Brennan, P., and Cooper, G. (2004). "Accelerating U.S. E H R Adoption: How to Get There From Here. Recommendations Based on the 2004 ACMI Retreat." *Journal of the Americana Medical Informatics Association.*12.

Milcent, C. (2005). "Hospital Ownership, Reimbursement Systems and Mortality Rates." *Health Economics.* 14.

Miller, R., and Sim, I. (2004). "Physicians' Use of Electronic Medical Records: Barriers And Solutions.' *Health Affairs.* 23(2).

O'Connell, R., Cho, C., Shah, N., Brown, K., and Shiffman, R. (2003). "Take Notes: Differential EHR Satisfaction with Two Implementations Under One Roof."*Journal of the American Medical Informatics Association.* 11.

Ozcan, Y. (2005). *Quantitative Methods in Health Care Management Techniques And Applications.*_ San Francisco: John Wiley and Sons.

Ozcan, Y. (1992-1993). "Sensitivity Analysis of Hospital Efficiency Under Alternative Output/Input and Peer Groups: A Review." *Knowledge and Policy: The International Journal of Knowledge Transfer and Utilization.* 5(4).

Ozcan, Y., Luke, R., and Haksever, C. (1992). "Ownership and Organizational Performance A Comparison of Technical Efficiency Across Hospital Types." *Medical Care.* 30(9).

Ozgen, H., and Ozcan, Y. (2004). "Longitudinal Analysis of Efficiency in Multiple Output Dialysis Markets." *Health Care Management Science.* 7(4).

Paganini, Jose Maria. 1993. Quality and Efficiency of Hospital Care: The Relationship Between Structure, Process, and Outcome. Washington, D.C. Pan American Health Organization. The World Health Organization.

Percent of Private Sector Employees Enrolled in Employer's Health Plan By Firm Size And State: United States, 1993. Retrieved on July 17, 2006. www.cdc.gov/nchs/data/nehis/tab18.pdf

Pestotnik, S., Classen, D., Evans, R., and Burke, J. (1996). "Implementing Antibiotic Practice Guidelines through Computer-Assisted Decision Support." *Annals of Internal Medicine.* 124(10).

Proenca, E., Rosko, M., and Zinn, J. 2002. "Correlates of Hospital Provision of Prevention and Health Promotion Services." *Medical Care Research and Review.* 60(1).

Rash, M. (2005). "Privacy Concerns Hinder Electronic Medical Records." *The Business Journal of the Greater Triad Area.*
www.bizjournals.com/industries/health_care/physician_practices/2005/04/04/triad_fo

Reinhardt, U., Hussey, P. and Anderson, G. (2004). "U.S. Health Care Spending In An International Context." *Health Affairs*. 23(3).

Renshaw, L., Kimberly, J., and Schwartz, J. (1990). Technology Diffusion and Ecological Analysis: The Case of Magnetic Resonance Imaging. In S. Mick, (Ed.). *Innovations In Health Care Delivery* (pp. 181-206). San Francisco: Jossey-Bass. John Wiley and Sons.

Retchin, S., and Wenzel, R. (1999). "Electronic Medical Record Systems at Academic Health Centers: Advantages and Implementation Issues." *Academic Medicine.* 74(5).

Rose, A., Schnipper, J., Park, E., Poon, E., Li, Q., and Middleton, B. (2005). "Using Qualitative Studies to Improve the Usability of an EMR." *Journal of Biomedical Informatics.* 38(1).

Rosko, M. (1999). "Impact of Internal and External Environmental Pressures on Hospital Inefficiency." *Health Care Management Science.* 2(2).

Rosko, M. (2004). "Performance of Major Teaching Hospitals During the 1990s: Adapting to Turbulent Times." *Journal of Health Care Finance.* 20(3).

Rosko, M, and Proenca, J. (2005). "Impact of Network and System Use on Hospital X-Efficiency." *Health Care Management Review.* 30(1).

Schmitt, K., and Wofford, D. (2002). "Financial Analysis Projects Clear Returns From Electronic Medical Records." *Healthcare Financial Management.*

"Senate Wants Patients to Carry Own Electronic Medical Records." (2005). www.foxnews.com/story/0,2933,176243,00.html

Shen, Y. (2003). "Changes in Hospital Performance After Ownership Conversions." *Inquiry.* 40(3).

Shortell, S. and Kaluzny, A. (2000). *Health Care Management Organizational DesignAnd Behavior 4th Edition.* Delmar.

Shortliffe, E. (1999). "The Evolution of Electronic Medical Records." *Academic Medicine.* 74(4).

