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An Exploration of the Impact of Electronic Medical Record Capabilities Selection, Implementation Sequence, and Adoption Timing on Healthcare Outcomes

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AN EXPLORATION OF THE IMPACT OF ELECTRONIC MEDICAL RECORD CAPABILITIES SELECTION, IMPLEMENTATION SEQUENCE, AND ADOPTION TIMING ON HEALTHCARE OUTCOMES

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By
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DISSERTAON APPROVAL FORM

This dissertation is approved as a credible and independent investigation by a candidate for the Doctor of Science in Information Systems degree and is acceptable for meeting the dissertation requirements for this degree. Acceptance of this dissertation does not imply that the conclusions reached by the candidate are necessarily the conclusions of the major department or university.

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ABSTRACT

Investments in Electronic medical records (EMR) is one of the largest components of overall health information technology investments. Examining the impact of EMR on quality of healthcare delivery is a topic of significant importance. This dissertation aims at exploring the relationship between the EMR capabilities and healthcare quality performance of hospitals. In particular, this study examines three important issues. First, the relationship between the synergy among different portfolios of EMR capabilities and quality of care at U.S. hospitals is studied. It also extends the analysis of EMR capabilities effects on quality of healthcare beyond the focus on the initial investment to examine how the assimilation and use of different EMR capabilities impact various healthcare quality measures. We used archival data to conduct a five-year (2008-2012) longitudinal study of a large panel of U.S. hospitals.

Second, this study seeks to determine whether early adopters of advanced EMR capabilities (CPOE and physician documentation) were able to improve quality of healthcare, and finally, this research also answers the question of whether EMR capabilities adoption path impacts healthcare quality outcomes.

Our results suggest that the synergy among full EMR capabilities portfolio is associated with better quality outcomes. Our results also suggest that the greater assimilation and use of EMR capabilities are also associated with improvement on only one quality outcomes measure. Further, the results highlight that early adopters of advanced EMR capabilities were able to improve quality outcomes relative to hospitals that were not early adopters. Furthermore, our results suggest that the sequence of EMR capabilities adoption does matter, and the findings empirically show improvement in quality outcomes when hospitals follow certain sequences of EMR capabilities adoption. We believe that this study has important implications for public policy focused on enhancing health IT investments in EMR capabilities and improving quality outcomes.

DECLARATION

I hereby certify that this project constitutes my own product, that where the language of others is set forth, quotation marks so indicate, and that appropriate credit is given where I have used the language, ideas, expressions or writings of another.

I declare that the project describes original work that has not previously been presented for the award of any other degree of any institution.

Signed,

_______Yousra Harb____________________

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CHAPTER 1

INTRODUCTION

1.1 IT Investment in Healthcare

Many organizations increased the investment in information technology (IT) to meet the growing demands for efficiency and effectiveness (Ghapanchi, Tavana, Khakbaz, & Low, 2012). According to Rivard, Raymond, and Verreault (2006), well-planned investments in IT that meet business mission requirements can have a positive impact on organizational performance. On the other hand, poorly planned IT investments can postpone or severely limit organizational performance (Gunasekarana, Love, Rahimic, & Miele, 2001).

In the current healthcare context, expenditures are approaching "$3 trillion and comprise about 20 percent of U.S. economic activity" (Briggs, 2014). Berwick and Hackbarth (2012) estimated that between $558 billion and $1264 billion of expenditures in 2011 may be considered as waste and provided no value to patients. The expenditures that are considered wasteful include failure in care delivery, failure of care coordination, overtreatment, administrative complexity, pricing failure, and fraud and abuse. Organizations view investments in information technology as a way to improve productivity, profitability, and the quality of operations (Devaraj & Kohli, 2003). To this end, healthcare organizations continue to make investments in IT to deliver better care. The premise is that investments in health information technology will improve healthcare processes and raise the quality and safety of patient care leading to better outcomes by reducing medical errors, reducing duplicate testing and overtreatment, and lowering administrative expenses (Johnston et al., 2012).

In the U.S., hospitals have taken steps to implement various health information technologies (HIT) in order to provide effective care that consistently results in improved outcomes. Examples of these technologies include electronic medical records (EMR), picture archiving and communication systems (PACS), and facilitating care from a distance. These distance technologies include access to medical journals and databases on the internet, videoconferencing, emails, or feedback via the internet (Lluch, 2011).

1.2 EMR Capabilities and Healthcare

Health IT is a subset of information technology used to make a decision concerning diagnosis, treatments, and control several medical conditions (Angst et al., 2011). Various technologies applied to healthcare setting including computerized practitioner order entry (CPOE), clinical decision support systems (CDSS), and EMR. EMR is one of the most important components of health information technology and is viewed as a system that will substantially contribute to improving quality of healthcare, patient safety, and cost effectiveness (Debbie, 2009). EMR is known by various other names including electronic health records (EHR), electronic patient record (EPR), and computerized patient record (CPR) (Menachemi & Brooks, 2006). In this study, the term EMR is used to represent all such technology.

According to a report published by the Institute of Medicine (2003), EMR should be capable of performing core related capabilities or basic functionalities in order to promote greater safety, quality, and efficiency in health care delivery. The committee of the Institute of Medicine has identified a set of eight core care delivery functions. These are: health information and data, result management, order management, decision support, electronic communication and connectivity, patient support, administrative processing and reporting, and reporting and population health management. This was necessary in order to leverage providers' knowledge of the functional capabilities of EMR systems, resulting in better decisions in systems purchasing. Systems are purchased that are more appropriate for their practice needs (Debbie, 2009).

EMR functionality is characterized by automation of patient information and medication data, documentation, and clinical decision processes. These processes include order entry management and support of clinical decision making (Furukawa, Raghu, & Shao, 2010b). Accordingly, achieving true EMR functionality requires adding capabilities including: Clinical data repository (CDR), clinical decision support systems (CDSS), computerized practitioner order entry (CPOE), and other provider-centric information technologies (Carter, 2008). In line with these characteristics, the Healthcare Information and Management Systems Society (HIMSS) analytics database[1]classifies EMR as a category. The following capabilities that could achieve the aforementioned EMR core related functionalities, include but are not limited to:

- CDR: CDR is a real time database that combines disparate information about patient in single database.
- CDSS: CDSS is a system that uses clinical information to help physicians diagnose patients, and provide advises in drug selection, dosage, interaction, and allergies by providing alerts, reminder, and recommendations based on patient history (Bates, 2010). CDSS is also intended to ensure adherence to clinical guidelines of patient treatment.
- Order Entry includes Order Communications: This provides electronic forms to streamline hospital operations (replacing paper forms).
- CPOE: CPOE is a more advanced and sophisticated type of order entry and include patient information and clinical guidelines. This application helps physicians order drugs, laboratory tests, and ensures the order is complete and legible.
- Physician Documentation: This helps physicians complete documentation/notes electronically in order to accurately assign diagnostic codes.

Further, as part of the Health Information Technology for Economic and Clinical Health (HITECH), part of the American Recovery and Reinvestment Act of 2009 (ARRA), practices must meet specific guidelines and requirements for EHR that is designed to improve patient care safety, healthcare quality, and efficiency. Known as "Meaningful Use"[2]. HITECH Act supports adoption of certified EHR and provides monetary incentives for hospitals only if specific meaningful use requirements are met. In this context, there is lack of research that inform EMR capabilities implementation and sequence of EMR capabilities adoption.

1.3 Research Gaps and Questions

Our goal in this study is to examine the relationship between the implementation of EMR capabilities and patient quality of care, and to derive further insight by studying how the complementarities among EMR capabilities impact healthcare quality. Several studies have examined the effects of IT on organizational performance in healthcare (e.g., Briggs, 2014;

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[1] http://apps.himss.org/foundation/histdata.asp
[2] https://www.healthit.gov

Chaudhry et al., 2006; Devaraj & Kohli, 2003; Mccullough, Wang, Parsons, & Shih, 2015; Setia, Setia, Krishnan, & Sambamurthy, 2011; Spaulding, Furukawa, Raghu, & Vinze, 2013). Recent studies have reported mixed evidence on the influence of health IT on healthcare outcomes (Bardhan & Thouin, 2013). Some studies in other industries suggest that the effects of IT varies based on the portfolio of IT capabilities implemented and used by an organization (Aral & Weill, 2007; Dehning, Richardson, & Zmud, 2003). Although some studies have found a significant impact of IT investment on firm performance, others have failed to do so (Devaraj & Kohli, 2003). One explanation for the inconsistent findings is that most studies have overlooked an important dimension that could influence the relationship between IT and firm performance. Recent studies have argued that IT synergy has a significant role in enhancing firm performance (Cho and Shaw 2013; Tanriverdi 2005, 2006). Synergy refers to the additional expected value that can be achieved from multiple IT capabilities investments, which cannot be obtained from stand-alone individual technology. A firm may be able to save cost or create additional values from IT synergies (Tanriverdi, 2005, 2006). Moreover, there is a lack of research on the impact of the synergy between health IT systems on healthcare quality. Therefore, the objective of this study is to advance our understanding of the impacts of the synergy between IT systems on organizational outcomes in healthcare context. In particular, the focus of this research is on EMR's which in recent years has been the focus of large investments. Thus the first question addressed is whether the synergy between different EMR capabilities yields better quality than stand-alone health IT investments?

Next, we acknowledge prior research suggesting that technology usage is critically important in order to leverage IT productivity improvement (Brynjolfsson, 2005). Devaraj and Kohli (2003) have argued that investment in technology alone is not sufficient for reaping the promised benefits of information technologies. The driver of IT's impact on performance, however, lies in the actual usage. IT assimilation and use are the key variables in enhancing organizational performance (Devaraj & Kohli, 2003). Assimilation here refers to the extent of adoption and use of information technologies within the work processes (Setia et al., 2011). Here, we address the second research question: Does the intensity of EMR capabilities' assimilation and use have an impact on healthcare quality?

In the first research question, we explore the relationship between the synergy among EMR capabilities and quality of healthcare. In the next study, we further explore this issue along the time dimension to explore the impact of the sequence of EMR capabilities adoption. As noted above, poorly planned IT investments can postpone or severely limit organizational performance. Therefore, the next research question how does the sequence of EMR capabilities adoption have an impact on healthcare quality?

Furthermore, according to some economic studies of first-mover advantage, one way for organizations to achieve higher returns is to seize new lucrative opportunities early. It is claimed that only early adopters obtain a competitive advantage from IT adoption (Porter & Millar, 1985). In a healthcare context, early adopters may both earn benefits from early investments in health IT capabilities and may also find the optimal combination of health IT capabilities for their unique situation. Late adopters, on the other hand, may take a longer time to mimic the early adopters' configuration of health IT capabilities to see similar results (Pye, Rai, & Baird, 2014). Therefore, in this study we also examine the effects of adoption timing associated with EMR capabilities. Accordingly, our fourth research question is whether early adoption of EMR capabilities have an impact on healthcare quality?

1.4 Outline of Dissertation

This dissertation has the following organization. Chapter 2, is literature review and includes a summary of the research studies on health IT and quality of healthcare. Chapter 3 describes the research objectives and the research model. Chapter 4 describes the research methodology including statistical model specifications, data sources, and study variables. Chapter 5 discusses the results and the dissertation concludes with Chapter 6, which includes a summary of research contribution and impact, discussion of study limitations, and suggestions for areas of future research.

CHAPTER 2

LITERATURE REVIEW

2.1 Health IT and Quality

In this chapter, we review relevant research on health IT and its impact on healthcare quality outcomes and identify research gaps that lead to our research objectives. The literature is organized into two categories: (1) Research studies that examine the impact of individual health IT systems on healthcare outcomes as shown in Table 1, (2) Research studies that assess the impact of health IT portfolios on healthcare outcomes as shown in Table 2.

Table 1 summarizes the studies that assess the effects of health IT on healthcare quality organized by the most investigated health technologies including EMR, clinical decision support systems (CDSS), and computerized practitioner order entry (CPOE).

Quality is an important, and sometimes overlooked, dimension in the debate over healthcare reform (Bardhan & Thouin, 2013), especially since health information technologies have the potential to improve both the quality of healthcare processes (Bardhan & Thouin, 2013; David Bates, 2002) and outcomes (Bélanger, Bartlett, Dawes, Rodríguez, & Hasson-Gidoni, 2012).

A growing body of research investigates the impact of health IT on various aspects of healthcare quality. Menon and Kohli (2013) studied the relationship between health IT expenditure and quality of patient care using readmission and mortality rates measures. The study found that health IT is associated with lower readmission and lower mortality rates resulting in higher quality of care. Similar significant association between IT expenditures and lower mortality rates are observed by Gholami, Higón, and Emrouznejad (2015). Amarasingham, Plantinga, Diener-West, Gaskin, and Powe (2009) investigated the influence of the level of automation on healthcare outcomes. Hospital automation areas include test results, notes and records, order entry, and decision support. The outcome measures used in the study are inpatient mortality, complications, and length of stay. Hospitals with more health IT systems are associated with lower levels of inpatient mortality and complication. However, no clear effect of health IT was noted for length of stay. Other studies, on the other hand, found that the effect of computerization on process quality measures such as myocardial infraction, heart failure, and pneumonia made little difference in quality (Himmelstein, Wright, & Woolhandler, 2010).

Several studies investigate the influence of EMR on various healthcare quality measures. Linder, Ma, Bates, Middleton, and Stafford (2007) conducted a national cross-sectional study to assess the association between EHR implementation and quality of ambulatory care. The results showed that for 14 of 17 quality indicators, there was no significant difference in performance between visits with and without EHR. These quality measures assess whether patients received recommended care and included indicators such as medical management of common diseases, recommended antibiotic prescribing, preventive counseling, screening tests, and avoiding potentially inappropriate medication prescriptions for the elderly.

McCullough et al. (2015) examined the impact of the transition from paper recordkeeping to EHR use on practice-level performance of nine clinical quality measures. The measures include both process and outcome measures such as antithrombotic therapy, body mass index (BMI) recorded, smoking status recorded, smoking cessation intervention offered, hemoglobin A1c (HbA1c) testing and control, cholesterol testing and control, and blood pressure control. The results showed that the effect of EHR adoption on performance on clinical quality measures is mixed. Lee, Kuo, and Goodwin (2013) assessed the relationship between basic EMR adoption and 30-day re-hospitalization, 30-day mortality, inpatient mortality and length of stay. In particular, they compared the outcomes of hospitalization before and after EMR adoption among hospitals that adopted EMR. The results showed small but statistically significant association of EMR adoption with healthcare outcomes.

O’Connor et al. (2005) conducted a 5-year longitudinal study and assessed the impact of EMR on diabetes quality of care. The study compared one practice with EMR and one practice without EMR. The processes and outcomes measures used are glycated hemoglobin (HbA1c) and low-density lipoprotein (LDL). The frequency of HbA1c tests improved in the practice with EMR compared with the frequency at non-EMR clinic. Similar results were noted for LDL levels.

Parente and McCullough (2009) estimated the impact of ITs on some patient safety measures using panel data analysis approach. They examined EMR, nurse charts, and PACS. The safety outcomes measures are infection from medical care, postoperative hemorrhage, and postoperative pulmonary embolism. The results showed that EMR is associated with positive effect on patient safety measures.

Others studies also showed that the impact of EMR on healthcare quality varies by measures, has no significant difference between practices with and without EMR, or has no statistically significant association with quality (Adams, Mann, & Bauchner, 2003; DesRoches et al., 2010; Romano & Stafford, 2011).

Overall, we observe that these studies have reported conflicting findings on the impact of EMR on the quality of patient care. Basically, these studies have reported mixed evidence on the influence of EMR on healthcare outcomes. On the other hand, in spite of a large volume of studies that investigated the influence of EMR on healthcare quality, there is a shortage of research that empirically examines the implementation of different EMR capabilities and their impact on the quality of healthcare.

Based on the systematic review of 257 published studies on the impact of health IT between 1995 and 2005, Chaudhry et al. (2006) reported on the major effect of health IT on various measures of quality of care. Most of the reviewed studies examined DSS and EHR. The systematic review found that well-implemented decision support systems can yield real benefits in terms of improvements in adherence to guidelines, enhanced monitoring and surveillance activities, and reduction in medication errors. In 2011, Jaspers, Smeulers, Vermeulen, and Peute conducted a systematic review on the effect of CDS systems on patient outcomes and practitioner performance. The results showed that 30 percent of the examined studies had a significant impact on patient outcomes and 57 percent on practitioner performance. Preventive care reminders and drug prescription system were the areas that CDS systems has the greatest impact. Romano and Stafford (2011) also investigated the impact of CDS on healthcare quality and reported that CDS had a significant positive impact on only one of 20 quality measures.

Overall, we note that these studies assessed the impact of one EMR capabilities on healthcare quality. Therefore, there is a lack of research that capture all EMR capabilities and their impact on patient quality of care.

A recent study conducted by Jones, Rudin, Perry, and Shekelle (2014) consists of a systematic review of 147 studies on the 170 key quality-related outcomes (care process, health outcomes, and patient or provider satisfaction) between 1995 and 2013. Most of the evaluation focused on clinical decision support (CDS) and computerized provider order entry (CPOE). The reported results showed: 1) Most studies of CDS have reported positive or mixed-positive results with respect to the improvements in the processes targeted by decision support; 2) Most evaluation of CPOE have reported positive or mixed-positive effects with respect to medication error reduction; and 3) A small proportion of studies reported neutral or negative results due to a particular intervention, context, or implementation. Kaushal, Shojania, and Bates (2003) performed a systematic review to examine the impact of CDS and CPOE on medication safety. Four studies showed improvements in adverse drug events and medication errors while three studies demonstrated statistically insignificant results. Radley et al. (2013) used a systematic review and hospital survey data on CPOE implementation in order to estimate medication errors reduction in hospitals that adopted CPOE in 2008. The results showed that the use of CPOE decreased the likelihood of a prescription drug order error by 48 percent.

We observe that the aforementioned studies focused on specific health IT capabilities rather than portfolios of capabilities and their impact on healthcare quality outcomes. Our research, in contrast, aims at investigating the impact of portfolios of different EMR capabilities on quality of care using panel data analysis.

Table 1. Individual Health IT Systems

Study	**Description**	**Results**
	EMR and Healthcare Quality	
(Mccullough et al., 2015)	Assessed the impact of the transition to EHR use on quality of healthcare.	Performance patterns after EHR adoption varied by measure.
(Lee et al., 2013)	Assessed the impact of basic EMR on healthcare quality outcomes.	The results showed small but statistically significant association of EMR adoption with healthcare outcomes.

(Romano & Stafford, 2011)	Examined the impact of EHRs on outpatient care in the United States.	Findings indicated no significant relationship between EHR with better quality.
(DesRoches et al., 2010)	Examined electronic health record adoption in U.S. hospitals and the relationship to quality and efficiency.	No evidence of significant differences in risk-adjusted length of stay, thirty-day readmission rates, and total hospital costs for hospitals that have implemented EHR systems and those without EHRs.
(Parente & McCullough, 2009)	Conducted panel data to assess the impact of EMR, nurse charts, and PACS on patient safety outcomes.	EMR was associated with low level of infection from medical care.
(Linder et al., 2007)	Cross-sectional study to assess the association between EHR implementation and quality of ambulatory care.	No significant difference in performance between visits with and without EHR.
(O'Connor et al., 2005)	Examined the impact of EMR on diabetes quality of care using panel data.	Improvements in HbA1c and LDL levels frequency with EMR practice compared with non-EMR practice. But there were no statistically significant difference between both practices at two or four years.
(Adams et al., 2003)	Evaluated the quality of pediatric primary care before and after the introduction of EMR.	The use of the EMR was associated with improved quality of care.
CDSS, CPOE and Healthcare Quality		

(Jones et al., 2014)	Systematic review of 147 studies on the 170 key quality-related outcomes between 1995 and 2013.	1) CDS reported positive or mixed-positive results with respect to the improvements in the processes targeted by decision support, 2) CPOE reported positive or mixed-positive effects with respect to medication error reduction. 3) A small proportion of studies reported neutral or negative results due to a particular intervention, context, or implementation.
(Radley et al., 2013)	Systematic review on CPOE implementation in order to estimate medication errors reduction in hospitals that adopted CPOE.	The use of CPOE decreased the likelihood of a prescription drug order error by 48 percent.
(Jaspers et al., 2011)	Conducted a systematic review on the effect of CDS systems on patient outcomes and practitioner performance.	A significant impact on patient outcomes and practitioner performance.
(Chaudhry et al., 2006)	Systematic review of 257 published studies on the impact of Health IT on healthcare outcomes between 1995 and 2005.	Well-implemented decision support systems can yield real benefits.