Sloan, F., Picone, G., Taylor, D., and Chou, S. (2001). "Hospital Ownership and Cost And Quality of Care: Is There a Dime's Worth of Difference?" *Journal of Health Economics.* 20(1).

Slutzky, S. (2004). "The Economies of Electronic Efficieny: A Three-Hospital Healthcare System Emerges from a Disparate, Paper-laden Clinical Report Process to a Swift, Centralized Electronic System." *Health Management Technology.* 25(2).

Spencer, E., Swanson, T., Hueston, W., and Edberg, D. (1999). "Tools to Improve

Documentation of Smoking Status, Continuous Quality Improvement and Electronic Medical Records." *Archives of Family Medicine.* 8(1).

Teich, J., Merchia, P., Schmiz, J., Kuperman, G., Spurr, C., and Bates, D. (2000). "Effects of Computerized Physician Order Entry on Prescribing Practices." *Archives of Internal Medicine.* 160(18).

Tierney, W., Overhage, J., and McDonald, C. (1997). "Demonstrating the Effects of an IAIMS on Health Care Quality and Cost." *Journal of the American Medical Informatics Association.* 4(S41-S46).

Townes, P., Benson, D., Johnston, P., and Vaughn, C. (2000). "Making EMRs Really Work: The Southeast Health Center Experience." *Journal of Ambulatory Care Management.* 23(2).

Varon, J., and Marik, P. (2002). "Clinical Information System and the Electronic Medical Record in the Intensive Care Unit." *Current Opinion in Critical Care.* 8(6).

Walker, J. (2005). "Electronic Medical Records and Health Care Transformation." *Health Affairs.* 24(5).

Wang, S., Middleton, B., Prosser, L, Bardon, C., Spurr, C., Carchidi, P., Kittler, A., Goldszer, R., ,Fairchild, D., Sussman, A., Kuperman, G., and Bates, D. (2003). "A Cost-benefit Analysis of Electronic Medical Records in Primary Care." *The American Journal of Medicine.* 114(5).

White, K., Cochran, C., and Patel, U. (2002). "Hospital Provision of End-Of-Life Services: Who, What, and Where?" *Medical Care.* 40(1).

White, K., and Ozcan, Y. (1996). "Church Ownership and Hospital Efficiency." *Hospital and Health Services Administration.* 41(3).

Winkelman, W., Leonard, K., and Rossos, P. (2005). "Patient-perceived Usefulness of On-line Electronic Medical Records: Employing Grounded Theory in the Development of Information and Communication Technologies for Use by Patients Living With Chronic Illness." *American Medical Informatics Association.*

Williams, S., and Torrens, P. (2002). Introduction to Health Services 6th Edition. Delmar Thompson Learning.

Wooldridge, J. (2003). *Introductory Econometrics, A Modern Approach, Second Edition.* Thomson.

Zinn, J., Proenca, J., and Rosko, M. (1997). "Organizational and Environmental Factors In a Hospital Alliance Membership and Contract Management: A Resource-Dependence Perspective." *Hospital and Health Services Administration.* 42(1).

Zakus, J. (1998). "Resource Dependency and Community Participation in Primary Health Care." *Social Sciences Medicine.* 46(4-5).

Zwillich, T. (2005). "Government Moves to Expand E-Medical Records." *FoxNews.com.* www.foxnews.com/story/0,2933,171518,00.html