(Kaushal, Shojania, & Bates, 2003)	Systematic review of CDS and CPOE implementation on medication safety.	1) Some studies showed that the use of CDS and CPOE improve adverse drug events and medication errors. 2) Other studies reported statistically insignificant results.

Other studies as shown in Table 2 focused on broad range of health IT capabilities. For example, Bardhan and Thouin (2013) conducted a three-year longitudinal study (2004 to 2006) of a large panel of U.S. hospitals to assess the impact of four health IT applications (clinical information systems, financial systems, scheduling systems, and human resource systems) on healthcare process-centric quality metrics, and include treatment of acute myocardial infraction, heart failure, pneumonia, and surgical infection prevention. The results indicated significant difference in the usage of health IT systems and their impact on healthcare processes quality. Setia et al. (2011) examined the impact of the assimilation and use of two health IT applications (clinical and business applications) on hospital performance. The results showed that the effect varies differently across the business and clinical process domains.

We observe that there is a lack of research on the influence of specific health IT combination on healthcare outcomes. In particular, to our knowledge no paper examines the influence of the synergy among EMR capabilities on healthcare outcomes. Our goal, in contrast, is to examine how the synergy among EMR capabilities portfolio impacts healthcare quality. Pinaire and Sarnikar (2015) recently published a paper that examines the synergy between health IT portfolios using cross sectional data. However, this study has data limitation and did not specifically address EMR capabilities portfolio. Our research, in contrast, focuses on the relationship between the synergy among EMR capabilities and healthcare outcomes using longitudinal data for five-year period from 2008 to 2012 inclusive.

Table 2. Health IT Portfolios

Study	Description	Results
(Bardhan & Thouin, 2013)	Used panel data to assess four health IT applications impact on healthcare process-centric quality metrics.	The results indicated significant difference in the impacts of health IT systems on healthcare processes quality.
(Pinaire & Sarnikar, 2015)	Assessed the impact of health IT portfolios on the quality of patient care.	Reported significant association between health IT portfolios synergistic impact and the quality of patient care.
(Setia et al., 2011)	Examined the impacts of the assimilation and use of IT on the financial performance of hospitals.	The effect of assimilation varies differently across the business and clinical process domains.
(Spaulding et al., 2013)	Evaluated the comparative importance of operational and organizational influences for complementary IT systems. Examined the relationship between the paths to IT adoption and financial performance.	Following the organizational model of adoption is associated with increase in net income per patient day; whereas the operational model of adoption is associated with decrease in net income per patient day.

Further, Cooper and Zmud (1990) argued that the mere adoption of IT may not be enough. According to some economic studies (Brynjolfsson, 2005), innovation in IT may be insufficient, and thousands of IT projects have failed to deliver on their productivity promise each year. Complementarities in IT investments and organizational and managerial practices, however, are the keys to the effective use of information technology in improving productivity and transforming an organization (Brynjolfsson, 2005). These IT-related practices create the synergies associated with growth in productivity.

In the context of healthcare, health IT adoption alone without consideration of the complementarities may substantially reduce the likelihood of benefiting from the investment in health information technology (Briggs, 2014). Therefore, we posit that the synergy between health ITs is important, and perhaps critically important to produce significant improvement in quality.

Further, earlier studies on assimilation and use have focused on the association between IT assimilation and performance (Angst & Agarwal, 2009; Devaraj & Kohli, 2003; Pavlou & Sawy, 2006; Setia et al., 2011). There is however a lack of research assessing the association between EMR capabilities assimilation and use and the quality of healthcare. This research addresses this gap by examining how the synergy between EMR capabilities and EMR capabilities' assimilation impact healthcare quality outcomes over time.

2.2 Early Health IT Adoption

Because the extensive use of information technology is relatively new in many healthcare settings, it is useful to review several studies in different disciplines that have tried to discover the relationship between technology investment and business value (Angst et al., 2011). In many industries, the use of information technology has been found to provide an opportunity to improve quality, increase value to customers, and reduce cost. As mentioned above, it has been claimed that early investment in information technology allows firms to improve their competitive position and perhaps even outperform their competitors (Clemons & Row, 1988; Copeland & McKenney, 1988). Basically, the main focus of this study is on the timing of the adoption event (Fichman, 2000). Adoption is defined as acquiring or purchasing a new invention or innovation (Fichman & Kemerer, 1999). Under this view, organizations that are early adopters are considered more innovative than later adopters or not at all (Fichman, 2000). Firms may reap different values from each new IT innovation. A new technology investment may provide an opportunity to gain competitive advantage in terms of cost reduction and productivity enhancement. However, this greatly depends on the new capabilities provided by the technology, and on firm and industry characteristics (Dos Santos & Peffers, 1993).

In the healthcare industry, quantification of the extent to which information technology adoption has improved quality or reduced cost is a difficult problem (Angst et al., 2011). A recent study conducted by Harvard Business Review/Verizon showed, “Only 27 percent of healthcare organizations proactively seek to get first-mover advantage, compared with 36 percent that buy new technology after others have proven its benefits and 35 percent that wait until something has become well established” (Diana, 2014). The general consensus is that health IT adoption rate is relatively slow in the U.S (Agarwal, Gao, DesRoches, & Jha, 2010). In general, the main determinants of new technology adoption are the cost and the benefits of adoption (Hall & Khan, 2003). The benefits received by the users are the difference in future expected profits when a firm switches to a newer technology.

Several studies investigated the factors influencing EMR adoption (Ash & Bates, 2005; Menachemi, Mazurenko, Kazley, Diana, & Ford, 2012; Nambisan, Kreps, & Polit, 2013). In particular, several factors are identified as major barriers to health IT adoption (Agarwal et al., 2010). Financial factors are often considered as the primary obstacle for health IT adoption. Hospitals are also concerned with the functionality and ease of use of health IT systems. This factor could have adverse effects on user acceptance and use of the technology. Regulations also play an important role in how hospitals adopt health IT solutions. Recently, the American Recovery and Reinvestment Act of 2009 (ARRA), encourages hospitals and physicians to increase the adoption of EHRs through monetary incentives. The goal is not adoption alone, but meaningful use of EHR. Therefore, if the provider does not become a meaningful user of EHR in 2015, penalties will be triggered through reduced Medicare reimbursement payments (ARRA, 2009).

However, there is limited research on the impact of EMR adoption timing on healthcare quality. Basically, there is limited empirical evidence that early adoption of health IT can provide health organizations with competitive advantages. Therefore, in the absence of strong evidence that early adoption provide value for the firm, decision makers would doubt that IT investments provide any real competitive advantage (Bittlestone, 1990). It is important to provide such evidence since the costs of new technology tend to be high and the benefits are difficult to determine in advance. According to Dos Santos and Peffers (1993), followers can implement IT applications at lower cost since the cost of IT adoption tends to decrease over time. Therefore, the benefits of early investment must be worthwhile for firms to take the lead in investing in a new IT application.

In this research, we present the results of a study of the effects of early hospital investments in advanced EMR capabilities, specifically CPOE and physician documentation. We attempt to answer this question: Did hospitals that were early adopters of advanced EMR capabilities gain significant benefits in terms of healthcare quality?

2.3 The Sequence of Health IT Implementation

Policy makers are giving considerable attention and resources to increase EMR capabilities adoption in order to improve the quality of healthcare. As mentioned earlier, EMR is one of the most important components of healthcare technology applications yet the adoption process is complex and often occurs incrementally over time.

As meaningful use requires adoption of certain EMR capabilities, knowing the sequence of adoption of EMR capabilities adoption may reveal how the incentive program will impact this approach and the unintended consequences (Adler-Milstein, Everson, & Lee, 2014).

In this context, little previous empirical evidence has examined the sequence of adoption of EMR capabilities. Although some industry models such as the seven-stage HIMSS EMR adoption model (EMRAM)[3] identify the sequence of EMR capabilities adoption, no previous study of which we are aware assesses the effects of the sequence of adoption on patient care and hospital performance. There is also a literature that examines questions related to sequencing. One study explored the relationship between technologies integration and hospital performance in terms of cost and quality. The findings showed that the adoption patterns did impact the cost and quality within the hospitals (Angst et al., 2011). Another study investigated the operational and organizational factors as the key of explaining the difference in health technology adoption patterns in healthcare settings (Spaulding et al., 2013). The findings from this study indicated that the adoption pattern does matter and following organizational model of adoption increases the net income per patient day.

Our goal, in contrast, is to identify the optimal sequence of EMR capabilities using panel data and examine the impact of EMR capabilities ordering adoption on patient quality of care. The seven-stage HIMSS EMRAM is a popular industry model that depicts different stages of adoption. It helps healthcare organizations to analyze their EMR adoption level. In each stage, a set of capabilities must be reached before moving to the next stage. In other words, EMRAM defines the standard sequence of EMR adoption. In EMRAM model, Stage 1 includes automation of

[3] Health Information Management and Systems Society. Electronic Medical Record Adoption Model (EMRAM). 2014. http://www.himssanalytics.org/emram/emram.

laboratory, pharmacy and radiology ancillaries. In Stage 2, all the results should be delivered electronically and linked to clinical data repository (CDR) that provides physician the access for retrieving and reviewing results. In Stage 3, the first level of clinical decision support is implemented to conduct error checking with order entry. In Stage 4, CPOE, for use by any clinicians, added to nursing and CDR environment. The second-level of clinical decision support related to evidence-based medicine protocols also exists in Stage 4. Stage 5 includes closed-loop medication administration. At this stage, it is expected to see reduction in errors and alerts associated with wrong medications. Physician documentation fits in Stage 6 of the EMR adoption model. Physicians, at this stage, interact with patients and input their documentation close to the point of care. Stage 7is full EMR implementation and fully paperless environment. Therefore, organizations have the potential for electronic health information exchange, and electronically and seamlessly share data with other organizations outside the enterprise.

Adler-Milstein, Everson, & Lee (2014) empirically assessed the sequence for EMR adoption in hospitals using cross-sectional national data and their findings are largely consistent with EMRAM. The results showed that decision support functions tended to be implemented in the early to middle part of the sequence, but CPOE functions were implemented, on average, later in the adoption sequence.

However, most (but not all) CPOE implementations have order communication (First Consulting Group, 2003) and thus include several manual and/or paper-based work systems that are prone to errors (Baron & Dighe, 2011). Order communication functionality allows CPOE system to automatically transmit provider orders and avoid several potentially inefficient and error-based steps. However, according to 2012 annual report of the U.S. hospital IT market, the new generation of CPOE applications continue to replace legacy order entry application as they can accommodate patient orders from all clinicians supported by clinical decision support (HIMSS, 2012).

We also investigated the logical dependency among certain EMR capabilities. Major ancillary clinical systems feed orders and results data to CDR which consists of a real time database that stores patient electronic records, including patient demographics, electronic reports and results from lab, imaging, and other diagnostic services (HIMSS, 2013). Physicians or any clinicians can enter orders directly into CPOE. At this point, CDR permits CPOE to display relevant clinical information and provide clinical decision support during the order entry process (Baron & Dighe, 2011). CDR includes CDSS for conflict checking such as duplicate orders (HIMSS, 2013). Therefore, it is obvious that CDR, order entry to feed orders, and some functionalities of CDSS precede CPOE implementations. Physician documentation, on the other hand, is concerned with the use of structured template and point-and–click capabilities. It helps physicians transit from written to electronic notes. As with CPOE, physician documentation systems are complex systems and included in the latter stages of EMR adoption (Dranove, Forman, Goldfarb, & Greenstein, 2012).

Based on EMRAM, the general trend is to implement EMR capabilities such as CDR, order entry, CDSS in the first stages and add more advanced EMR capabilities such as CPOE and physician documentation later in the sequence. Since EMRAM identifies the standard sequence, and (Adler-Milstein et al., 2014) study tracked hospital EMR adoption using cross sectional data, in this study, we will track EMR capabilities adoption sequence using longitudinal data and examine the impact of the sequence of EMR capabilities on healthcare quality.

In this study, we used seven quality measures from the hospital compare database. These include heart attack mortality, heart attack readmission, heart failure mortality, heart failure readmission, pneumonia mortality, pneumonia readmission. These quality measures capture the degree to which hospitals provide the recommended treatments for specific types of health conditions. We also examine patient experience using a patient satisfaction measure. A more detailed description of these quality measures is reported in Appendix A and B.

CHAPTER 3

RESEARCH MODEL

3.1 Research Objectives

There are three main research objectives in this dissertation. First, examining the impact of the complementarities among EMR capabilities and the implementation of different EMR capabilities on the quality of healthcare. Second, investigating the effects of adoption timing associated with EMR capabilities on healthcare quality. Third, exploring the impact of the sequence of EMR capabilities adoption on healthcare quality.

Overall, this research answers three questions related to EMR: What to adopt? When to adopt? And in what sequence?

3.1.1 Research Objective 1

Examining the synergistic impact of electronic medical records (EMR) capabilities, and the effects of assimilation and use on the healthcare quality performance of hospitals.

Objective 1.a: *Explore the relationship between the synergy among different EMR capabilities and their impact on the quality of healthcare delivery over time using large cross-section of hospitals over a multi-year period.*

In addressing the above research objective, we focus on the portfolio of EMR capabilities and the complementarities, or synergy between the capabilities in a given EMR portfolio and its impact the quality of healthcare. The IT portfolio of an organization is defined as "its total investment in computing and communication technology" (Weill & Vitale, 2002). In a healthcare context, our view is that, when a hospital moves from a level of individual EMR capability investment for its work processes to a portfolio level, the synergies between the portfolio components can lead to greater benefits, i.e., increased quality of patient care. Cho and Shaw (2009) argued that greater potential synergy enhancement between IT investment units may enable an organization to earn additional value from its investment. This research views the synergy between EMR capabilities portfolio as a potential source for a healthcare facility to achieve improvements in the quality of healthcare. This study tracks the synergy between different EMR capabilities and their impact on quality of care using hospital panel data over the period from 2008 to 2012. The measure of quality improvement, QI, can be represented as:

$$QI = QI(expected\ improvements\ of\ individual\ EMR\ capabilities, synergy)$$

The concept of synergy has been discussed in strategy and economic literatures and is defined as the additional value the organization can achieve from multiple investment units which cannot be attained from stand-alone individual units (Tanriverdi, 2005, 2006). Basically, two types of synergies were discussed; sub-additive cost and super-additive value. Business units that use common resources such as IT infrastructure technologies and IT management practices (relatedness) lead to sub-additive cost while complementarities between the two is the major source of super-additive value synergy. Complementarities here refers to the relationship between inputs, and the enhancement of one resource's value in the presence of another resource (Milgrom & Roberts, 1990, 1995).

The term complementarity was first introduced in economic to illustrate the idea that the increase in one variable level will increase the return of increasing its complementary variables (Barua, Sophie Lee, & Whinston, 1996). Complementary assets or resources are more valuable when used together than when used in isolation (Brynjolfsson, Hitt, & Yang, 1998). IT organizational characteristics and processes are complementary factors and they cannot succeed if done separately (Barua et al., 1996). Although resources are distinct, they are interdependent and mutually support each other (Tanriverdi, 2006), and the presence of the interaction among these resources is the factor that explains variance in the return from a given IT resource (Ray, Muhanna, & Barney, 2005).

Cho and Shaw (2013) have argued that IT resources have a greater potential for synergy enhancement than non-IT resources. The unique characteristics of IT resources justify this argument. Basically, IT resources are more sharable than non-IT resources. Different business investment units can share business processes and exchange data. Therefore, the unique characteristics of IT enhance the complementarities between IT systems and the data provided by one IT system makes other systems more valuable. In this study, synergy refers to the additional expected quality return that can be achieved from multiple health IT investments (EMR capabilities) which cannot be obtained from stand-alone individual technology.

Objective 1.b: *Exploring the relationship between different EMR capabilities' assimilation and use and their impact on the quality of healthcare delivery over time.*

A number of research studies argue that IT assimilation and use have an important role in enhancing organizational performance (Devaraj & Kohli, 2003; Setia et al., 2011). IT assimilation and use can be classified into two categories; IT exploration and IT exploitation. IT exploration refers to the "number of technological solutions adopted and used by the organization", while IT exploitation is the "average years of experience with these solutions" (Setia et al., 2011). In organizational studies, exploration's returns are often uncertain, while exploitation's returns are more predictable (Chen & Katila, 2008). In this context, the benefits from exploration are uncertain, unless it is subsequently followed by an extended period of exploitation (Setia et al., 2011). Zima (2002) argued that a large number of technologies are not enough to achieve efficient performance without the hospital's ability to develop extensive experience with these technologies. This research focuses on examining how the complementarities between the exploration and exploitation of a different EMR capabilities impact the quality of healthcare. Complementarities here refer to the enhancement of one resource's value in the presence of another resource (Milgrom & Roberts, 1995).

We expect that hospitals will realize greater benefits in terms of quality of healthcare outcomes from a given EMR capabilities portfolio if they are combined with higher levels of assimilation and use. According to Devaraj and Kohli (2003), higher levels of use enhance the performance impacts of information technologies. Higher technologies exploration captures the hospital's efforts to explore more information technologies for digitizing its work processes. While higher technologies exploitation measures the length of time for which the information technologies have been used (Setia et al., 2011).

3.1.2 Research Objective 2

Understand how hospitals' early adoption of EMR capabilities effects various healthcare quality measures.

The goal is to explore the effect of adoption timing of EMR capabilities portfolio on healthcare quality. The concepts of adoption can be defined broadly as moving from not having to having the technology. In a healthcare context, adoption of health IT starts with a contract to purchase a health IT, installation, and then integration of the health system/s into the work processes. In other words, adoption usually consists of acquiring, implementing, and using the system within the work processes. The assumption behind adoption is that the investment in technology will lead to better quality, efficiency, and lower-cost processes. As mentioned in the introduction, to ensure successful technology initiatives, project management should be used to plan, develop, test, and deploy technologies across all organizational units. The literature distinguishes between two types of adopters: early adopters versus late adopters. Early adopters who are interested in a technology and willing to take risks. They learn through their own trial-and-error process and may find the proper combination of EMR capabilities that applies best to their situation.

Further, the health information technology report shows adoption statistics of EMR systems in non-federal acute care hospitals from 2008 to 2013, hospital adoption of EMR systems increased from 9.4 percent to 59.4 percent. In 2008, only 1.6 percent of hospitals adopted comprehensive EMR functionalities and the majority adopted basic EMR functionalities (Charles, Gabriel, & Furukawa, 2014). The basic EMR system includes order entry, CDR, CDSS capabilities (Dranove et al., 2012). In 2008, another national survey shows about 42 percent of office-based physicians used any EMR systems and only 16.9 percent of physicians who reported having systems meeting the criteria for a basic EMR system (Hsiao, Hing, Socey, & Cai, 2011). Based on HIMSS analytics database, CDR, CDSS, and order entry are older technologies and the adoption rate for each of these technologies is about 85 percent in 2008. While the adoption rate for the advanced EMR capabilities (CPOE and physician documentation) is very low. According to American Hospital Association and the Federation of American Hospitals survey, less than 5 percent of American hospitals adopted CPOE in 2002 and less than 22 percent in 2008, while less than 21 percent adopted physician documentation by 2008 (Dranove et al., 2012). Therefore, in this study, we only focus on examining the effects of early adoption of advanced EMR capabilities.

To determine the effects of early investment in CPOE and physician documentation, we gathered data on these applications adoption and patient quality measures. As shown in HIMSS analytics database, CPOE emerges at the end of 2002 and at the beginning of 2003. While physician documentation emerges in 2005. In this study, we are interested in determining whether hospitals that invested in CPOE and physician documentation in the early adoption period were able to improve patient quality. We determined the early adoption period for CPOE and physician documentation as follows:

- CPOE early period data used in this study is from 2003-2008. During this period, the hospitals adopted CPOE may have been able to appropriate much of the value to be gained from early adoption of this technology (Dos Santos & Peffers, 1993; Lieberman & Montgomery, 1988).
- HIMSS analytics database first introduced physician documentation in 2005. Therefore, the adoption data for physician documentation covers the period 2005-2008.

Since the adoption rate is low for both technologies, it is unlikely that any effects of adoption would be observed immediately after implementation. In the sample data, about 22 percent of the hospitals adopted CPOE by 2008 and less than 21 percent adopted physician documentation by 2008. Hence gains in quality improvements resulting from CPOE and physician documentation may be observed after 2008 for CPOE and physician documentation. Therefore, patient quality measures data for 2009 will be used to measure patient quality after the early adoption period of CPOE and physician documentation.

3.1.3 Research Objective 3

Explore the effects of the sequence of EMR capabilities implementation on various healthcare quality measures.

In this research, we aim at investigating the impact of EMR capabilities' sequence of adoption on healthcare quality. HIMSS analytics database specifies the stages of EMR adoption. It starts with basic EMR (CDR, CDSS, or order entry) and then moves to advanced EMR (CPOE, or physician documentation). In this study, we will explore the current EMR adoption sequences and then compare these sequences to the EMR reference sequence and then examine the performance effects related to the sequence of EMR adoption. The question is whether the order of adoption impacts various healthcare quality measures.

Our approach to define the reference EMR capabilities adoption sequence is as follows:

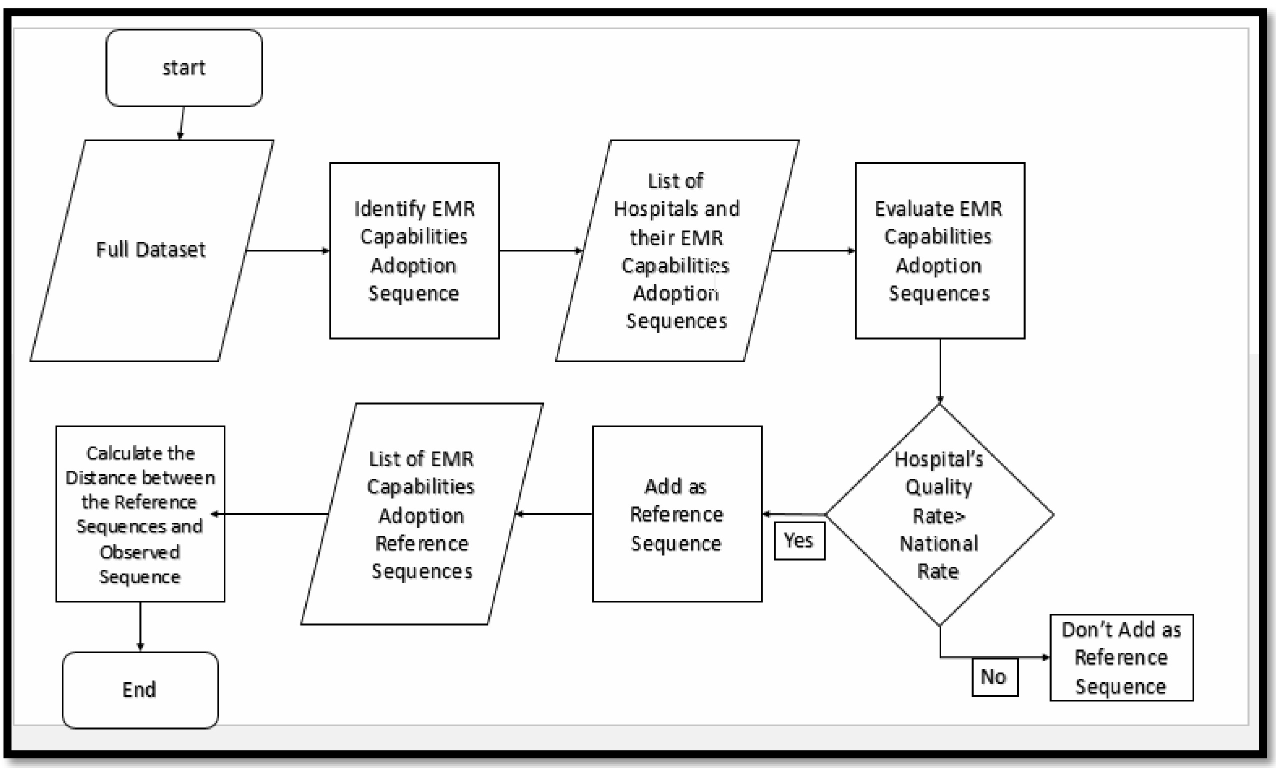

Figure 1: EMR Reference Sequence

- Track EMR capabilities sequence adoption longitudinally from 2005-2012.
- Identify EMR sequence capabilities adoption from the full dataset.

- Evaluate the sequences of EMR capabilities adoption based on hospital quality rate. If the hospital quality rate greater than national rate, then the sequence corresponds to that hospital is considered as a reference sequence. In order to identify hospital performance, we use "mortality and readmission rates comparison to the national level" data. In particular, if the hospital's "Mortality Rate" and "Readmission Rate" is better than (i.e. less than) the average national rate, then the EMR capabilities sequence corresponds to that hospital is considered as a reference sequence in this study.
    - This step may result in more than one EMR reference sequences.
- Because of the existence of multiple EMR adoption reference sequences, we will calculate the Levenshtein distance for each hospital's EMR capabilities adoption sequence against all the reference sequences. The smallest distance obtained from the comparisons to the reference sequences will be used as EMR sequence distance (Spaulding et al., 2013).

Further, we note the hospital that adopted more than one EMR capability in a single year will be dropped from the sample set because it is not possible to distinguish which application was adopted first especially if the data on "Month" variable is missing.

CHAPTER 4

RESEARCH METHODOLOGY

4.1 Model Specifications

4.1.1 Research Objective 1: Model Specification

We estimated the following two regression models using fixed effects, and with various quality measures as the dependent variable.

The following regression model tests the relationship between the synergy among different EMR capabilities and their impact on the quality of healthcare delivery over time. In line with HIMSS analytics database classification of EMR capabilities, our analysis focuses on portfolios of different combinations of EMR capabilities as specified in equation (1):

$$(1)\ Yi,t = a0 + \alpha 1CDRi,t + \alpha 2CDSSi,t + \alpha 3OEi,t + \alpha 4PDi,t + \alpha 5CPOEi,t + \alpha 6SYN(CDR,CDSS,OE)i,t + a7SYN\ (CDR,CDSS,OE,PD,CPOE)i,t + \alpha 8hosp\_sizei,t + \alpha 9CMIi,t + \alpha 10hosp\_owneri,t + \alpha 11academic\_hospi,t + \alpha 12hosp\_agei,t + \varepsilon i,t$$

Where $Y_{i,t}$ represents the quality measure results in hospital i in year t. $(\alpha 1CDRi,t + \alpha 2CDSSi,t + \alpha 3OEi,t + \alpha 4PDi,t + \alpha 5CPOEi,t)$ represent individual EMR capabilities in hospital i in year t. The coefficients of these capabilities capture the effect of individual EMR capabilities on healthcare quality when the synergy effects are not present. $(\alpha 6SYN(CDR,CDSS,OE)i,t)$ represents the synergies (interaction) between EMR capabilities in the basic EMR portfolio in hospital i in year t. $(\alpha 7SYN(CDR,CDSS,OE,PD,CPOE)i,t)$ represents the synergies (interaction) between EMR capabilities in the full EMR portfolio in hospital i in year t.$(\alpha 8hosp\_sizei,t + \alpha 9CMIi,t + \alpha 10hosp\_owneri,t + \alpha 11academic\_hospi,t + \alpha 12hosp\_agei,t)$ represent the control variables in hospital i in year t. $\varepsilon i,t$ represents the error term for hospital i in year t.

We focused on five health IT systems described in the HIMSS data: CDR, CPOE, CDSS, Order Entry (OE), and Physician Documentation (PD). These capabilities constitute EMR portfolios. Building on HIMSS report on EMR categorizations (Charles et al., 2014), we identify two portfolios of EMR capabilities: Basic EMR portfolio and full (comprehensive) EMR portfolio. Basic EMR capabilities portfolio includes two levels: basic EMR portfolio and includes three EMR capabilities-CDR, CDSS, and OE; and basic EMR capabilities with PD and include four EMR capabilities- CDR, CDSS, OE, and PD. The full EMR capabilities portfolio also has two levels: full EMR capabilities with PD and includes all five EMR capabilities, and full EMR capabilities with no PD. In our regression model, we only focused on the basic EMR (with no PD) and the full EMR (with PD) portfolios. (See section 4.1.1.2 for more details.)

Hospitals that adopt full EMR portfolio have more thorough implementation of EMR systems. Figure 2 presents the average adoption levels of EMR capabilities and EMR portfolios from 2008-2012. The adoption rate of basic EMR is 58 percent while only 22 percent of hospitals adopted basic EMR with PD. One the other hand, the adoption rate of full EMR capabilities portfolio is 23 percent and only 14 percent of hospitals adopt full EMR capabilities with PD portfolio. The numbers reflect only <u>live and operational</u> capabilities. In our study, the synergy between EMR capabilities in a portfolio is measured as the product (interaction) of EMR systems. For example, if the hospital has adopted CDR, CDSS, and OE in the basic EMR portfolio and all of them are live and operational then the value taken by the synergy variable is one, otherwise zero. This measure indicates that hospitals that achieve a score of one have a more thorough implementation of EMR systems.

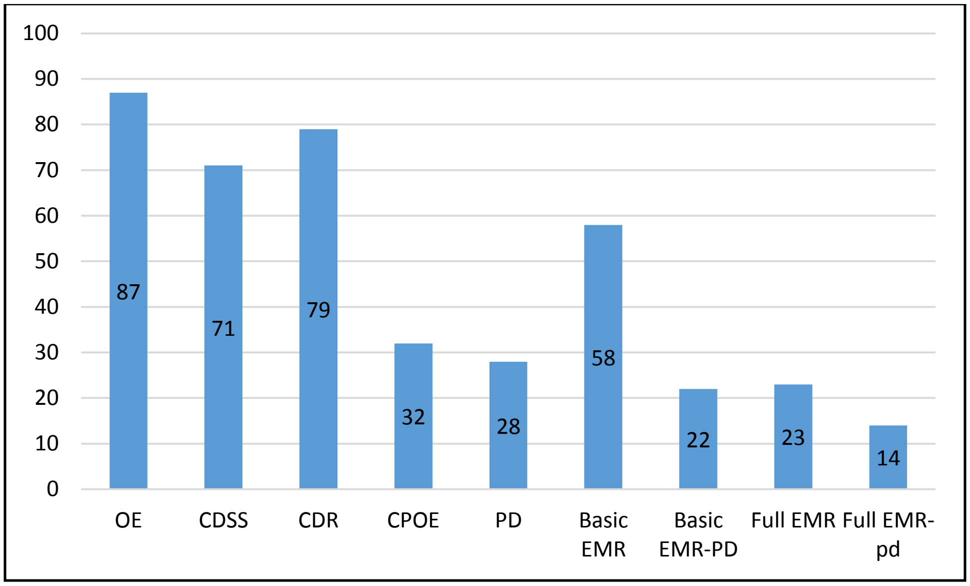

Figure 2. Average Adoption Level of EMR Capabilities (2008-2012)

Model 2 estimates the relationship between different EMR capabilities' assimilation and use and to determine their impact on quality of healthcare delivery over time:

$$(2)\ \text{Quality measure i, t} = \alpha 0 + \alpha 1\text{EMRExploration i, t} + a2\text{EMRExploitation i, t} + \alpha 3\text{InteractionEE i, t} + \alpha 4\text{hsop\_size i, t} + \alpha 5\text{CMI i, t} + \alpha 6\text{hosp\_owner i, t} + \alpha 6\text{academic\_hosp i, t} + \alpha 7\text{hosp\_age i, t} + \varepsilon\text{i, t}$$

Where quality measure represents the quality measure results in hospital i in year t. [α1EMRExploration i,t] represents the extent of health IT applications adoption in the EMR portfolio in hospital i in year t, [a2EMRExploitation i,t] represents the average years of experience with EMR portfolio in hospital i in year t, [α3InteractionEE i,t] represents the interaction (product) of EMR exploration and exploitation in hospital i in year t, [α4hosp_size i,t + α5CMI i,t + α6hosp_owner i,t + α6academic_hosp i,t + α7hosp_age i,t] represent the control variables Hospital Size, CMI, Hospital Ownership, Academic Hospitals, and Hospital Age respectively in hospital i in year t. εi, t represents the error term for hospital i in year t.

In this model, the coefficient of interest is α_3 which estimates the quality improvement from the assimilation and use of EMR capabilities.

Our data set contains large number of hospitals observed over five time periods. We estimate a panel regression model for each quality measure using unbalanced panel (at least two years of data), and then using a balanced panel (all five years of data). The statistical analysis was conducted using Base SAS 9.4. Our initial analysis on the full panel data indicated both heteroscedasticity and autocorrelation. More specifically, we conduct Breusch-Pagan test to check for heteroscedasticity (Breusch & Pagan, 1980). The results indicate the presence of heteroscedasticity. In particular, the p-value is less than 0.05. Therefore, we reject the null hypothesis of homoscedasticity. We also conducted a Pesaran (2004) CD test to check for autocorrelation. The results confirm the existence of significant autocorrelation in our panel data based on the p-value ($p < 0.05$). Autocorrelation is common in panel data (Certo & Semadeni, 2006). We correct for these issues by using heteroscedasticity and the autocorrelation consistent (HAC) standard errors. This known as Newey-West standard errors (Newey & West, 1994). We also check for multi-collinearity in our models and found that variance inflation factors were below the acceptable threshold (less than 10) as shown in Table 3 (Kennedy, 2003). In addition to VIF results, we conduct a Spearman correlation test because our independent variables in the first sub-objective (Synergy between EMR capabilities) are binary variables. The threshold point is less than 0.5 and indicates no significant multicollinearity problem exist (Oh, Agrawal, & Rao, 2013), and less than 0.7 indicates no serious multicollinearity problem exist (Tabachnick & Fidell, 2001).

The results of Spearman's rank correlation (as shown in Appendix E) show that there are some correlation between the individual variables and EMR portfolios and correlation between EMR portfolios as well. According to Tabachnick and Fidell (2001), it is recommended to omit one of the variables from the model to handle multicollinearity problem. Therefore, we evaluated our model by including only one variable and then measured the effect of placing correlated variables in the same model (Muir, Berg, Chesworth, Klar, & Speechley, 2010). As a result, we decided to omit basic EMR-PD and full EMR-No PD portfolios from our model[4]. The results of Spearman correlation test show that no serious multicollinearity problem exists between the remaining independent variables.

[4] We tested the model with all four portfolios and results patterns are similar (See Appendix F).

Further, the Hausman test is regularly deployed as a test to examine whether fixed effects can be used, or whether random effects should be used instead (Hausman, 1978). The null hypothesis indicates that the random effects model is the appropriate model while the alternative hypothesis states that the fixed effects model is the appropriate model. In this study, the p-value in Hausman test is less than 0.05 and hence we rejected the null hypothesis. In this study, the fixed effects is the appropriate model.

Table 3. Variance Inflation Factors in Panel Data across Health Conditions

Variables/Quality Measures	HAM	HAR	HFM	HFR	PNM	PNR	PS
First Sub-Objective (Synergy Between EMR Capabilities) Variables							
OE	1.38	2.89	1.37	1.14	1.39	1.43	1.39
CDSS	3.63	2.80	3.62	3.62	3.56	3.57	3.75
CDR	1.87	1.51	1.89	1.87	1.88	1.86	2.04
CPOE	3.87	2.72	3.59	3.94	3.59	3.95	3.90
PD	4.60	3.32	4.61	4.80	4.64	4.81	5.00
Basic EMR	6.55	6.59	6.57	6.62	6.47	6.55	7.70
Basic EMR-PD	6.50	6.07	6.50	6.81	6.53	6.83	8.75
Full EMR	3.87	4.80	5.34	4.01	3.82	4.02	6.67
Full EMR-No PD	5.42	4.89	5.34	5.79	5.35	5.80	7.54
Hospital size	2.02	1.88	2.15	2.17	2.15	2.16	1.76
Hospital age	1.21	1.22	1.21	1.21	1.21	1.21	1.19
For-Profit	1.28	1.26	1.28	1.29	1.28	1.29	1.12
Academic	1.18	1.18	1.17	1.15	1.16	1.15	1.14
Second Sub-Objective (Assimilation and Use) Variables							
EMR Exploration	4.66	4.90	4.81	4.87	4.76	4.85	4.95

EMR Exploitation	5.97	5.77	5.96	6.12	5.95	6.13	6.92
EMR Assimilation and Use	8.05	7.65	8.24	8.10	8.21	8.08	7.37

The first objective of this study is to estimate the impact of different implementations of EMR capabilities and their assimilation and use on healthcare quality using panel data model design. In this design, however, there is a large possibility of confounding variables biasing the effect of the portfolio of EMR capabilities and EMR capabilities assimilation and use. One possible solution to handle this issue is to use control variables in order to identify these confounding variables and include them in the regression models. However, the likelihood of ruling out all possible confounding variables is very small, and as a result leads to omitted variable bias.

In this research, we used a fixed effects model which exploits the within-hospital effect of EMR capabilities implementation across time. The strength of the fixed effects model is the ability to control for confounding variables (Furukawa, Raghu, & Shao, 2010a). Therefore, the use of fixed effects modeling allows for a partial solution to the omitted variable bias issue (Wooldridge, 2010). Another important benefit of fixed effects, this technique controls for all observed and unobserved time-invariant characteristics of the hospitals. Consequently, this technique removes potential sources of bias from the estimates by controlling for all time-invariant hospital characteristics, whether they are observed or not. However, health IT adoption might affect our results. For instance, high quality hospitals may be more prevalent in health IT adoption and this would cause cross-sectional regressions to overestimate the effect of health IT on quality. Low quality hospitals, on the other hand, might adopt health IT to improve their performance and this would cause the cross-regressions to underestimate the effect of health IT on quality (McCullough, Casey, Moscovice, & Prasad, 2010). To address this issue, we include both hospital and time fixed effects in our regression models. In this case, fixed effects include a separate indicator variable for each hospital and each year in the regression. Although this approach improves the analysis, we discuss some potential limitations in Chapter 6.

All regression models in this study include control variables for hospital size, hospital ownership, case mix index, teaching status, and hospital age. Finally, to test the robustness of our results, we analyze the panel data on large hospitals (at least 100 beds) that are most likely to have a thorough implementation of EMR capabilities (Appari, Eric Johnson, & Anthony, 2013). The pattern of the results did not change. (Results are reported in Appendix C.)

4.1.2 Objective 2: Model Specification

In order to determine whether early investors in CPOE and physician documentation were able to gain more improvement on quality, we formulated the following regression models to separately measure the effects of CPOE and physician documentation early adoption:

$$(1)\ \text{Quality measure} = \alpha 0 + \alpha 1\text{CPOEAdopt} + \alpha 2\text{TechMaturity} + \alpha 3\text{hosp\_size} + \alpha 4\text{CMI} + \alpha 5\text{hosp\_owner} + \alpha 6\text{academic\_hosp} + \alpha 7\text{hosp\_age} + \varepsilon$$

Where

CPOEAdopt = 1 if a hospital has adopted CPOE before 2008

= 0 otherwise.

TechMaturity: a control variable measures the number of years the hospital has had CPOE.

[α3hosp_size + α4CMI + α5hosp_owner + α6academic_hosp + α7hosp_age] represents the other control variables Hospital Size, CMI, and Hospital Ownership, Academic Hospital, and Hospital Age respectively. ε represents the error term.

The key coefficient of interest is α_1, which estimates the quality improvement from early adoption of CPOE.

The model coefficients will be estimated for the year 2009. A summary of the results will be obtained by ordinary least squares (OLS) estimation of the model.

The following regression model determines whether early investors in physician documentation were able to gain more improvement on quality:

$$(2)\ \text{Quality measure} = \alpha 0 + \alpha 1\text{PDAdopt} + \alpha 2\text{TechMaturity} + \alpha 3\text{hosp\_size} + \alpha 4\text{CMI} + \alpha 5\text{hosp\_owner} + \alpha 6\text{academic\_hosp} + \alpha 7\text{hosp\_age} + \varepsilon$$

Where

PDAdopt = 1 if a hospital has adopted physician documentation before 2008

= 0 otherwise.

TechMaturity: a control variable measures the number of years the hospital has had physician documentation.

[α3hosp_size + α4CMI + α5hosp_owner + α6academic_hosp + α7hosp_age] represents the other control variables Hospital Size, CMI, and Hospital Ownership Academic Hospital, and Hospital Age respectively. ε represents the error term

The key coefficient of interest is $\alpha 1$, which estimates the quality improvement from early adoption of physician documentation. The model coefficients will be estimated for the year 2009. A summary of the results will be obtained by OLS estimation of the model.

We estimated the OLS using the REG procedure using SAS statistical software. We checked for multi-collinearity in our model using variance inflation factors and the results are within the acceptable threshold (less than 10) (Kennedy, 2003). We performed the White standard error correction to correct for heteroscedasticity (White, 1980). The initial investigations revealed that some control variables (NofBeds and Age) were not normally distributed. Therefore, we performed a logarithmic transformation on these variables (Gelman & Hill, 2007).

Further, we included the following status during the early adoption period for both CPOE and physician documentation applications: (contracted/not yet installed, installation in process, live and operational, to be replaced). The reason for including (contracted/not yet installed) application status because it is assumed that the implementation begins, on average, one year after the contract date (Furukawa et al., 2010b).