APPENDICES

Appendix A: Multicollinearity Analysis

ations	1	2	3	4	5	6	7
l Size	1	-0.532**	-0.173**	0.380**	0.151**	0.016	0.19**
.ching Status	-0.532**	1	0.125**	-0.271**	-0.09**	0.012	-0.067**
'er Mix	-0.173**	0.125**	1	-0.219**	-0.054**	-0.004	-0.041**
Capita Income	0.38**	-0.271**	-0.219**	1	0.224**	0.012	0.178**
:mployment Change	0.151**	-0.09**	-0.054**	0.224**	1	0.003	0.068**
:rating Margin	0.016	0.012	-0.004	0.012	0.003	1	0.041**
ı-profit	0.19**	-0.067**	-0.041**	0.178**	0.068**	0.041**	1
›lic	-0.173**	0.008	0.01	-0.206**	-0.104**	-0.084**	-0.698**
ıtralized System	0.129**	-0.119**	-0.039**	0.118**	0.08**	0.011	0.141**
:ntralized Physician n	0.07**	-0.06**	0.004	0.01	0.006	0.015	0.142**
oderately Centralized n	0.155**	-0.078**	-0.034*	0.129**	0.086**	0.013	0.187**
:centralized System	-0.041**	0.083**	-0.024	-0.047**	0.005	0.04**	-0.189**
dependent System	-0.031*	0.02	-0.012	0.016	0.013	-0.075**	-0.047**
:rfindahl Index	-0.353**	0.197**	0.159**	-0.495**	-0.187**	0.01	-0.117**
ꞦBAN1	0.355**	-0.217**	-0.17**	0.551**	0.284**	0	-0.084**
ꞦBAN2	0.137**	-0.05**	-0.035*	0.037*	-0.013	-0.027	0.057**
ꞦBAN3	0.039**	0.034*	0.018	-0.087**	-0.101**	0.029*	0.018
ꞦBAN4	-0.085**	0.072**	0.086**	-0.117**	0.013	0.015	0.03*
ꞦBAN5	-0.034*	0.042**	0.046**	-0.064**	-0.097**	0.01	-0.009
ꞦBAN6	-0.233**	0.096**	0.101**	-0.275**	-0.05**	-0.007	-0.075**
ꞦBAN7	-0.196**	0.087**	0.045**	-0.176**	-0.123**	0.008	-0.068**
ꞦBAN8	-0.115**	0.044**	0.035*	-0.12**	-0.036*	-0.008	-0.027

:relation is significant at the 0.01 level (2-tailed).
elation is significant at the 0.05 level (2-tailed).

ıtions	8	9	10	11	12	13	14
Size	-0.173**	0.129**	0.07**	0.155**	-0.041**	-0.031*	-0.353**
ching Status	0.008	-0.119**	-0.06**	-0.078**	0.083**	0.02	0.197**
er Mix	0.01	-0.039**	0.004	-0.034*	-0.024	-0.012	0.159**
Capita Income	-0.206	0.118	0.01	0.129	-0.047	0.016	-0.495
:mployment e	-0.104**	0.08**	0.006	0.086**	0.005	0.013	-0.187**
:rating Margin	-0.084**	0.011	0.015	0.013	0.04**	-0.075**	0.01
ı-profit	-0.698**	0.141**	0.142**	0.187**	-0.189**	-0.047**	-0.117**
lic	1	-0.084**	-0.097**	-0.143**	-0.134**	-0.02	0.299**
tralized ı	-0.084**	1	-0.042**	-0.096**	-0.12**	-0.048**	-0.13**
ntralized ian System	-0.097**	-0.042**	1	-0.083**	-0.103**	-0.042**	-0.019
ɔderately lized System	-0.143**	-0.096**	-0.083**	1	-0.235**	-0.095**	-0.19**
:centralized ı	-0.134**	-0.12**	-0.103**	-0.235**	1	-0.117**	-0.064**
lependent ı	-0.02	-0.048**	-0.042**	-0.095**	-0.117**	1	-0.088**
:rfindahl Index	0.299**	-0.13**	-0.019	-0.19**	-0.064**	-0.088**	1
ꞦBAN1	-0.193**	0.166**	-0.024	0.161**	-0.031*	0.066**	-0.657**
ꞦBAN2	-0.094**	-0.017	0.06**	0.031**	0.002	0.006	-0.24**
ꞦBAN3	-0.035*	-0.019	0.011	0.005	0.018	-0.01	0.019
ꞦBAN4	-0.015	-0.023	0.041**	-0.029*	0.002	-0.029*	0.162**
ꞦBAN5	0.017	-0.03*	-0.009	-0.004	0.019	-0.005	0.114**
ꞦBAN6	0.115**	-0.058**	0	-0.086**	0.003	-0.022	0.377**
ꞦBAN7	0.146**	-0.059**	-0.039**	-0.083**	0.027	-0.034*	0.328**
ꞦBAN8	0.062**	-0.026	-0.011	-0.032*	-0.03*	0.001	0.165**

relation is significant at the 0.01 level (2-tailed).
elation is significant at the 0.05 level (2-tailed).

Appendix A Continued: Multicollinearity Analysis

	15	16	17	18	19	20	21	22
	0.355**	0.137**	0.039**	-0.085**	-0.034*	-0.233**	-0.196**	-0.115**
Status	-0.217**	-0.05**	0.034*	0.072**	0.042**	0.096**	0.087**	0.044**
x	-0.17**	-0.035*	0.018	0.086**	0.046**	0.101**	0.045**	0.035**
a Income	0.551	0.037	-0.087	-0.117	-0.064	-0.275	-0.176	-0.12
yment	0.284**	-0.013	-0.101**	0.013	-0.097**	-0.05**	-0.123**	-0.036*
g Margin	0	-0.027	0.029*	0.015	0.01	-0.007	0.008	-0.008
it	0.084**	0.057**	0.018	0.03*	-0.009	-0.075**	-0.068**	-0.027
	-0.193**	-0.094**	-0.035*	-0.015	0.017	0.115**	0.146**	0.062**
ed	0.166**	-0.017	-0.019	-0.023	-0.03*	-0.058**	-0.059**	-0.026
zed yste	-0.024	0.06**	0.011	0.041**	-0.009	0	-0.039**	-0.011
ely Syst	0.161**	0.031*	0.005	-0.029*	-0.004	-0.086**	-0.083**	-0.032*
alized	-0.031*	0.002	0.018	0.002	0.019	0.003	0.027	-0.03*
dent	0.066**	0.006	-0.01	-0.029*	-0.005	-0.022	-0.034*	0.001
ahl Index	-0.657**	-0.24**	0.019	0.162**	0.114**	0.377**	0.328**	0.165**
I1	1	-0.28**	-0.231**	-0.189**	-0.125**	-0.273**	-0.23**	-0.115**
I2	-0.28**	1	-0.143**	-0.117**	-0.077**	-0.169**	-0.143**	-0.071**
I3	-0.231**	-0.143**	1	-0.097**	-0.064**	-0.139**	-0.118**	-0.059**
I4	-0.189**	-0.117**	-0.097**	1	-0.052**	-0.114**	-0.096**	-0.048**
I5	-0.125**	-0.077**	-0.064**	-0.052**	1	-0.075**	-0.064**	-0.032*
I6	-0.273**	-0.169**	-0.139**	-0.114**	-0.075**	1	-0.139**	-0.069**
I7	-0.23**	-0.143**	-0.118**	-0.096**	-0.064**	-0.139**	1	-0.059**
I8	-0.115**	-0.071**	-0.059**	-0.048**	-0.032*	-0.069**	-0.059**	1

on is significant at the 0.01 level (2-tailed).
n is significant at the 0.05 level (2-tailed).

Appendix B: Quality Score Descriptives and Frequency

		Raw Quality
N	Valid	2891
Mean		0.6903
Median		0.75
Mode		1
Std. Deviation		0.25704
Variance		0.06607
Percentiles	25	0.5
	50	0.75
	75	0.9

Appendix B Continued: Quality Scores

Raw Quality Score	Frequency	Percent	Valid Percent	Cumulative Percent
0	73	1.6	2.5	2.5
0.1	7	0.2	0.2	2.8
0.11	19	0.4	0.7	3.4
0.13	4	0.1	0.1	3.6
0.14	9	0.2	0.3	3.9
0.17	13	0.3	0.4	4.3
0.2	22	0.5	0.8	5.1
0.22	25	0.5	0.9	5.9
0.25	83	1.8	2.9	8.8
0.29	23	0.5	0.8	9.6
0.3	24	0.5	0.8	10.4
0.33	84	1.8	2.9	13.4
0.38	8	0.2	0.3	13.6
0.4	55	1.2	1.9	15.5
0.43	27	0.6	0.9	16.5
0.44	52	1.1	1.8	18.3
0.5	243	5.3	8.4	26.7
0.56	58	1.3	2	28.7
0.57	37	0.8	1.3	30
0.6	145	3.1	5	35
0.63	16	0.3	0.6	35.5
0.67	167	3.6	5.8	41.3
0.7	140	3	4.8	46.1
0.71	46	1	1.6	47.7
0.75	153	3.3	5.3	53
0.78	117	2.5	4	57.1
0.8	258	5.6	8.9	66
0.83	37	0.8	1.3	67.3
0.86	53	1.2	1.8	69.1
0.88	22	0.5	0.8	69.9
0.89	148	3.2	5.1	75
0.9	194	4.2	6.7	81.7
1	529	11.5	18.3	100
Total	2891	62.8	100	

VITA

Abby Swanson was born in Ann Arbor, Michigan. In 2001, she earned her Bachelor's of Art with a major in Sociology and her Master's in Teaching from the University of Virginia in Charlottesville. While working as a Public Education Coordinator in the organ and tissue donation field in Richmond, VA, she began her doctoral studies in Health Services Organization and Research at Virginia Commonwealth University in 2003. During her time at VCU, Abby served as a research assistant on projects including examining primary care services areas (PCSAs) and studying the physician workforce in Virginia. She also taught an introductory course overview of the the U.S. Health Care System, HCMG 300. Abby is currently an Assistant Professor of Health Administration and Policy at the Medical University of South Carolina in Charleston.