4.1.3 Research Objective 3: Model Specification

We estimated the following regression model using ordinary least squares regression, and with quality measures results as the dependent variable.

The following regression model tests the relationship between the paths to EMR capabilities adoption and its impact on the quality of healthcare delivery:

$$(1)\ \text{Quality measure} = \alpha 0 + \alpha 1 \text{EMRSQDIS} + \alpha 2 \text{hosp\_size} + \alpha 3 \text{CMI} + \alpha 4 \text{hosp\_owner} + \alpha 5 \text{academic\_hosp} + \alpha 6 \text{hosp\_age} + \varepsilon$$

Where quality measure represents the quality measure results, EMRSQDIS captures the distance between the observed EMR capabilities sequences and EMR capabilities reference sequence (i.e. the smaller the distance the greater the similarity to the reference sequence), [α3hosp_size + α4CMI + α5hosp_owner + α5academic_hosp + α6hosp_age] represents the control variables Hospital Size, CMI, and Hospital Ownership, Academic Hospitals, and Hospital Age respectively. ε represents the error term.

In order to conduct sequences comparison, it is required to use dynamic programming methods to calculate the distance between pairs of sequences. For example, suppose we have the following reference and observed EMR sequences followed by the hospitals in the dataset:

Reference sequence (A): CDR- OE -CDSS-CPOE-PD
Observed sequence (B): CDSS- CDR-OE -CPOE- PD

The algorithm for calculating the distance score is as follows:

IF two elements in sequence A and B at i^{th} and j^{th} position are same **THEN** The distance score is 0 (D(i,j)=0) **ELSE IF** i^{th} and j^{th} position are not the same **THEN** Distance score is assumed as 1 (D(i,j)= 1)

END IF

- Distance score of zero means the hospital followed the theorized sequence
- The distance score different from zero (penalty gap **(δ))** can be user defined

The distance score between i^{th} and j^{th} is determined by:

1. a Match (i^{th}, j^{th}) → $i^{th} = j^{th}$
2. a Deletion (d) → score (i^{th}, j^{th}) is based on the value of δ
3. an Addition (a) → score (i^{th}, j^{th}) is based on the value of δ

The perfect sequence match between two sequences each with a length of five elements would be 5; 1 credit for every matching between two elements in the sequence. In the above example, sequence (A) is 5 elements and (B) is also 5. However, the observed sequence (B) does not perfectly follow the reference one. For the first step, the Levenshtein distance will be used: A measure from information technology that counts the number of operations needed to transform one sequence to another (Brzinsky-Fay, Kohler, & Luniak, 2006). The penalty of each operation is 1. This means that each operation increases the distance by 1. In our study context, the maximum number of operations to transform any sequence is five.

Let $\mathrm{C(x)} = \sum \mathrm{C(d)}, \mathrm{C(a)}$, where C(x) is the total number of deletion and addition operations; C(d) is the number of deletion operations; C(a) is the number of addition operations.

The overall distance between sequence A and B is equal:

$\mathrm{S(A, B)} = \mathrm{C}$ (x) where δ(d)= δ(a)=1.

In the observed sequence, CDR should occur before CDSS and not after it. This can be corrected with one deletion and one insertion.

The observed sequence after first transformation: CDR-> CDSS->OE-> CPOE-> PD

Further, order entry should occur before CDSS. This can be corrected with one deletion and one insertion.

The observed sequence after first transformation: CDR-> OE-> CDSS-> CPOE->PD
The total number of operation is 4 (two deletion and two insertion). Hence, the hospital would receive a distance of 4.

We conduct the analysis using R software package and used the procedure (levenshteinDist) to calculate the distance between the observed and reference sequences. After the data transformed to short form, we analyze it with SAS software to estimate the impact of EMR capabilities sequences on healthcare quality outcomes using OLS (REG procedure). We check for multi-collinearity in our model using variance inflation factors and the results are within the acceptable threshold (less than 10) (Kennedy, 2003). The initial investigations revealed that some control variables (NofBeds and Age) were not normally distributed. Therefore, we perform a logarithmic transformation on these variables (Gelman & Hill, 2007).

4.2 Data Sources

We now describe the data sources used in this study along with description of the variables used in model development.

We collected the research data from three sources. First, we obtained data on hospital EMR capabilities portfolio from HIMSS Analytics[5]. It represents the comprehensive set of different categories of IT applications across a large cross-section of U.S. hospitals. For the purpose of this study, we used panel data to conduct the analysis. According to Devaraj and Kohli (2003), a cross-sectional set of hospitals combined with time-series data is ideal to examine the effect of IT investment on measures of profitability and quality, while controlling for other factors. Therefore, this study aims to conduct a more granular and comprehensive examination on the aforementioned research questions using panel data.

Second, we obtained data on quality of patient care measures from the Medicare’s Hospital Compare website[6]. The data obtained on quality outcome measures is for the same set of hospitals on which EMR capabilities data was available through the HIMSS Analytics database.

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[5] Formerly The Dorenfest Integrated Healthcare Delivery System + (IHDS+) database
[6] Hospital Compare. http://www.hospitalcompare.hhs.gov/.

Third, we used Center for Medicare and Medicaid Services (CMS) to obtain data on one of the control variables-Case Mix Index (CMI). The three data sources were combined using the Medicare Number or Provider Number available at each source.

4.3 Quality Measures

In this research, several types of quality outcomes measures are considered. These include heart attack mortality rates, heart attack readmission rates, heart failure mortality rates, heart failure readmission rates, pneumonia mortality rates, pneumonia readmission rates. We obtained these measures from Medicare's Hospital Compare website. Basically, these quality measures capture the degree to which hospitals provide the recommended treatments for specific types of health conditions. Understanding the effect of health IT on the quality measures is essential, as these explain the downstream differences in the overall patient outcomes, such as mortality rates (Bardhan & Thouin, 2013).

We also examine a patient satisfaction measure. The Centers for Medicare and Medicaid Services (CMS) developed a national, standardized survey instrument and data collection methodology for measuring patients' perception of their hospital experiences. The instrument is called the Hospital Consumer Assessment of Healthcare Providers and Systems (HCAHPS) survey. The survey captures patient experience on care and patient rating items that include nine key dimensions: communication with doctors, communication with nurses, responsiveness of hospital staff, pain management, communication about medicines, discharge information, cleanliness of the hospital environment, quietness of the hospital environment, and transition of care[7]. In our study, we considered the following question from the survey:

Would you recommend the hospital to friends and family? For this question, we focused on the percentage of respondents who said they would definitely recommend the hospital.

Mortality, readmission, and patient satisfaction are often used as indicators of healthcare quality (Amarasingham et al., 2009; DesRoches et al., 2010; Lee et al., 2013; McCullough et al., 2010; Pinaire & Sarnikar, 2015; Piontek et al., 2010; Restuccia, Cohen, Horwitt, & Shwartz, 2012;

[7] http://www.hcahpsonline.org/

Vest & Miller, 2011). Basically, high quality health care provides the required clinical care processes that are supposed to achieve the health outcomes desired by the patient (Nelson, Mohr, Batalden, & Plume, 1996). Therefore, improving patient care outcomes is the primary goal of hospital quality improvement. According to the Medicare's Hospital Compare[8], health outcomes are used as measures of health care quality. For instance, readmission indicators provide information about the potential issues with a hospital's systems. These include: "transiting patients to the outpatient setting, collaborating with communities and providers, and communicating with patients and caregivers". Just as importantly, mortality measures provide information about the potential issues with a hospital's clinical quality. This information will inform hospitals and other stakeholders (employers, payers such as insurance company, and health plans) about the key aspects of quality of care; comprehensive assessment of patient outcomes as well as the value of care for patients with these conditions. Therefore, patients who receive high level of care quality during the hospital stays and transition to the outpatient setting will likely have better outcomes, such as functional ability, survival, and quality of life. Although, in certain cases, the deaths may not be the results of quality failure, the expectation is that there are many preventable death cases[9]. In summary, outcomes indicators allow hospitals, policy makers, and other stakeholders to assess the patient quality of care in order to seek improvements that will impact patient wellbeing.

McCullough, Casey, Moscovice, and Prasad (2010) investigated the relationship between quality measures and health IT systems through consultations with physicians, nurses, administrators, and health informatics practitioners and consultants. The results indicated that the process quality measures "largely reflect the quality of hospitals' medication administration processes." Consequently, health IT systems such as EMR and CPOE are designed to retrieve and communicate information pertaining to medication prescribing and delivery. McCullough et al. (2010), "clinical errors cause at least 44,000 deaths annually in the United States." The main causes of this high death rates come from "process errors or the failure to provide recommended treatments for patients with certain medical conditions." However, health IT systems have been proven to hold the potential to improve the quality of healthcare. Basically, the health IT systems, such as CPOE and CDSS, are designed to facilitate the implementation of care guidelines and

[8] Hospital Compare. http://www.hospitalcompare.hhs.gov/
[9] https://www.medicare.gov/

decision support tools, which may be essential in preventing or reducing process errors (Hillestad et al., 2005; McCullough et al., 2010; Radley et al., 2013).

We build on this literature by measuring the effect of the portfolio of EMR capabilities on various quality measures and patient satisfaction. Our data follows hospitals over time, allowing us to examine the change in the quality measures that followed the adoption of health IT systems within individual hospitals.

4.4 Hospitals Characteristics

Consistent with past studies (Bardhan & Thouin, 2013; Devaraj & Kohli, 2003; Lee et al., 2013; Setia et al., 2011), we included a set of control variables that may influence the impact of EMR capabilities on quality measures. Specifically, we control for hospital size; hospital ownership; hospital case mix index (CMI); teaching status; and hospital age.

4.5 Variables

Table 4 presents the study variables for each objectives. The dependent variables for all objectives are the quality outcome measures results obtained from Medicare's Hospital Compare Database. The quality measures include heart attack mortality rates, heart attack readmission rates, heart failure mortality rates, heart failure readmission rates, pneumonia mortality rates, pneumonia readmission rates, and the level of patient satisfaction. Consistent with past studies, we include a set of control variables that may influence the impact of EMR on hospital quality outcomes measures. Specifically, we control for: **Hospital size**, which represents the number of hospital beds and it is measured as the logarithm of the total number of hospital bed. **Profit status**, where for-profit hospitals are coded as one and not-for-profit hospitals are coded as zero. **Hospital case mix index (CMI)** which accounts for the average severity of patient disease case mix in a hospital. **Teaching status**: where academic hospitals are assigned a value of one and non-academic hospitals are assigned a value of zero. **Hospital age**: we included the logarithm of hospital age as a control variable in the estimation model. The literature suggests that newer hospitals may be better in acquiring and using recent technologies than older hospitals (Devaraj & Kohli, 2003).

Table 4. Models Variables

Variable	Measures
Objective one- Independent variables	
EMR capabilities (CDR, CDSS, CPOE, order entry includes order communications, and physician documentation)	Binary variable which equals one if the hospital has adopted the technology during the study period. The health IT application in EMR portfolio is coded as one if it is live and operational, and coded zero if the health technology is not used.
Synergy between EMR capabilities	It is calculated as the product of the health IT applications (capabilities) in the portfolio.
EMR exploration EMR exploitation EMR Assimilation and use	IT exploration is the number of EMR capabilities adopted and used by each hospital. For example, if a hospital is using CDR, CDSS, and order entry, while not using CPOE and physician documentation, then EMR exploration equals 3 capabilities (i.e.$\sum 1,1,1,0,0$). IT exploitation is defined as the "average years of experience" with each of EMR capabilities. For example, if a hospital's years of experience with CDR, CDSS, and order entry are: 10, 10, and 7 respectively then EMR exploitation is 9 (i.e. $\mathrm{AVG}(10,10,7)$. The complementarities between exploration and exploitation are measured as the product of EMR capabilities exploration and exploitation (Setia et al., 2011).
Objective Two- Independent variable	
CPOEAdopt	It is a binary variable equal to one if a hospital adopted CPOE before 2008, otherwise zero.
PDAdopt	It is a binary variable equal to one if a hospital adopted physician documentation before 2008, otherwise zero.

Objective Three[10]-Independent variable	
EMRSEQDIS	Represents the distance between the observed sequence and the EMR capabilities reference sequence.

[10] The dependent variables, for objective 3-model 3, will be collected from 2012 database Medicare's Hospital Compare Database. The independent variables data is constructed from the 2005–2012 HIMSS Analytics database.

CHAPTER 5

RESULTS

5.1 Objective 1 Results

5.1.1 Descriptive statistics

The descriptive statistics of hospital EMR capabilities, synergies, assimilation and use, and quality outcomes performance are reported in Tables 5 and 7. In Table 5, for the panel data on all hospitals, the highest adoption rate is for order entry followed by CDR and CDSS, and then CPOE and physician documentation. Hospitals have invested the most in basic EMR portfolio including order entry, CDSS, and CPOE capabilities. Among all of the hospitals in the panel, the mean quality outcomes across the five health quality measures ranged from 11.26 to 24.80.

Table 5. Descriptive Statistics of Individual EMR Capabilities, EMR Capabilities Portfolios, Hospital Characteristics, and Quality Outcomes Measures.

EMR Capability over Time (in Percentages)							
Variable	HAM	HAR	HFM	HFR	PNM	PNR	PS
OE	91	73	90	90	90	90	86
CDSS	67	74	67	68	67	68	83
CDR	78	79	77	78	77	78	84
CPOE	29	42	29	30	29	30	34
PD	26	28	26	27	26	27	34
Basic EMR	57	48	56	58	56	57	77
Full EMR	21	22	20	22	20	22	32
Hospital Characteristics*							
Hospital size (log)	5.3 (0.69)	5.41 (0.64)	5.17 (0.76)	5.16 (0.77)	5.16 (0.77)	5.16 (0.77)	5.04 (0.86)

CMI	1.42 (0.24)	1.47 (0.23)	1.39 (0.25)	1.40 (0.25)	1.39 (0.25)	1.39 (0.25)	1.39 (0.28)
For-Profit	0.22	0.21	0.22	0.22	0.22	0.22	0.22
Hospital Age (log)	3.42 (0.86)	3.44 (0.87)	3.39 (0.87)	3.38 (0.88)	3.39 (0.87)	3.38 (0.77)	3.36 (0.88)
Academic	0.06	0.06	0.05	0.05	0.05	0.05	0.05

* For all categorical variables proportion estimates are reported and for continuous variables mean (standard deviation) is reported.

Quality Outcomes Performance over Time

Mean (Standard Deviation) Estimates of Quality Outcomes

Quality Measure	Mean (Standard Deviation)
HAM: Heart Attack Mortality	16.07 (1.59)
HAR: Heart Attack Readmission	19.78 (1.73)
HFM: Heart Failure Mortality	11.26 (1.55)
HFR: Heart Failure Readmission	24.80 (2.14)
PNM: Pneumonia Mortality	11.74 (1.85)
PNR: Pneumonia Readmission	18.51 (1.69)
PS: Patient Satisfaction	67.31 (10.11)

We created multiple analytic datasets: an unbalanced panel spanning 2008-2012 where each hospital must have at least two observations, and balanced panel dataset for each health condition where each hospital must present in all years. The percentage of the balanced panel from the full panel dataset is between 42 percent and 64 percent. The number of cross sections and length of time series vary by health conditions as shown in the following Table.

Table 6: Description of the Panel Data, Length of Time Series, and Number of hospitals across Health Conditions.

Quality measure/Length of time series	**5***	**4**	**3**	**2**	**Balanced**	**Unbalanced**
HAM	689	242	199	178	689	1308
HAR	NA	657	217	205	657	1079
HFM	820	255	203	192	820	1470
HFR	NA	899	255	247	899	1401

PNM	825	259	204	195	825	1484
PNR	NA	906	253	249	906	1408
PS	810	640	268	223	810	1941
*Length of time series (5 years, 4 years, 3 years, and 2 years) Balanced: balanced panel Unbalanced: unbalanced panel NA: hospitals do not have data about the health condition.						

Table 7 shows the descriptive statistics of EMR capabilities assimilation and use, hospital characteristics, and quality outcomes performance. Across all measures, the average EMR exploration in all hospitals is about three EMR capabilities. The average hospital's experience with EMR capabilities is about 10.06 years. Finally, the average assimilation and use across all hospitals is 29.03.

Table 7. Descriptive Statistics of Assimilation and Use, Hospital Characteristics, and Quality Outcomes Measures.

EMR Capability Assimilation and Use							
Variable	HAM	HAR	HFM	HFR	PNM	PNR	PS
EMR Exploration	2.93 (1.25)	2.99 (1.26)	2.90 (1.25)	2.95 (1.27)	2.90 (1.25)	2.95 (1.27)	3.34 (1.37)
EMR Exploitation	9.98 (4.9)	10.32 (4.91)	10.05 (4.91)	10.19 (4.99)	10.04 (4.93)	10.17 (4.99)	9.68 (4.86)
EMR Assimilation	28.34 (17.43)	29.76 (17.35)	28.35 (17.51)	29.04 (17.76)	28.32 (17.61)	29.00 (17.76)	30.42 (17.54)
Hospital Characteristics*							
Hospital size (log)	5.3 (0.69)	5.41 (0.64)	5.17 (0.76)	5.16 (0.77)	5.16 (0.77)	5.16 (0.77)	5.18 (0.79)
CMI	1.42 (0.24)	1.47 (0.23)	1.39 (0.25)	1.40 (0.25)	1.39 (0.25)	1.39 (0.25)	1.41 (0.26)
For-Profit	0.22	0.21	0.22	0.22	0.22	0.22	0.22
Hospital Age (log)	3.42 (0.86)	3.44 (0.87)	3.39 (0.87)	3.38 (0.88)	3.39 (0.87)	3.38 (0.77)	3.36 (0.88)
Academic	0.06	0.06	0.05	0.05	0.05	0.05	0.05

* For all categorical variables proportion estimates are reported and for continuous variables mean (standard deviation) is reported.	
Quality Outcomes Performance over Time Mean (Standard Deviation) Estimates of Quality Outcomes	
Quality Measure	Mean (Standard Deviation)
HAM: Heart Attack Mortality	16.07 (1.59)
HAR: Heart Attack Readmission	19.78 (1.73)
HFM: Heart Failure Mortality	11.26 (1.55)
HFR: Heart Failure Readmission	24.80 (2.14)
PNM: Pneumonia Mortality	11.74 (1.85)
PNR: Pneumonia Readmission	18.51 (1.69)
PS: Patient Satisfaction	67.80 (9.77)

5.1.2 Effect of synergy between EMR capabilities on hospital quality outcomes

In this study, we focus our analysis on the association between different capabilities of EMR and patient quality care measures. The results of the panel data regressions are shown in Tables 8 and 9. Table 8 shows the results of the association between the synergetic impacts of EMR capabilities on the quality of healthcare in the unbalanced dataset.

In the heart attack mortality column, the results on the impact of stand-alone individual technologies on quality are not different from zero because the estimates are not statistically significant except CDSS. The investment in CDSS as individual technology reduces the heart attack mortality rate; the coefficient of CDSS is negative and significant (coeff. = 0.24, $p < 0.05$). However, we observe that the synergy between all EMR capabilities (full EMR capabilities) is associated with lower heart attack mortality rate (coeff. = -0.17, $p < 0.05$), the coefficient is negative and significant.

In the heart failure mortality column, we also observe a significant association between full EMR capabilities synergetic impact and a lower heart failure mortality rate (coeff. = -0.13, $p < 0.1$). However, the results on the impact of stand-alone individual technologies on quality are not different from zero because the estimates are not statistically significant.

We also observe that, in the pneumonia readmission column, the synergy between basic EMR capabilities reduces pneumonia mortality rate by 0.22 ($p < 0.1$), and this cannot be achieved from the investment in EMR capabilities as stand-alone individual technologies. For example, the investment in CDSS as a stand-alone technology is associated with an increase in the pneumonia readmission rate. The coefficient is positive and significant (coeff. = 0.25, $p < 0.05$). Moreover, we note that the synergy among full EMR capabilities portfolio increases patient satisfaction by 1.33 ($p < 0.01$), and this cannot be achieved from the investment in EMR capabilities as stand-alone individual technologies. For example, the investment in CDSS, CPOE, and PD as stand-alone technologies is associated with a decrease in the level of patient satisfaction. The coefficients are negative and significant.

Further, in heart attack readmission, heart failure readmission and pneumonia mortality rates, we do not observe a significant relationship between the synergy among any EMR capabilities portfolios and pneumonia mortality and the two readmission rates.

Table 8. Estimation of the effects of the synergy between the portfolios of EMR capabilities on healthcare quality outcomes at U.S. Hospitals (Unbalanced Panel; 2008-2012)

Variable	**HAM**	**HAR**	**HFM**	**HFR**	**PNM**	**PNR**	**PS**
Order Entry	0.01	0.19**	-0.03	0.20	-0.19*	0.17	-0.37
CDSS	-0.24**	0.04	0.01	-0.02	0.07	0.25**	-0.88**
CDR	-0.07	-0.21**	0.02	-0.02	0.004	-0.15	0.08
CPOE	0.01	-0.08*	0.07	-0.11	0.04	-0.08	-0.61***
Physician Documentation	0.03	-0.11	0.02	-0.15	0.02	-0.10	-0.47*
The Synergy Between Basic EMR Capabilities							
Basic EMR	0.06	-0.07	0.02	-0.12	0.10	-0.22*	-0.06
The Synergy Between Full EMR Capabilities							
Full EMR	-0.17**	0.06	-0.13*	0.20	-0.83	-0.03	1.33***
Control variables							
Hospital size (log)	0.23	0.14	0.20	0.24	0.18	0.28*	-0.87
Case mix index	-0.75***	-0.55*	-0.70***	-1.89**	-0.91***	-1.0***	3.87***

For-Profit Hospitals	0.14	-0.26*	0.14	0.28*	0.16	0.01	0.01
Hospital Age (log)	0.11	-0.10	0.09	-0.08	0.16	-0.01	-0.87
Academic Hospitals	0.18	0.19	-0.18	0.52**	0.15	0.85***	-0.52
R-Square F Value Cross Sections #	0.71 7.10*** 1308	0.77 7.35*** 1079	0.73 8.53*** 1470	0.82 9.66*** 1401	0.74 8.66*** 1484	0.80 9.01*** 1408	0.86 15.16*** 1941
* = significance at p < 0.10, **=p < 0.05, and ***=p < 0.01							

Examining the influence of the control variables on quality of healthcare, we note that large hospitals are associated with higher rates of pneumonia readmission. CMI reveals that hospitals handling more complex cases with greater patient severity exhibit lower levels of mortality and readmission rates in all health conditions as well as higher patient satisfaction. Examining the relationship between hospital type and quality outcomes, we observe that for-profit hospitals exhibit a lower level of heart attack readmission while not for-profit hospitals are associated with lower rate of heart failure readmission. Further, academic hospitals exhibit higher rates of heart failure readmission and pneumonia readmission.

Table 9 shows the results of the association between the synergetic impacts of EMR capabilities on the quality of healthcare in the balanced dataset.

In the heart attack mortality column, the results on the impact of stand-alone individual technologies on quality are not different from zero because the estimates are not statistically significant except CDSS. The investment in CDSS as individual technology reduces the heart attack mortality rate; the coefficient of CDSS is negative and significant (coeff. = -0.33, p < 0.05). However, we observe that the synergy between all EMR capabilities (full EMR capabilities) is associated with a lower heart attack mortality rate (coeff. = -0.17, p < 0.1), the coefficient is negative and significant.

In the heart failure readmission column, we observe that the synergy between basic EMR capabilities portfolio is associated with a lower heart failure rate. The coefficient is negative and significant (coeff= -0.30, $p < 0.1$). However, the performance impacts of the individual technologies vary by technology. For example, the investment in OE is associated with a higher hear failure readmission rate. The coefficient is positive and significant (coeff=0.45, $p < 0.01$). While the investment in PD as a stand-alone individual technology reduces the heart failure readmission rate. The coefficient is negative and significant (coeff=-0.30, $p < 0.01$).

Moreover, we note that the synergy among full EMR capabilities portfolio increases patient satisfaction level by 0.87 ($p < 0.05$), and this cannot be achieved from the investment in EMR capabilities as stand-alone individual technologies. For example, the investment in OE, and CDSS as stand-alone technologies is associated with a decrease in patient satisfaction. The coefficients are negative and significant.

However, we observe that the synergy between EMR capabilities is not significantly associated with heart attack readmission, heart failure mortality, pneumonia mortality, and pneumonia readmission rates.

Table 9. Estimation of the effects of the synergy between the portfolios of EMR capabilities on healthcare quality outcomes at U.S. Hospitals (Balanced Panel; 2008-2012)

Variable	**HAM**	**HAR**	**HFM**	**HFR**	**PNM**	**PNR**	**PS**
Order Entry	-0.03	0.19**	-0.02	0.45***	-0.03	0.35***	-0.86*
CDSS	-0.33**	0.05	-0.01	0.13	0.24*	0.13	-0.73*
CDR	-0.18	-0.22**	-0.06	0.02	-0.06	-0.23*	-0.14
CPOE	0.03	-0.06	0.08	-0.16	0.04	-0.07	-0.28
Physician Documentation	0.02	-0.15*	0.04	-0.30***	-0.11	-0.08	-0.04
The Synergy Between Basic EMR Capabilities							
Basic EMR	0.07	-0.04	0.03	-0.30*	-0.02	-0.21	0.19
The Synergy Between Full EMR Capabilities							
Full EMR	-0.17*	0.08	-0.10	0.39	-0.02	0.03	0.87**
Control Variables							

Hospital size (log)	0.02	0.12	0.09	0.21	0.06	0.23	0.13
Case mix index	-1.01***	-0.46	-0.51*	-2.21***	-1.18***	-1.01***	4.10***
For-Profit Hospitals	0.09	-0.15	0.30**	0.17	0.25*	0.08	0.30
Hospital Age (log)	0.14	-0.07	-0.01	-0.21	0.06	-0.01	0.48
Academic Hospitals	0.30*	0.18	-0.21	0.44*	0.15	0.86***	-1.43**
R-Square F Value Cross Sections #	0.68 7.86*** 689	0.76 8.29*** 657	0.71 9.30*** 820	0.81 10.19*** 899	0.71 9.35*** 825	0.79 9.78*** 906	0.83 15.14*** 810
* = significance at p < 0.10, **=p < 0.05, and ***=p < 0.01							

Examining the influence of the control variables on the quality of healthcare, CMI reveals that hospitals handling more complex cases with greater patient severity exhibit lower rates of mortality and readmission in almost all quality measures. We also observe that for-profit hospitals exhibit higher level of heart failure mortality and pneumonia mortality. Furthermore, academic hospitals are associated with higher rates of heart attack mortality, heart failure readmission and pneumonia readmission as well as lower level of patient satisfaction.

5.1.3 Effect of EMR capabilities assimilation and use on hospital quality outcomes

In the second sub-objective, we focus our analysis on the association between the assimilation and use of EMR capabilities and patient quality care measures. The results of the panel data regressions are shown in Tables 10 and 11. Table 10 shows the results of the association between the impacts of EMR capabilities assimilation and use on the quality of healthcare in the unbalanced dataset.

We observe that greater assimilation and use of EMR capabilities is significantly associated with only one quality measure-pneumonia mortality rate (coeff. = -0.01, p < 0.05). However, we do not observe that assimilation and use of different EMR capabilities is significantly associated with the heart attack mortality rate, heart attack readmission rate, heart failure readmission rate, pneumonia readmission rate, and level of patient satisfaction. Further, we observe that higher EMR exploration is associated with lower rates of heart attack mortality, heart attack readmission, and pneumonia readmission. The coefficients are negative and significant.

Examining the influence of the control variables on the quality of healthcare, we observe that large hospitals are associated with higher rates of pneumonia readmission. An examination of CMI reveals that hospitals handling more complex cases with greater patient severity exhibit lower rate of mortality and readmission in all conditions as well as higher patient satisfaction. Examining the relationship between hospital type and quality outcomes, we observe that for-profit hospitals exhibit higher rate of heart failure readmission and level of patient satisfaction, and lower rate of heart attack readmission. Further, academic hospitals are associated with higher rate of pneumonia readmission

Table 10. Estimation of the Effects of the Assimilation and Use of EMR Capabilities on Healthcare Quality Outcomes at U.S. Hospitals (Unbalanced Panel; 2008-2012)

Variable	**HAM**	**HAR**	**HFM**	**HFR**	**PNM**	**PNR**	**PS**
EMR Exploration	-0.09**	-0.10**	0.02	-0.05	0.105**	-0.09**	-0.30
EMR Exploitation	-0.01	-0.01	0.005	0.003	0.03***	-0.01	-0.02
Assimilation	0.001	0.004	-0.003	0.004	-0.01**	0.004	0.01
Hospital size (log)	0.23	0.12	0.20	0.24	0.22	0.26*	0.06
Case mix index	-0.75**	-0.63**	-0.69**	-1.82**	-0.86***	-1.09**	6.79***
For-Profit Hospitals	0.31	-0.31*	0.13	0.29*	0.16	-0.02	2.11**
Hospital Age (log)	0.10	-0.10	0.09	-0.07	0.15	-0.01	0.67
Academic Hospitals	0.12	0.26	-0.12	0.39	0.13	0.89***	-1.22

R-Square	0.71	0.77	0.73	0.82	0.74	0.80	0.87
F Value	7.09***	7.33***	8.57***	9.71***	8.66***	9.01***	16.13***
Cross Sections #	1305	1076	1465	1395	1479	1402	888
* = significance at p < 0.10, **=p < 0.05, and ***=p < 0.01							

Table 11 shows the results of the association between the impacts of EMR capabilities assimilation and use on the quality of healthcare in the balanced dataset.

As shown in Table 11, we do not find a statistically significant association between EMR capabilities assimilation and use and quality outcomes measures. In particular, we do not observe that assimilation and use of different EMR capabilities is significantly associated with the heart attack mortality rate, heart attack readmission rate, heart mortality rate, heart failure readmission rate, pneumonia mortality rate, pneumonia readmission rate, and level of patient satisfaction. In our study, we measured the effect of EMR assimilation and use in only seven quality measures. However, Health IT may well improve other aspects of quality unmeasured by our data. Further, we observe that higher EMR exploration is associated with a lower heart attack mortality rate and pneumonia readmission rate. The coefficients are negative and significant.

Furthermore, an examination of CMI reveals that hospitals handling more complex cases with greater patient severity exhibit lower rates of all health quality outcomes measures as well as higher patient satisfaction. Moreover, for-profit hospitals are associated with a higher level of patient satisfaction while not for-profit hospitals exhibit a lower heart failure mortality rate. Finally, academic hospitals are associated with a higher heart attack mortality rate.

Table 11. Estimation of the Effects of the Assimilation and Use of EMR Capabilities on Healthcare Quality Outcomes at U.S. Hospitals (Balanced Panel; 2008-2012)

Variable	**HAM**	**HAR**	**HFM**	**HFR**	**PNM**	**PNR**	**PS**
EMR Exploration	-0.12**	0.08	0.02	-0.4	0.06	-0.12***	-0.26
EMR Exploitation	-0.01	0.04**	0.01	0.01	0.03	-0.02	0.09
Assimilation	0.001	-0.01	-0.002	0.001	-0.001	0.01	0.002

Hospital size (log)	0.03	0.08	0.08	0.21	0.29	0.22	0.37
Case mix index	-0.99***	-1.36***	-0.51*	-2.14***	-1.19***	-1.39***	7.40***
For-Profit Hospitals	0.07	0.25	0.30**	0.17	0.17	0.07	2.98**
Hospital Age (log)	0.14	0.04	-0.002	0.21	0.02	-0.04	0.32
Academic Hospitals	0.37*	0.12	-0.14	0.3	0.05	0.91	-0.92
R-Square F Value Cross Sections #	0.68 7.93*** 689	0.71 9.28*** 825	0.71 9.37*** 820	0.81 10.25*** 892	0.71 9.40*** 624	0.78 9.83*** 899	0.83 15.12*** 391
* = significance at p < 0.10, **=p < 0.05, and ***=p < 0.01							

5.2 Objective 2 Results

In the next section, we describe our analysis of the impact of advanced EMR capabilities early adoption on quality measures. The descriptive statistics are reported in Appendix D, Tables A and B.

5.3.1 Quality improvements from early investment in CPOE

The results of the regression model are shown in Table 12. Table 12 shows the results of the impact of the early investment in CPOE on healthcare quality measures. In the heart attack mortality column, we observe that the early adoption of CPOE is associated with lower heart attack mortality rate (coeff. = -0.231, $p < 0.05$), the coefficient is negative and significant. We observe a similar association between early adoption of CPOE and a lower heart failure readmission rate (coeff. = -0.324, $p < 0.05$), the coefficient is negative and significant. In the heart failure mortality column, we do not observe a significant relationship between early investment in CPOE and the heart failure mortality rate. In the pneumonia mortality column, we also observe a similar significant association between the early investment in CPOE and a lower pneumonia mortality rate. In particular, the hospitals that invested early in CPOE were able to reduce the pneumonia mortality rate by -0.395. The coefficient is negative and significant at 0.1. In the pneumonia readmission columns, we also observe that early investment in CPOE results in a lower pneumonia readmission rate (coeff. = -0.239, $p < 0.1$).

In the patient satisfaction column, we note a significant association between early investment in CPOE and higher level of patient satisfaction, the coefficient is positive and significant (coeff. = 2.028, $p < 0.05$). That means early investment in CPOE increased patient satisfaction by 2.028.

Examining the relationship between hospital size and quality measures, we note that larger hospitals are more likely to exhibit lower rates of heart attack mortality, heart failure mortality and pneumonia mortality, while smaller hospitals are associated with lower rates of heart failure readmission, pneumonia readmission and a higher level of patient satisfaction. Furthermore, in evaluating the relationship between hospital age and quality, we find that old hospitals are associated with higher rates of heart failure mortality and pneumonia mortality.

An examination of CMI reveals that hospitals handling more complex cases with greater patient severity exhibit lower rates of heart attack mortality, heart failure readmission, pneumonia readmission as well as higher level of patient satisfaction. We also note that academic hospitals are associated with a lower rates of heart attack and heart failure mortality, while non-academic hospitals are associated with lower heart failure and pneumonia readmission rates. Finally, our results indicate that for-profit hospitals exhibit lower heart failure mortality rate and patient satisfaction, and higher rates of heart attack mortality and heart failure readmission.

Table 12. Estimation of the Effects of Early Adoption of CPOE on Quality of Care

Variables	**HAM**	**HFR**	**HFM**	**PNM**	**PNR**	**PS**
Constant	18.19***	28.35***	11.12***	12.021***	20.38***	65.28***
CPOE	-0.231**	-0.324**	-0.088	-0.395*	-0.239*	2.028***
Hospital Size (log)	-0.176***	0.391***	-0.253***	-0.189***	0.435***	-4.348***
Hospital Age (log)	-0.008	-0.019	0.075**	0.112***	0.005	0.122
CMI	-0.943***	-3.059***	0.250*	-0.186	-2.028***	16.790***
Maturity	0.024	0.032	-0.012	0.023	0.003	-0.240**

Academic	-0.3**	1.320***	-0.544***	-0.132	1.233***	0.532
For-Profit Hospitals	0.215**	0.494***	-0.147	0.042	0.143	-4.780***
R Square Adjusted R F N	.077 .075 34.54*** 2912	0.121 0.119 56.87*** 2912	0.045 0.042 18.37*** 2912	0.023 0.020 9.24*** 2912	0.081 0.079 36.99*** 2912	.140 .138 62.63*** 2688

5.3.2 Quality improvements from early investment in physician documentation

The results of the regression model are shown in Table 13. Table 13 shows the results of the impact of the early investment in physician documentation on healthcare quality measures. In the heart attack mortality column, we observe that the early adoption of physician documentation is associated with a lower heart attack mortality rate (coeff. = -0. 203, p < 0.1), the coefficient is negative and significant. We observe a similar significant association between early adoption of physician documentation and a lower heart failure readmission rate (coeff. = -0. 277, p < 0.05), the coefficient is negative and significant. In the heart failure mortality column, we do not observe a significant relationship between early investment in physician documentation and the heart failure mortality rate. In the pneumonia mortality column, we also observe a significant association between the early investment in physician documentation and a lower pneumonia mortality rate. In particular, the hospitals that invested early in physician documentation were able to reduce pneumonia mortality rate by -0.444. The coefficient is negative and significant at 0.01. In the pneumonia readmission columns, we also observe that early investment in physician documentation results in a lower pneumonia readmission rate (coeff. = -0.332, p < 0.01).

In the patient satisfaction column, we observe a significant association between early investment in physician documentation and higher level of patient satisfaction, the coefficient is positive and significant (coeff. = 1.942, p < 0.01). That means early investment in physician documentation increased patient satisfaction by 1.942.

Examining the relationship between hospital size and on quality measures, we note that larger hospitals are more likely to exhibit lower rate of heart failure mortality, while smaller hospitals are associated with lower rates of heart attack mortality, heart failure readmission, pneumonia mortality, pneumonia readmission as well as higher level of patient satisfaction. Furthermore, in evaluating the relationship between hospital age and quality, we find that old hospitals are associated with higher rate of heart failure mortality.

An examination of CMI reveals that hospitals handling more complex cases with greater patient severity exhibit lower rates of heart attack mortality, heart failure readmission, pneumonia mortality, pneumonia readmission as well as a higher level of patient satisfaction. We observe that physician documentation that has been adopted since a long period of time are associated with higher rates of heart attack mortality, heart failure readmission, pneumonia mortality, pneumonia readmission as well as a lower level of patient satisfaction. We also note that academic hospitals are associated with lower rates of heart attack and heart failure mortality, while non-academic hospitals are associated with lower heart failure readmission, pneumonia mortality and pneumonia readmission rates. Finally, our results indicate that for-profit hospitals are associated with higher heart attack mortality rate, heart failure readmission, pneumonia mortality, pneumonia readmission rates as well as lower patient satisfaction.

Table 13. Estimation of the Effects of Early Adoption of PD on Quality of Care

Variable	**HAM**	**HFR**	**HFM**	**PNM**	**PNR**	**PS**
Constant	15.714***	26.881***	12.037***	17.996***	18.814***	65.959***
PD	-0.203*	-0.277**	0.075	-0.444***	-0.332***	1.942***
Hospital Size (Log)	0.259***	0.414***	-0.265***	0.684***	0.442***	-4.281***
Hospital Age(Log)	-0.012	-0.018	0.062**	0.016	-0.015	0.071
CMI	-0.579***	-3.319***	0.195	-2.476***	-2.054***	16.758***
Maturity	0.028**	0.026*	-0.011	0.035**	0.033**	-0.230***
Academic	-0.718***	1.421***	-0.701***	1.087***	1.213***	0.625
For-Profit Hospitals	0.234**	0.548***	-0.075	0.181*	0.143*	-4.729***
R Square Adjusted R F N	0.022 0.020 9.96*** 3059	0.120 0.118 59.68*** 3059	0.041 0.039 18.70*** 3059	0.086 0.084 41.11*** 3059	0.083 0.081 39.60*** 3060	0.140 0.138 62.12*** 2670

5.3 Objective 3 Results

As stated in the methodology section, we tracked all hospitals sequences from 2005-2012, and identified the order of EMR capabilities adoption that correspond to the best performer hospitals (reference sequences). This process yields seven EMR capabilities adoption sequences as shown in Table 14.

Table 14. EMR capabilities adoption reference sequences

Reference sequence	Number of hospitals in the sample data set
CDR-CDSS-OE-CPOE-PD	5
CDR-CDSS-OE-PD-CPOE	3
CDR-OE-CDSS-CPOE-PD	5
CDSS-CDR-OE-CPOE-PD	7
CDSS-OE-CDR-CPOE-PD	3
OE-CDR-CDSS-CPOE-PD	21
OE-CDR-CDSS-PD-CPOE	16

Sequence analysis provides insights about how close each hospital's adoption pattern of EMR capabilities is to the EMR capabilities adoption reference sequences. As presented in Table 14, we observe that all the reference sequences started with basic EMR capabilities first, and then advanced EMR capabilities last. This is largely consistent with HIMSS EMRAM discussed in section (2.3). Moreover, we find that about 16 percent of the hospitals in the sample dataset followed (OE-CDR-CDSS-CPOE-PD) sequence and 12 percent of hospitals with (OE-CDR-CDSS-PD-CPOE) sequence. This result is largely consistent with the logical dependency of EMR capabilities discussed in section (2.3).

Descriptive statistics are presented in Table 15. Across all hospitals in the dataset, the mean quality measures ranged from 11.65 to 24.38. On average, the Levenshtein distance from the EMR capabilities adoption reference sequences is about 1.10 in all quality measures.

Further, we conducted two procedures to investigate the relationship between EMR capabilities adoption sequences and healthcare quality. First, we compared the means of various quality measures as dependent variables and EMR capabilities adoption sequences as independent variable as shown in Table 16. The results show that the hospitals with EMR capabilities adoption reference sequences perform better on all three quality measures than the other EMR capabilities adoption sequences. They had lower readmission and mortality rates than other hospitals.

Table 15. Descriptive Statistics in the Sample Dataset

Variable	**HFR**	**HFM**	**PNM**
	Mean (SD)	**Mean (SD)**	**Mean (SD)**
Mortality/Readmission rates	24.38 (1.76)	11.65 (1.81)	11.85 (2.11)
SeqDist	1.10 (1.05)	1.12 (1.06)	1.09 (1.05)
Hospital Size (Log)	2.3 (0.34)	2.3 (0.34)	2.3 (0.34)
Hospital Age (Log)	1.47 (0.43)	1.47 (0.43)	1.47 (0.43)
CMI	1.48 (0.28)	1.48 (0.28)	1.48 (0.28)
	Proportional Estimate	Proportional Estimate	Proportional Estimate
Academic	0.03	0.03	0.03
For-profit	0.12	0.12	0.12

Table 16. Compare Means Results for Performance of EMR Capabilities Reference Sequences

		HFM	**PNM**	**HFR**
EMR capabilities Reference Sequences	Mean	11.380	11.772	24.131
	N	54	54	54
	Std. Deviation	1.8796	2.2805	1.7185
Other Sequences	Mean	11.845	11.907	24.555
	N	76	76	76
	Std. Deviation	1.7544	1.9943	1.7898

Next, we estimated OLS regression model for each quality measure with independent variable- SeqDist, quality measures as dependent variables, and control variables. This study did not have sufficient data for heart attack mortality, heart attack readmission, pneumonia readmission and patient satisfaction quality outcomes measures. Therefore, we examined the impact of EMR capabilities adoption sequence distance on heart failure readmission, heart failure mortality, and pneumonia mortality rates. For ease of interpretation, we reversed the distance measures (5 – SeqDist=EMRSEQ) [11]. In the first row of Table 17, we observe that EMRSEQ relates significantly to two quality measures after controlling for other factors. Hospitals that closely follow reference EMR capabilities adoption sequences were able to reduce heart failure mortality rate by -0.30. The coefficient is negative and significant ($p < 0.05$). We also observe that these hospitals that closely match with reference EMR capabilities adoption sequences experienced a lower pneumonia mortality rate than other hospitals by -0.32. The coefficient is negative and significant ($p < 0.1$).

Table 17. Estimation of the Effects of EMR Capabilities Implementation Sequence on Quality of Care

Variable	**HFR**	**HFM**	**PNM**
Constant	26.86***	14.53***	14.24***
EMRSEQ	-0.30**	0.02	-0.32*
Hospital Size (Log)	1.24*	-0.01	-1.08
Hospital Age (Log)	-0.08	0.06	0.97**
CMI	-2.79***	-2.11**	-0.19
Academic	0.91	0.19	-0.25
For-Profit Hospitals	0.67	0.72	1.59***
R Square	0.16	0.13	0.15
Adjusted R	0.12	0.09	0.10
F	3.94***	3.12***	3.48***
N	130	130	130

[11] The maximum number of operations to transform any sequence is five.

Examining the relationship between hospital size and quality outcomes, we observe that large hospitals are associated with a higher failure readmission rate. We also note that old hospitals are associated with a higher pneumonia mortality rate. An examination of CMI reveals that hospitals handling more complex cases with greater patient severity exhibit lower rates of heart failure readmission and heart failure mortality. Finally, our results indicate that for-profit hospitals are associated with a higher pneumonia mortality rate.

CHAPTER 6

DISCUSSION AND CONCLUSION

6.1 Discussion

In this dissertation, we studied three different aspects of EMR implementations that include the exploration of synergy between EMR capabilities, the impact of early adoption of EMR capabilities, and the optimal sequence of EMR capabilities adoption. We also tested the impact of these dimensions on various healthcare quality outcomes measures.

In exploring the relationship between the synergy among different portfolios of EMR capabilities and quality outcomes of care at U.S. hospitals, we employed a panel dataset for the period (2008-2012) to examine how the synergy between different EMR capabilities implementations impacts quality compared to the impact of individual EMR capabilities investment. More specifically, whether the synergy between EMR capabilities is capable of achieving better quality of care compared to stand-alone EMR capabilities investment. Overall, we found that the synergy between full EMR capabilities is capable of achieving better quality than stand-alone individual EMR systems.

This study contributes to our understating of emerging health IT in some important ways. To our knowledge, this study is one of the first to quantify the association between the synergy among different EMR systems implementations with quality outcomes measures. This study also applies panel data analysis to conduct a more granular and comprehensive examination that enumerates the impact of EMR capabilities on care quality outcomes using panel data for five years period from 2008 to 2012.

Our findings also have significant implications for hospitals' CIOs since the results provide empirical evidence on the effectiveness of measuring the impact of the synergy and assimilation and use of EMR capabilities on healthcare quality outcomes.

The findings, however, indicated variations in the performance impact of EMR capabilities assimilation and use on healthcare quality. We found the greater assimilation and use of EMR capabilities are only associated with reducing pneumonia mortality conditions' negative effects. We did not find a statistically significant association between EMR capabilities assimilation and use and heart attack mortality rate, heart attack readmission rate, heart mortality rate, heart failure readmission rate, pneumonia readmission rate, and level of patient satisfaction. However, Health IT may well improve other healthcare outcomes unmeasured by our data.

Second, our study results also suggest that early-adopter hospitals were able to improve healthcare quality as a result of advanced EMR adoption. In fact, early adoption was associated with a decrease in mortality and readmission rates as well as higher patient satisfaction, which means higher quality of healthcare.

Another significant finding of our study pertains to the consistent pattern in the impacts of hospital age, technology maturity, and CMI. Old hospitals are more likely to report high mortality and readmission rates, which means lower healthcare quality. We also observe that the physician documentation that has been adopted since a long period of time have negative impact on the quality measures. This might because the technology advancement issue. For instance, 2008 physician documentation is more advanced than 2005 physician documentation version. Finally, we note that case mix index has a significant impact on improving almost all quality measures such hospitals that treat patients with more complex cases exhibit higher quality rates.

These results on early adoption have important implications for policy makers since they provide empirical evidence on the positive impact of early adoption of advanced EMR capabilities on various healthcare quality measures. To the best of our knowledge, our study is the first to estimate the impact of early adoption on healthcare quality outcomes from the investment in EMR capabilities.

Third, in this study, we tracked the sequences of EMR capabilities adoption longitudinally across U.S. hospitals and assessed their impact on healthcare quality outcomes. Our results on EMR capabilities adoption reference sequences are largely consistent with the seven-stage HIMSS EMRAM. The EMR capabilities adoption patterns results showed that best performer hospitals adopted basic EMR capabilities first while advanced EMR capabilities were adopted later in the sequence. The analysis provides support for our assumption about EMR sequence analysis. The assumption posits that EMR capabilities adoption sequences do matter and have an impact on healthcare quality. The analysis shows that hospitals that closely follow reference EMR capabilities adoption sequences experienced better quality outcomes than other hospitals. According to McKinsey (2002), IT does matter and it has an impact on productivity. However, the extent of this impact depends on how it is employed. When implemented in an appropriate sequence, its impact on productivity can be large.

Our results provide useful insights and important implications for management. For example, the closer a hospital adheres reference EMR sequences, the better the quality outcomes. Thus, we believe that this is an actionable finding and hospital's CIOs or decision makers can help determine optimal EMR capabilities adoption patterns from these findings as well. Moreover, knowing the reference EMR capabilities adoption sequence would cut implementation time and cost, as well as reduce uncertainties associated with the next application to adopt. The results suggest strategies for EMR capabilities adoption to help decide which systems may be best implemented first. In the context of this study, best-performer hospitals adopted basic EMR capabilities first, and then more advanced EMR capabilities were implemented last. On the other hand, the findings of this study provide better guidelines for meaningful use about the best order of EMR capabilities adoption and how adoption patterns potentially impact hospital's performance.

To our knowledge, this study is the first paper to explicitly examine the sequence of EMR capabilities adoption using longitudinal data and assess the impact of the sequence of adoption on healthcare quality measures. Another important contribution of this study is our methodology in identifying EMR capabilities adoption reference sequences in relation to hospital performance.

6.2 Limitations

This study has the following limitations. First, the effect of EMR capabilities implementation may be biased due to endogeneity. While fixed effects models control for all observed and unobserved time-invariant characteristics of the hospitals, our results may still be biased by the presence of time-varying unobserved effects that occurred concurrently with EMR. Potential confounders that might impact healthcare outcomes apart from the effects of the portfolio of EMR capabilities include: care delivery models and quality improvement (QI) initiatives (Tiedeman & Lookinland, 2004; Weiner et al., 2006), organizational and management strategies, and physicians' perception of EMR use (Lee et al., 2013).

Second, the study does not address other related issues of importance. Due to the constraints of the dataset, we were unable to examine the effect of the EMR capabilities on other outcomes such adverse drug events, length of stay, and myocardial infarction (AMI). Moreover, our variables in the synergy objective are based on a binary scale. This measure may not fully capture the actual effect of the synergy among EMR capabilities. An augmented measure of synergy would be a potentially interesting avenue for future research.

Third, on the impact of early adoption of advanced EMR capabilities on healthcare quality, this study fails to determine whether the impact of early adoption on quality outcomes from the investment in EMR capabilities resulted in sustained improvement in quality outcomes.
Moreover, a limitation of a longitudinal study is that it is not easy to specify other possible explanations for the findings. Although we control for many hospital characteristics, it could still be that the better managed hospitals were early adopters and that quality improvements are the results of better management, rather than investment in EMR capabilities. Such studies are also hampered by the difficulty of obtaining the necessary data (Dos Santos & Peffers, 1993). Usually, panel data is difficult to obtain, and good secondary data sources are rarely available.

Fourth, in Objective 3, our analysis does not suggest that there is a causal relationship between EMR adoption patterns and quality outcomes. It is likely that other factors such as management factors could have impact on quality outcomes. This deserves further investigation in future studies. Moreover, this study was missing data on some quality measures. Therefore, we were not able to analyze the impact of EMR adoption patterns on several other quality outcome measures previously mentioned in this study.

6.3 Conclusion and Future Work

This research is extending earlier work on the benefits of EMR technology by focusing on the synergistic impact of different EMR capabilities on healthcare quality. This is one of the first studies to examine the relative performance contributions of different capabilities of EMR and their impact on outcomes and patient levels measures of healthcare quality of care. The results highlight that hospitals should consider the synergy between EMR capabilities to realize greater quality performance. On the other hand, hospitals should explore many EMR capabilities and develop deep experience with different EMR capabilities in order to realize lower pneumonia mortality.

This study also sought to determine whether early adopters of advanced EMR capabilities were able to improve the quality of healthcare. More specifically, the results suggest that early advanced EMR capabilities were able to improve the quality outcomes relative to hospitals that were not early adopters.

This research also answers the question whether the adoption path of EMR capabilities impacts healthcare quality outcomes. Our results suggest that the sequence of EMR capabilities adoption does matter. This finding provides valuable insights as hospitals aim to show the value derived from health IT investments. This study empirically shows improvement in quality outcomes when hospitals follow the optimal sequence of EMR capabilities adoption.

Future studies on health IT may benefit from measuring the impact of synergy between EMR capabilities as well their assimilation and use on other quality measures such as process quality outcomes. It may also be useful to study the impact of the synergy between EMR capabilities on other performance measures such as cost and efficiency.

On the early adoption results, it is recommended to further explore whether the impact of early adoption from advanced EMR capabilities investment is sustained for the years after the early adoption period. This research also suggests that it may be useful to explore the impact of EMR capabilities adoption patterns using additional performance measures and quality measures such as length of stay.

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APPENDICES

APPENDIX A: Healthcare Quality Outcomes Measures

Readmission and Deaths[12]	
Description	- They measure the complication, injuries, or other certain conditions happened to patients after they got hospital care. - 30-days readmission rates focus on whether patients were readmitted again to the hospitals within 30 days of discharge. - 30-days mortality rates “focus on whether patients died within 30 days of being admitted to the hospital”.
Calculation	The calculation of readmission and death rates is based on the followings: - Medicare enrollment, - Claims records, and - Specific statistical procedure such as hierarchical logistic regression model. - The calculation considers how sick patients when they were first admitted to the hospital[13].
Why they are important?	- Shows hospitals’ performance compare to the national rate.

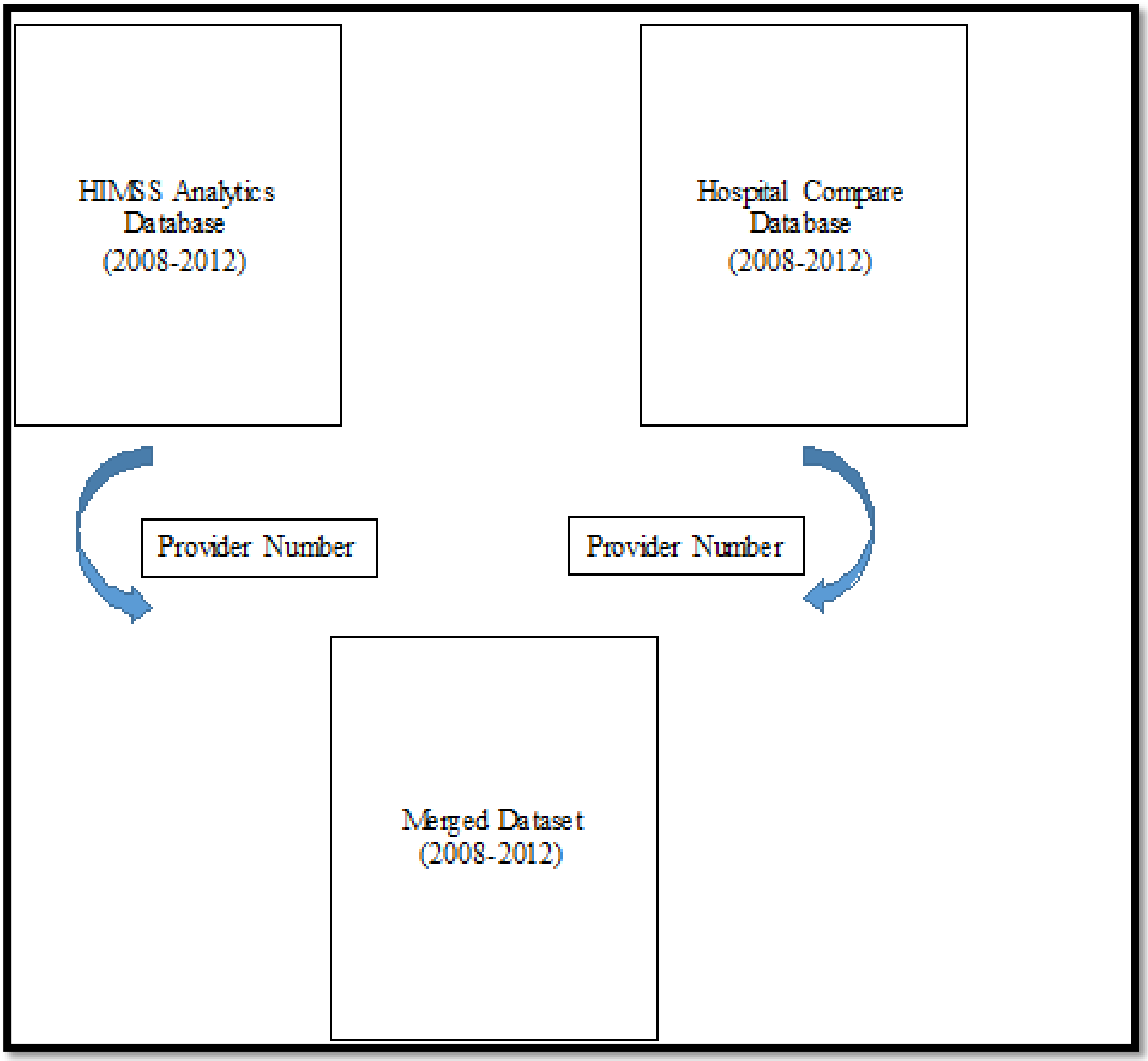
[12] https://www.medicare.gov/HospitalCompare/Data
[13] This is known as “risk-adjusted” and helps make the comparisons between hospitals accurate and meaningful.

	- If the readmission and death rates are lower than national rates then hospital's performance is better than national rate. - If the readmission and mortality rates are higher than national rates then hospital's performance is worse than national rate. - If readmission and mortality rates are same as national rates then hospital's performance is no different than the national rate. - Mortality rates "provide information about important aspects of hospital care that affect patients' outcomes- like prevention of and response to complications, emphasis on patient safety, and the timeliness of care." - Readmission rates provide information about hospital's performance in preventing complications, clear information to the patients about discharge instructions, and help patients make an easy transition to their home.

Patient satisfaction	
Description	- HCAHPS (Hospital consumer assessment of healthcare providers and systems): “is a standardized survey instrument and data collection methodology that has been in use since 2006 to measure patients’ perspectives of hospital care.” - Hospital Compare website shows the survey results. This helps consumers make comparisons between hospitals on important aspects of patients’ perspectives of treatment and care.
Survey methodology	- The sample are chosen randomly from recently discharged adult patients. - The survey includes questions about patients’ feedback about topics such as nurses and doctors communication and hospital environment.
Survey topics	- “How often did nurses communicate well with patients?” - “How often did doctors communicate well with patients?” - “How often did patients receive help quickly from hospital staff?” - “How often was patients’ pain well controlled?” - “How often did staff explain about medicines before giving them to patients?”

	- “How often were the patients’’ rooms and bathrooms kept clean?” - “How often was the area around patients’ rooms kept quiet at night?” - “Were patients given information about what to do during their recovery at home?” - “How well did patients understand the type of care they would need after leaving the hospital?” - “How do patients rate the hospital overall?” - “Would patients recommend the hospital to friends and family?”

APPENDIX B: Datasets Merging Process



Tables and Fields

HIMSS Analytic Database			
Table Name	**Description**	**Fields**	**Description**
HAEntity	HAEntity table contains demographic information for all facilities in the database.	HAEntityid	“Identification number associated with surveyed entity. Unique within survey year.”
		Name	Facility's Name
		HAEntityType	Description of facility type (e.g., Ambulatory, Hospital, Home Health, etc.)
		MedicareNumber	Medicare identification number
		State	State where facility is located
		Zip	Facility's Postal Zip Code
		Type	Description of the facilities primary service provided (e.g., Academic, Psychiatric, Diabetes Center, etc.)

		YearOpened	Year Facility was acquired
		OwnershipStatus	Ownership Status; “Owned, Managed, Leased, or Affiliated”
		NofBeds	Number of Licensed Beds
		NofStaffedBeds	“Number of Beds that can be operated at present staffing levels”
		ProfitStatus	Not for Profit or Profit
HAEntityApplication	HAEntityApplication “contains the automation information for all the facilities in the database”	HAEntityId	“Identification number associated with surveyed entity. Unique within survey year.”
		AppId	Record identification number
		Application	Software application name (e.g., Clinical Data Repository, Clinical Decision Support System (CDSS), etc.)
		ApplicationId	Unique identification

			number for application
		Category	“The category the software application is associated with”
		CategoryId	Unique identification number for application category (e.g., category id for Electronic Medical Record is 6)
		Status	Indicates the status of an application (Not Automated, Live and Operational, Installation in Process, Contacted/Not Yet Installed, Not Reported, To be Replaced, Not Yet Contracted)
		ContractMonth	The month the software application was contracted
		ContractYear	The year the software application was contracted

Hospital Compare Database			
Table Name	**Description**	**Field Name**	**Description**
dbo_vwHQI_HOSP	This table provide demographic information for all hospitals in the database.	Provider Number	Unique identification number
		Hospital Name	Hospital's Name
		State	The state where hospital is located
		Zip Code	Hospital's Postal Zip Code
		Hospital Ownership	Ownership Status; Acute Care Hospitals, Children Hospitals, Critical Access Hospitals.
		Hospital Type	Description of hospital type
dbo_vwHQI_HOSP_MORTALITY_READM_XWLK	This table provides information about health conditions, quality outcomes measures, comparison to the national rate, and mortality and readmission rates for all hospitals in the database.	Provider Number	Unique identification number
		Hospital Name	Hospital's Name
		Condition	Description of health conditions (e.g., Heart attack, Heart failure, Pneumonia)
		Measure Name	Description of health quality outcomes measures (e.g.

			Hospital 30-Day Death (Mortality) Rates for Heart Attack, Hospital 30-Day Readmission Rates for Heart Attack, Hospital 30-Day Death (Mortality) Rates for Heart Failure, Hospital 30-Day Readmission Rates for Heart Failure, etc.)
		Category	Comparison to the national rate (Better than U.S. National Rate, No different than U.S. National Rate, Worse than U.S. National Rate)
		Mortality Rate	Hospital's mortality and readmission rates.
dbo_vwHQI_HOSP_HCAHPS_MSR	This table provides information about patient experience on care and patient rating items that include nine key dimensions: communication with	Provider Number	Unique identification number
		Hospital Name	Hospital's Name
		HCAPS Question	Description about the HCAPS survey questions.

	doctors, communication with nurses, responsiveness of hospital staff, pain management, communication about medicines, discharge information, cleanliness of the hospital environment, quietness of the hospital environment, and transition of care	HCAPS Answer Description	Description about patients' answer.
		HCAPS Answer	Answer scores for HCAPS survey questions.

Hospital Compare-CMI Dataset			
Table Name	**Description**	**Field Name**	**Description**
Case Mix Index (CMI)	This table provide information about the average severity of patient disease case mix in all hospital in the database.	Provider Number	Unique identification number
		CMI	Case mix index scores for all hospitals in the database.

Application Lists and Categories-HIMSS Analytic Database

Category	Application
Ambulatory	Ambulatory EMR
Ambulatory	Ambulatory Laboratory
Ambulatory	Ambulatory PACS
Ambulatory	Ambulatory Pharmacy
Ambulatory	Ambulatory Radiology
Ambulatory	Practice Management
Cardiology & PACS	Cardiology - Cath Lab
Cardiology & PACS	Cardiology - CT (Computerized Tomography)
Cardiology & PACS	Cardiology - Echocardiology
Cardiology & PACS	Cardiology - Intravascular Ultrasound
Cardiology & PACS	Cardiology - Nuclear Cardiology
Cardiology & PACS	Cardiology Information System
ED/Operating Room/Respiratory	Emergency Department Information System (EDIS)
ED/Operating Room/Respiratory	Operating Room (Surgery) - Peri-Operative
ED/Operating Room/Respiratory	Operating Room (Surgery) - Post-Operative
ED/Operating Room/Respiratory	Operating Room (Surgery) - Pre-Operative
ED/Operating Room/Respiratory	OR Scheduling
ED/Operating Room/Respiratory	Respiratory Care Information System
Electronic Medical Record	Clinical Data Repository
Electronic Medical Record	Clinical Decision Support
Electronic Medical Record	Computerized Practitioner Order Entry (CPOE)
Electronic Medical Record	Order Entry (Includes Order Communications)
Electronic Medical Record	Physician Documentation
Financial Decision Support	Budgeting
Financial Decision Support	Business Intelligence
Financial Decision Support	Contract Management
Financial Decision Support	Cost Accounting

Financial Decision Support	Data Warehousing/Mining - Financial
Financial Decision Support	Executive Information System
Financial Decision Support	Financial Modeling
General Financials	Accounts Payable
General Financials	General Ledger
Health Information Management (HIM)	Abstracting
Health Information Management (HIM)	Chart Deficiency
Health Information Management (HIM)	Chart Tracking/Locator
Health Information Management (HIM)	Dictation
Health Information Management (HIM)	Dictation with Speech Recognition
Health Information Management (HIM)	Encoder
Health Information Management (HIM)	In-House Transcription
Health Information Management (HIM)	Transcription - Remote Hosted/ASP
Health Information Management (HIM)	Document Management
Health Information Management (HIM)	Electronic Forms
Home Health	Home Health Administrative
Home Health	Home Health Clinical
Human Resources	Benefits Administration
Human Resources	Payroll
Human Resources	Personnel Management

Human Resources	Time and Attendance
Information Sharing	Browser
Information Sharing	DBMS
Information Sharing	Email
Information Sharing	Interface Engines
Information Sharing	Single Sign-On
Information Sharing	Turnkey Portal
Information Sharing	Web Development Tool
Information Sharing	Disaster Recovery System
Information Sharing	Encryption
Information Sharing	Firewall
Information Sharing	Spam Filter/ Spyware
Laboratory	Anatomical Pathology
Laboratory	Blood Bank
Laboratory	Laboratory Information System
Laboratory	Microbiology
Laboratory	Molecular Diagnostics
Laboratory	Outreach Services
Nursing	Electronic Medication Administration Record (EMAR)
Nursing	Intensive Care
Nursing	Nurse Acuity
Nursing	Nurse Staffing/Scheduling
Nursing	Nursing Documentation
Nursing	Obstetrical Systems (Labor and Delivery)
Pharmacy	Pharmacy Management System
Radiology & PACS	Radiology – Angiography
Radiology & PACS	Radiology - CR (Computed Radiography)
Radiology & PACS	Radiology - CT (Computerized Tomography)
Radiology & PACS	Radiology - DF (Digital Fluoroscopy)

Radiology & PACS	Radiology - Digital Mammography
Radiology & PACS	Radiology - DR (Digital Radiography)
Radiology & PACS	Radiology - MRI (Magnetic Resonance Imaging)
Radiology & PACS	Radiology - Nuclear Medicine
Radiology & PACS	Radiology – Orthopedic
Radiology & PACS	Radiology - US (Ultrasound)
Radiology & PACS	Radiology Information System
Revenue Cycle Management	ADT/Registration
Revenue Cycle Management	Bed Management
Revenue Cycle Management	Credit/Collections
Revenue Cycle Management	Electronic Data Interchange (EDI) - Clearing House Vendor
Revenue Cycle Management	Enterprise Master Person Index (EMPI)
Revenue Cycle Management	Patient Billing
Revenue Cycle Management	Patient Scheduling
Financial Decision Support	Medical Necessity Checking Content
Supply Chain Management	Enterprise Resource Planning
Supply Chain Management	Materials Management
Utilization Review/Risk Management	Case Mix Management
Utilization Review/Risk Management	Data Warehousing/Mining - Clinical
Utilization Review/Risk Management	Outcomes and Quality Management

Application Automation Status

Status
Contracted/Not Yet Installed
Installation in Process
Live and Operational
Not Automated
Not Reported
Not Yet Contracted
To be Replaced

APPENDIX C: Robustness Check Analysis Results

Table A. Estimation of the effects of the synergy between the portfolios of EMR capabilities on healthcare quality outcomes at large U.S. Hospitals (Unbalanced Panel; 2008-2012)

Variable	**HAM**	**HAR**	**HFM**	**HFR**	**PNM**	**PNR**	**PS**
Order Entry	-0.02	0.13	-0.12	0.16	-0.09	0.06	0.19
CDSS	-0.26**	0.07	0.02	0.01	-0.13	0.26**	0.01
CDR	-0.08	-0.25*	0.01	-0.07	0.03	-0.02	-0.18
CPOE	-0.01	-0.15***	0.08	-0.03	-0.08	0.01	-0.34
Physician Documentation	0.04	-0.15*	-0.06	-0.17	-0.02	-0.15	-0.34
The Synergy Between Basic EMR Capabilities							
Basic EMR-No PD	0.05	-0.04	0.04	-0.12	-0.02	-0.19	-0.61
The Synergy Between Full EMR Capabilities							
Full EMR-With PD	-0.16*	0.19	-0.16*	0.10	-0.13	-0.15	1.83***
Control Variables							
Hospital size	0.35*	0.07	0.18	0.32	0.33	0.21	-1.68**
Case mix index	-0.81***	-0.88**	-0.54**	-2..40***	-1.01***	-0.85**	2.80***
For-Profit Hospitals	0.07	-0.29	0.12	0.25	0.10	0.14	0.46
Hospital Age	0.10	-0.07	0.18	-0.12	0.33	0.10	0.69*
Academic Hospitals	0.18	0.16	-0.30	0.66***	0.11	0.92***	0.18
R-Square F Value N	0.72 7.53*** 1087	0.77 7.53*** 962	0.74 8.86*** 1125	0.83 10.50*** 1066	0.74 8.65*** 1128	0.81 9.46*** 1068	0.89 19.66*** 1330
* = significance at p < 0.10, **=p < 0.05, and ***=p < 0.01							

Table B. Estimation of the effects of the synergy between the portfolios of EMR capabilities on healthcare quality outcomes at large U.S. Hospitals (Balanced Panel; 2008-2012)

Variable	**HAM**	**HAR**	**HFM**	**HFR**	**PNM**	**PNR**	**PS**
Order Entry	-0.02	0.13	-0.04	-0.41*	0.03	0.24*	0.07
CDSS	-0.37**	0.01	0.01	0.17	0.25*	0.14	0.34
CDR	-0.11	-0.26*	-0.05	0.01	-0.05	-0.11	-0.20
CPOE	0.04	-0.15**	0.10	0.06	0.13	-0.03	0.59
Physician Documentation	0.03	-0.15*	0.04	-0.21*	-0.16	-0.01	-0.50
The Synergy Between Basic EMR Capabilities							
Basic EMR-No PD	0.03	-0.04	0.02	-0.29*	-0.07	-0.17	-0.82
The Synergy Between Full EMR Capabilities							
Full EMR- With PD	-0.09	0.19	0.13	0.28	-0.18	-0.12	1.71***
Control Variables							
Hospital size	0.17	0.07	-0.08	0.29	0..26	0.12	-2.50**
Case mix index	-1.22***	-0.89**	-0.38	-2.65**	-1.87***	-0.99**	1.54
For-Profit Hospitals	0.02	-0.30	0.29*	0.15	0.17	0.23*	0.87
Hospital Age	0.04	0.01	0.03	-0.15	0.01	-0.14	0.48
Academic Hospitals	0.32*	0.17	-0.16	0.61	0.61*	0.93***	-0.79
R-Square F Value N	0.69 8.10*** 590	0.76 8.41*** 600	0.72 9.54*** 623	0.82 8.67*** 502	0.71 9.33*** 624	0.79 10.07*** 685	0.87 19.76 617
* = significance at p < 0.10, **=p < 0.05, and ***=p < 0.01							

APPENDIX **D: Descriptive Statistics-Objective 2**

Table A. The Descriptive Statistics of Early Adoption of CPOE, Quality Outcomes Measures, and Hospital Characteristics.

Variables	HAM	HFR	HFM	PNM	PNR	PS
	M (SD)*	M (SD)	M (SD)	M (SD)	M (SD)	M (SD)
Mortality/Readmission/ Patient Satisfaction Rates	16.56 (1.7)	24.56 (2.15)	11.07 (1.58)	11.5 (1.9)	18.29 (1.74)	66.6 (10.2)
CPOE*	0.58	0.58	0.58	0.58	0.58	0.59
Hospital Size (Log)	5.14 (0.85)	3.14 (0.85)	5.14 (0.85)	5.14 (0.85)	5.14 (0.85)	5.14 (0.86)
Hospital Age (Log)	3.33 (0.88)	3.15 (1.04)	3.33 (0.85)	3.33 (0.88)	3.33 (0.85)	3.32 (0.88)
CMI	1.37 (0.27)	1.37 (0.27)	1.37 (0.29)	1.37 (0.28)	1.37 (0.28)	1.37 (0.28)
Maturity	3.1 (3.09)	3.1 (3.09)	3.1 (3.09)	4.8 (4.42)	3.1 (3.0)	3.14 (3.1)
Academic	.09	0.08	0.09	0.09	0.09	0.09
For-profit	0.17	0.17	0.17	0.17	0.17	0.18

- The analysis includes the following automation status (live and operational, to be replaced, installation in process, and contracted but not yet installed)
- Mean and SD for continuous variables and proportional estimate for categorical variables (CPOE, Academic, and For-profit)

Table B. The Descriptive Statistics of Early Adoption of PD, Quality Outcomes Measures, and Hospital Characteristics.

Variables	HAM	HFR	HFM	PNM	PNR	PS
	M (SD)	M (SD)	M (SD)	M (SD)	M (SD)	M (SD)
Mortality/Readmission/ Patient Satisfaction Rates	16.18 (1.8)	24.56 (2.14)	11.05 (1.57)	18.09 (2.0)	18.30 (1.73)	66.6 (10.2)
PD*	0.52	0.52	0.52	0.52	0.52	0.51
NofBeds (log)	5.18 (0.84)	5.18 (0.84)	5.18 (0.84)	5.18 (0.84)	5.18 (0.84)	5.14 (0.86)
Age (log)	3.12 (1.03)	3.12 (1.03)	3.12 (1.03)	3.12 (1.03)	3.12 (1.03)	3.14 (1.04)
CMI	1.37 (0.27)	1.37 (0.27)	1.37 (0.27)	1.37 (0.27)	1.37 (0.27)	1.37 (0.27)
Maturity	3.3 (4.05)	3.33 (4.05)	3.33 (4.05)	3.33 (4.05)	3.33 (4.05)	3.31 (4.13)
Academic	0.08	0.08	0.08	0.08	0.08	0.09
For-profit	0.17	0.17	0.17	0.17	0.17	0.17

- The analysis includes the following automation status (live and operational, to be replaced, installation in process, and contracted but not yet installed)
- Mean and SD for continuous variables and proportional estimate for categorical variables (PD, Academic, and For-profit)

APPENDIX E: Multicollinearity Test

The following table shows the results of Spearman rank correlation test for all quality measures used in this study.

As shown in the following table, Basic EMR with PD portfolio has high multicollinearity with PD, and Full EMR with no PD has high multicollinearity with CPOE. Both portfolios also have high multicollinearity with Full EMR portfolio in all quality measures. We also notice that there is multicollinearity issue between Basic EMR portfolio and CDSS. However, when we evaluate the model, we observe that this correlation does not cause serious problems in terms of standard errors, significant level, and coefficients amount.

HAM Measure

	MORTALITY_READM_RATE	OE	CDSS	CDR	CPOE	PD	Basic_EMR	Basic_PD	Full_EMR4	Full_EMR5	NOFBEDS_log	Age_log	CMI	proprietary	academic
MORTALITY_READM_RATE MORTALITY_READM_RATE	1.00000	0.02526 0.0643	-0.04740 0.0005	-0.04343 0.0015	-0.13193 <.0001	-0.08308 <.0001	-0.03530 0.0097	-0.08185 <.0001	-0.11935 <.0001	-0.12355 <.0001	-0.15693 <.0001	-0.02220 0.1039	-0.19849 <.0001	0.07731 <.0001	-0.08298 <.0001
OE OE	0.02526 0.0643	1.00000	0.10065 <.0001	0.14938 <.0001	0.05468 <.0001	0.10015 <.0001	0.36368 <.0001	0.16252 <.0001	0.16216 <.0001	0.11889 <.0001	-0.04034 0.0031	-0.00678 0.6193	-0.05202 0.0001	0.09299 <.0001	-0.04890 0.0003
CDSS CDSS	-0.04740 0.0005	0.10065 <.0001	1.00000	0.35987 <.0001	0.16914 <.0001	0.22518 <.0001	0.80104 <.0001	0.35797 <.0001	0.35717 <.0001	0.26188 <.0001	0.03230 0.0180	0.03645 0.0076	0.07189 <.0001	-0.04821 0.0004	-0.01840 0.1779
CDR CDR	-0.04343 0.0015	0.14938 <.0001	0.35987 <.0001	1.00000	0.14741 <.0001	0.19161 <.0001	0.61236 <.0001	0.27365 <.0001	0.27304 <.0001	0.20020 <.0001	0.07831 <.0001	0.05868 <.0001	0.10037 <.0001	-0.10622 <.0001	0.04563 0.0008
CPOE CPOE	-0.13193 <.0001	0.05468 <.0001	0.16914 <.0001	0.14741 <.0001	1.00000	0.38655 <.0001	0.18820 <.0001	0.34095 <.0001	0.80157 <.0001	0.58772 <.0001	0.13554 <.0001	0.07987 <.0001	0.13778 <.0001	-0.22255 <.0001	0.13901 <.0001
PD PD	-0.08308 <.0001	0.10015 <.0001	0.22518 <.0001	0.19161 <.0001	0.38655 <.0001	1.00000	0.26317 <.0001	0.85535 <.0001	0.38167 <.0001	0.62575 <.0001	0.03310 0.0153	0.02472 0.0702	0.05064 0.0002	-0.08076 <.0001	0.05298 0.0001
Basic_EMR	-0.03530 0.0097	0.36368 <.0001	0.80104 <.0001	0.61236 <.0001	0.18820 <.0001	0.26317 <.0001	1.00000	0.44688 <.0001	0.44588 <.0001	0.32692 <.0001	0.02613 0.0556	0.02689 0.0489	0.06421 <.0001	-0.01955 0.1522	-0.01820 0.1826
Basic_PD	-0.08185 <.0001	0.16252 <.0001	0.35797 <.0001	0.27365 <.0001	0.34095 <.0001	0.85535 <.0001	0.44688 <.0001	1.00000	0.48599 <.0001	0.73157 <.0001	0.02542 0.0626	0.01595 0.2427	0.05823 <.0001	-0.04319 0.0016	0.04162 0.0023
Full_EMR4	-0.11935 <.0001	0.16216 <.0001	0.35717 <.0001	0.27304 <.0001	0.80157 <.0001	0.38167 <.0001	0.44588 <.0001	0.48599 <.0001	1.00000	0.73321 <.0001	0.10966 <.0001	0.08118 <.0001	0.12618 <.0001	-0.17764 <.0001	0.08695 <.0001
Full_EMR5	-0.12355 <.0001	0.11889 <.0001	0.26188 <.0001	0.20020 <.0001	0.58772 <.0001	0.62575 <.0001	0.32692 <.0001	0.73157 <.0001	0.73321 <.0001	1.00000	0.08656 <.0001	0.05572 <.0001	0.11175 <.0001	-0.15059 <.0001	0.06169 <.0001
NOFBEDS_log NOFBEDS_log	-0.15693 <.0001	-0.04034 0.0031	0.03230 0.0180	0.07831 <.0001	0.13554 <.0001	0.03310 0.0153	0.02613 0.0556	0.02542 0.0626	0.10966 <.0001	0.08656 <.0001	1.00000	0.14958 <.0001	0.70682 <.0001	-0.07745 <.0001	0.33990 <.0001
Age_log Age_log	-0.02220 0.1039	-0.00678 0.6193	0.03645 0.0076	0.05868 <.0001	0.07987 <.0001	0.02472 0.0702	0.02689 0.0489	0.01595 0.2427	0.08118 <.0001	0.05572 <.0001	0.14958 <.0001	1.00000	0.04983 0.0003	-0.38102 <.0001	0.08952 <.0001
CMI CMI	-0.19849 <.0001	-0.05202 0.0001	0.07189 <.0001	0.10037 <.0001	0.13778 <.0001	0.05064 0.0002	0.06421 <.0001	0.05823 <.0001	0.12618 <.0001	0.11175 <.0001	0.70682 <.0001	0.04983 0.0003	1.00000	-0.02229 0.1025	0.25431 <.0001
proprietary proprietary	0.07731 <.0001	0.09299 <.0001	-0.04821 0.0004	-0.10622 <.0001	-0.22255 <.0001	-0.08076 <.0001	-0.01955 0.1522	-0.04319 0.0016	-0.17764 <.0001	-0.15059 <.0001	-0.07745 <.0001	-0.38102 <.0001	-0.02229 0.1025	1.00000	-0.12267 <.0001
academic academic	-0.08298 <.0001	-0.04890 0.0003	-0.01840 0.1779	0.04563 0.0008	0.13901 <.0001	0.05298 0.0001	-0.01820 0.1826	0.04162 0.0023	0.08695 <.0001	0.06169 <.0001	0.33990 <.0001	0.08952 <.0001	0.25431 <.0001	-0.12267 <.0001	1.00000

Mortality_READM_RATE: Represents HAM rate (Dependent variable)
Basic_EMR: Basic EMR portfolio with no PD
Basic_PD: Basic EMR portfolio with PD
Full_EMR4: full EMR portfolio with no PD
Full EMR5: full EMR portfolio with PD

HAR Measure (Mortality_ReadM_Rate)

	MORTALITY_READM_RATE	OE	CDSS	CDR	CPOE	PD	Basic_EMR	Basic_PD	Full_EMR4	Full_EMR5	NOFBEDS_log	Age_log	CMI	proprietary	academic
MORTALITY_READM_RATE MORTALITY_READM_RATE	1.00000	-0.02204 0.1808	0.01935 0.2401	-0.00704 0.6692	0.00298 0.8562	-0.00007 0.9966	-0.00238 0.8850	-0.00600 0.7155	-0.01969 0.2319	-0.01332 0.4187	-0.02093 0.2037	-0.00356 0.8291	-0.18056 <.0001	-0.02083 0.2060	0.10468 <.0001
OE OE	-0.02204 0.1808	1.00000	-0.09629 <.0001	0.11475 <.0001	-0.13884 <.0001	0.17290 <.0001	0.58078 <.0001	0.30139 <.0001	0.32491 <.0001	0.24127 <.0001	0.02686 0.1029	0.00997 0.5448	0.09333 <.0001	0.00158 0.9236	0.01892 0.2506
CDSS CDSS	0.01935 0.2401	-0.09629 <.0001	1.00000	0.29618 <.0001	0.25337 <.0001	0.19020 <.0001	0.57345 <.0001	0.29758 <.0001	0.32081 <.0001	0.23823 <.0001	0.01523 0.3551	0.05431 0.0010	0.01152 0.4842	-0.05986 0.0003	-0.00123 0.9406
CDR CDR	-0.00704 0.6692	0.11475 <.0001	0.29618 <.0001	1.00000	0.19299 <.0001	0.18386 <.0001	0.48805 <.0001	0.25326 <.0001	0.27303 <.0001	0.20275 <.0001	0.05202 0.0016	0.05976 0.0003	0.06744 <.0001	-0.10250 <.0001	0.04110 0.0125
CPOE CPOE	0.00298 0.8562	-0.13884 <.0001	0.25337 <.0001	0.19299 <.0001	1.00000	0.34987 <.0001	0.08753 <.0001	0.27153 <.0001	0.63304 <.0001	0.47008 <.0001	0.10059 <.0001	0.05375 0.0011	0.07130 <.0001	-0.17837 <.0001	0.08281 <.0001
PD PD	-0.00007 0.9966	0.17290 <.0001	0.19020 <.0001	0.18386 <.0001	0.34987 <.0001	1.00000	0.28406 <.0001	0.79848 <.0001	0.39589 <.0001	0.63921 <.0001	0.03117 0.0584	0.01564 0.3423	0.04927 0.0028	-0.11163 <.0001	0.06924 <.0001
Basic_EMR	-0.00238 0.8850	0.58078 <.0001	0.57345 <.0001	0.48805 <.0001	0.08753 <.0001	0.28406 <.0001	1.00000	0.51893 <.0001	0.55943 <.0001	0.41542 <.0001	0.03922 0.0172	0.05302 0.0013	0.10206 <.0001	-0.08510 <.0001	0.03373 0.0405
Basic_PD	-0.00600 0.7155	0.30139 <.0001	0.29758 <.0001	0.25326 <.0001	0.27153 <.0001	0.79848 <.0001	0.51893 <.0001	1.00000	0.55627 <.0001	0.80054 <.0001	0.04424 0.0072	0.01064 0.5183	0.08345 <.0001	-0.09494 <.0001	0.06636 <.0001
Full_EMR4	-0.01969 0.2319	0.32491 <.0001	0.32081 <.0001	0.27303 <.0001	0.63304 <.0001	0.39589 <.0001	0.55943 <.0001	0.55627 <.0001	1.00000	0.74258 <.0001	0.11470 <.0001	0.07858 <.0001	0.12352 <.0001	-0.19012 <.0001	0.09330 <.0001
Full_EMR5	-0.01332 0.4187	0.24127 <.0001	0.23823 <.0001	0.20275 <.0001	0.47008 <.0001	0.63921 <.0001	0.41542 <.0001	0.80054 <.0001	0.74258 <.0001	1.00000	0.09016 <.0001	0.04381 0.0078	0.11450 <.0001	-0.16328 <.0001	0.08544 <.0001
NOFBEDS_log NOFBEDS_log	-0.02093 0.2037	0.02686 0.1029	0.01523 0.3551	0.05202 0.0016	0.10059 <.0001	0.03117 0.0584	0.03922 0.0172	0.04424 0.0072	0.11470 <.0001	0.09016 <.0001	1.00000	0.12886 <.0001	0.66880 <.0001	-0.08407 <.0001	0.34372 <.0001
Age_log Age_log	-0.00356 0.8291	0.00997 0.5448	0.05431 0.0010	0.05976 0.0003	0.05375 0.0011	0.01564 0.3423	0.05302 0.0013	0.01064 0.5183	0.07858 <.0001	0.04381 0.0078	0.12886 <.0001	1.00000	0.01654 0.3151	-0.38827 <.0001	0.09126 <.0001
CMI CMI	-0.18056 <.0001	0.09333 <.0001	0.01152 0.4842	0.06744 <.0001	0.07130 <.0001	0.04927 0.0028	0.10206 <.0001	0.08345 <.0001	0.12352 <.0001	0.11450 <.0001	0.66880 <.0001	0.01654 0.3151	1.00000	-0.00071 0.9658	0.26103 <.0001
proprietary proprietary	-0.02083 0.2060	0.00158 0.9236	-0.05986 0.0003	-0.10250 <.0001	-0.17837 <.0001	-0.11163 <.0001	-0.08510 <.0001	-0.09494 <.0001	-0.19012 <.0001	-0.16328 <.0001	-0.08407 <.0001	-0.38827 <.0001	-0.00071 0.9658	1.00000	-0.12203 <.0001
academic	0.10468	0.01892	-0.00123	0.04110	0.08281	0.06924	0.03373	0.06636	0.09330	0.08544	0.34372	0.09126	0.26103	-0.12203	1.00000

HFM Measure (Mortality_ReadM_Rate)

	MORTALITY_READM_RATE	OE	CDSS	CDR	CPOE	PD	Basic_EMR	Basic_PD	Full_EMR4	Full_EMR5	NOFBEDS_log	Age_log	CMI	proprietary	academic
MORTALITY_READM_RATE MORTALITY_READM_RATE	1.00000	0.02111 0.0989	-0.02273 0.0756	0.00948 0.4588	-0.00833 0.5148	-0.03189 0.0126	0.00566 0.6584	-0.01992 0.1194	0.00178 0.8892	-0.02042 0.1104	-0.13006 <.0001	0.02419 0.0586	-0.06396 <.0001	-0.02457 0.0547	-0.11303 <.0001
OE OE	0.02111 0.0989	1.00000	0.10907 <.0001	0.15786 <.0001	0.03896 0.0023	0.09817 <.0001	0.36628 <.0001	0.16253 <.0001	0.16391 <.0001	0.11893 <.0001	-0.02576 0.0440	0.00732 0.5673	-0.04881 0.0001	0.08842 <.0001	-0.04270 0.0008
CDSS CDSS	-0.02273 0.0756	0.10907 <.0001	1.00000	0.38106 <.0001	0.17723 <.0001	0.22774 <.0001	0.80582 <.0001	0.35757 <.0001	0.36060 <.0001	0.26164 <.0001	0.04123 0.0013	0.03724 0.0036	0.08506 <.0001	-0.05748 <.0001	-0.01059 0.4078
CDR CDR	0.00948 0.4588	0.15786 <.0001	0.38106 <.0001	1.00000	0.15168 <.0001	0.20155 <.0001	0.62157 <.0001	0.27581 <.0001	0.27815 <.0001	0.20181 <.0001	0.08263 <.0001	0.07648 <.0001	0.10123 <.0001	-0.11093 <.0001	0.04630 0.0003
CPOE CPOE	-0.00833 0.5148	0.03896 0.0023	0.17723 <.0001	0.15168 <.0001	1.00000	0.37938 <.0001	0.19194 <.0001	0.33721 <.0001	0.80167 <.0001	0.58165 <.0001	0.11328 <.0001	0.08009 <.0001	0.12572 <.0001	-0.21644 <.0001	0.12709 <.0001
PD PD	-0.03189 0.0126	0.09817 <.0001	0.22774 <.0001	0.20155 <.0001	0.37938 <.0001	1.00000	0.26495 <.0001	0.85741 <.0001	0.37799 <.0001	0.62737 <.0001	0.04169 0.0011	0.03128 0.0145	0.05345 <.0001	-0.07351 <.0001	0.04941 0.0001
Basic_EMR	0.00566 0.6584	0.36628 <.0001	0.80582 <.0001	0.62157 <.0001	0.19194 <.0001	0.26495 <.0001	1.00000	0.44373 <.0001	0.44749 <.0001	0.32468 <.0001	0.02462 0.0543	0.03343 0.0090	0.06285 <.0001	-0.02229 0.0814	-0.01339 0.2951
Basic_PD	-0.01992 0.1194	0.16253 <.0001	0.35757 <.0001	0.27581 <.0001	0.33721 <.0001	0.85741 <.0001	0.44373 <.0001	1.00000	0.48018 <.0001	0.73170 <.0001	0.03068 0.0164	0.01942 0.1291	0.05959 <.0001	-0.03590 0.0050	0.03863 0.0025
Full_EMR4	0.00178 0.8892	0.16391 <.0001	0.36060 <.0001	0.27815 <.0001	0.80167 <.0001	0.37799 <.0001	0.44749 <.0001	0.48018 <.0001	1.00000	0.72555 <.0001	0.08786 <.0001	0.08042 <.0001	0.11248 <.0001	-0.17438 <.0001	0.07990 <.0001
Full_EMR5	-0.02042 0.1104	0.11893 <.0001	0.26164 <.0001	0.20181 <.0001	0.58165 <.0001	0.62737 <.0001	0.32468 <.0001	0.73170 <.0001	0.72555 <.0001	1.00000	0.07926 <.0001	0.05999 <.0001	0.10679 <.0001	-0.14561 <.0001	0.05770 <.0001
NOFBEDS_log NOFBEDS_log	-0.13006 <.0001	-0.02576 0.0440	0.04123 0.0013	0.08263 <.0001	0.11328 <.0001	0.04169 0.0011	0.02462 0.0543	0.03068 0.0164	0.08786 <.0001	0.07926 <.0001	1.00000	0.16821 <.0001	0.73526 <.0001	-0.06548 <.0001	0.33180 <.0001
Age_log Age_log	0.02419 0.0586	0.00732 0.5673	0.03724 0.0036	0.07648 <.0001	0.08009 <.0001	0.03128 0.0145	0.03343 0.0090	0.01942 0.1291	0.08042 <.0001	0.05999 <.0001	0.16821 <.0001	1.00000	0.07848 <.0001	-0.38063 <.0001	0.08734 <.0001
CMI CMI	-0.06396 <.0001	-0.04881 0.0001	0.08506 <.0001	0.10123 <.0001	0.12572 <.0001	0.05345 <.0001	0.06285 <.0001	0.05959 <.0001	0.11248 <.0001	0.10679 <.0001	0.73526 <.0001	0.07848 <.0001	1.00000	-0.03638 0.0044	0.25803 <.0001
proprietary proprietary	-0.02457 0.0547	0.08842 <.0001	-0.05748 <.0001	-0.11093 <.0001	-0.21644 <.0001	-0.07351 <.0001	-0.02229 0.0814	-0.03590 0.0050	-0.17438 <.0001	-0.14561 <.0001	-0.06548 <.0001	-0.38063 <.0001	-0.03638 0.0044	1.00000	-0.11601 <.0001
academic academic	-0.11303 <.0001	-0.04270 0.0008	-0.01059 0.4078	0.04630 0.0003	0.12709 <.0001	0.04941 0.0001	-0.01339 0.2951	0.03863 0.0025	0.07990 <.0001	0.05770 <.0001	0.33180 <.0001	0.08734 <.0001	0.25803 <.0001	-0.11601 <.0001	1.00000

HFR Measure (Mortality_ReadM_Rate)

	MORTALITY_READM_RATE	OE	CDSS	CDR	CPOE	PD	Basic_EMR	Basic_PD	Full_EMR4	Full_EMR5	NOFBEDS_log	Age_log	CMI	proprietary	academic
MORTALITY_READM_RATE MORTALITY_READM_RATE	1.00000	0.01512 0.2923	-0.02543 0.0765	-0.07059 <.0001	-0.03073 0.0322	0.03710 0.0097	-0.02951 0.0398	0.01298 0.3660	-0.03939 0.0061	-0.02296 0.1097	-0.05241 0.0003	-0.05526 0.0001	-0.24617 <.0001	0.10116 <.0001	0.08160 <.0001
OE OE	0.01512 0.2923	1.00000	0.10788 <.0001	0.16900 <.0001	0.05355 0.0002	0.10102 <.0001	0.37823 <.0001	0.17036 <.0001	0.17343 <.0001	0.12699 <.0001	-0.01596 0.2663	0.00586 0.6833	-0.05314 0.0002	0.07990 <.0001	-0.03409 0.0175
CDSS CDSS	-0.02543 0.0765	0.10788 <.0001	1.00000	0.38625 <.0001	0.19674 <.0001	0.23219 <.0001	0.80395 <.0001	0.36212 <.0001	0.36865 <.0001	0.26993 <.0001	0.04369 0.0023	0.04412 0.0021	0.07983 <.0001	-0.08206 <.0001	0.00622 0.6648
CDR CDR	-0.07059 <.0001	0.16900 <.0001	0.38625 <.0001	1.00000	0.16274 <.0001	0.20083 <.0001	0.62124 <.0001	0.27982 <.0001	0.28487 <.0001	0.20858 <.0001	0.08320 <.0001	0.08410 <.0001	0.09959 <.0001	-0.13142 <.0001	0.04731 0.0010
CPOE CPOE	-0.03073 0.0322	0.05355 0.0002	0.19674 <.0001	0.16274 <.0001	1.00000	0.40459 <.0001	0.21190 <.0001	0.35703 <.0001	0.81366 <.0001	0.59577 <.0001	0.10357 <.0001	0.08898 <.0001	0.11537 <.0001	-0.23664 <.0001	0.11813 <.0001
PD PD	0.03710 0.0097	0.10102 <.0001	0.23219 <.0001	0.20083 <.0001	0.40459 <.0001	1.00000	0.26483 <.0001	0.85627 <.0001	0.38801 <.0001	0.63828 <.0001	0.04564 0.0015	0.02816 0.0497	0.05146 0.0003	-0.08827 <.0001	0.06070 <.0001
Basic_EMR	-0.02951 0.0398	0.37823 <.0001	0.80395 <.0001	0.62124 <.0001	0.21190 <.0001	0.26483 <.0001	1.00000	0.45042 <.0001	0.45855 <.0001	0.33575 <.0001	0.02512 0.0800	0.04424 0.0020	0.05164 0.0003	-0.05600 <.0001	0.00232 0.8715
Basic_PD	0.01298 0.3660	0.17036 <.0001	0.36212 <.0001	0.27982 <.0001	0.35703 <.0001	0.85627 <.0001	0.45042 <.0001	1.00000	0.49486 <.0001	0.74542 <.0001	0.03525 0.0140	0.01870 0.1926	0.05648 <.0001	-0.05315 0.0002	0.04985 0.0005
Full_EMR4	-0.03939 0.0061	0.17343 <.0001	0.36865 <.0001	0.28487 <.0001	0.81366 <.0001	0.38801 <.0001	0.45855 <.0001	0.49486 <.0001	1.00000	0.73222 <.0001	0.08515 <.0001	0.08886 <.0001	0.09623 <.0001	-0.19712 <.0001	0.08541 <.0001
Full_EMR5	-0.02296 0.1097	0.12699 <.0001	0.26993 <.0001	0.20858 <.0001	0.59577 <.0001	0.63828 <.0001	0.33575 <.0001	0.74542 <.0001	0.73222 <.0001	1.00000	0.08204 <.0001	0.06290 <.0001	0.10118 <.0001	-0.16376 <.0001	0.07578 <.0001
NOFBEDS_log NOFBEDS_log	-0.05241 0.0003	-0.01596 0.2663	0.04369 0.0023	0.08320 <.0001	0.10357 <.0001	0.04564 0.0015	0.02512 0.0800	0.03525 0.0140	0.08515 <.0001	0.08204 <.0001	1.00000	0.16401 <.0001	0.73640 <.0001	-0.05926 <.0001	0.32162 <.0001
Age_log Age_log	-0.05526 0.0001	0.00586 0.6833	0.04412 0.0021	0.08410 <.0001	0.08898 <.0001	0.02816 0.0497	0.04424 0.0020	0.01870 0.1926	0.08886 <.0001	0.06290 <.0001	0.16401 <.0001	1.00000	0.07694 <.0001	-0.38793 <.0001	0.09230 <.0001
CMI CMI	-0.24617 <.0001	-0.05314 0.0002	0.07983 <.0001	0.09959 <.0001	0.11537 <.0001	0.05146 0.0003	0.05164 0.0003	0.05648 <.0001	0.09623 <.0001	0.10118 <.0001	0.73640 <.0001	0.07694 <.0001	1.00000	-0.03211 0.0253	0.25659 <.0001
proprietary proprietary	0.10116 <.0001	0.07990 <.0001	-0.08206 <.0001	-0.13142 <.0001	-0.23664 <.0001	-0.08827 <.0001	-0.05600 <.0001	-0.05315 0.0002	-0.19712 <.0001	-0.16376 <.0001	-0.05926 <.0001	-0.38793 <.0001	-0.03211 0.0253	1.00000	-0.11092 <.0001
academic academic	0.08160 <.0001	-0.03409 0.0175	0.00622 0.6648	0.04731 0.0010	0.11813 <.0001	0.06070 <.0001	0.00232 0.8715	0.04985 0.0005	0.08541 <.0001	0.07578 <.0001	0.32162 <.0001	0.09230 <.0001	0.25659 <.0001	-0.11092 <.0001	1.00000

PNM Measure (Mortality_ReadM_Rate)

	MORTALITY_READM_RATE	OE	CDSS	CDR	CPOE	PD	Basic_EMR	Basic_PD	Full_EMR4	Full_EMR5	NOFBEDS_log	Age_log	CMI	proprietary	academic
MORTALITY_READM_RATE MORTALITY_READM_RATE	1.00000	0.05347 <.0001	-0.00888 0.4859	0.00664 0.6024	-0.04335 0.0007	-0.01288 0.3120	0.02911 0.0223	0.00390 0.7594	-0.01799 0.1578	-0.02174 0.0879	-0.12585 <.0001	0.02583 0.0426	-0.12116 <.0001	0.01899 0.1360	-0.06578 <.0001
OE OE	0.05347 <.0001	1.00000	0.10372 <.0001	0.15236 <.0001	0.04423 0.0005	0.10395 <.0001	0.36965 <.0001	0.16418 <.0001	0.16597 <.0001	0.12041 <.0001	-0.01581 0.2147	0.01121 0.3790	-0.04892 0.0001	0.09055 <.0001	-0.04042 0.0015
CDSS CDSS	-0.00888 0.4859	0.10372 <.0001	1.00000	0.38160 <.0001	0.17566 <.0001	0.22519 <.0001	0.80168 <.0001	0.35605 <.0001	0.35993 <.0001	0.26113 <.0001	0.03712 0.0036	0.03924 0.0021	0.08422 <.0001	-0.05946 <.0001	-0.01113 0.3823
CDR CDR	0.00664 0.6024	0.15236 <.0001	0.38160 <.0001	1.00000	0.15346 <.0001	0.20268 <.0001	0.62034 <.0001	0.27551 <.0001	0.27852 <.0001	0.20206 <.0001	0.07931 <.0001	0.07819 <.0001	0.09968 <.0001	-0.11294 <.0001	0.04622 0.0003
CPOE CPOE	-0.04335 0.0007	0.04423 0.0005	0.17566 <.0001	0.15346 <.0001	1.00000	0.38099 <.0001	0.19490 <.0001	0.33935 <.0001	0.80246 <.0001	0.58219 <.0001	0.11204 <.0001	0.07960 <.0001	0.12302 <.0001	-0.21728 <.0001	0.12662 <.0001
PD PD	-0.01288 0.3120	0.10395 <.0001	0.22519 <.0001	0.20268 <.0001	0.38099 <.0001	1.00000	0.26681 <.0001	0.85819 <.0001	0.37991 <.0001	0.62940 <.0001	0.04343 0.0006	0.03239 0.0110	0.05357 <.0001	-0.07341 <.0001	0.04984 <.0001
Basic_EMR	0.02911 0.0223	0.36965 <.0001	0.80168 <.0001	0.62034 <.0001	0.19490 <.0001	0.26681 <.0001	1.00000	0.44414 <.0001	0.44898 <.0001	0.32573 <.0001	0.02557 0.0447	0.03495 0.0061	0.06116 <.0001	-0.02168 0.0888	-0.01268 0.3195
Basic_PD	0.00390 0.7594	0.16418 <.0001	0.35605 <.0001	0.27551 <.0001	0.33935 <.0001	0.85819 <.0001	0.44414 <.0001	1.00000	0.48170 <.0001	0.73341 <.0001	0.03065 0.0161	0.02053 0.1070	0.05852 <.0001	-0.03611 0.0046	0.03885 0.0023
Full_EMR4	-0.01799 0.1578	0.16597 <.0001	0.35993 <.0001	0.27852 <.0001	0.80246 <.0001	0.37991 <.0001	0.44898 <.0001	0.48170 <.0001	1.00000	0.72550 <.0001	0.08449 <.0001	0.08086 <.0001	0.10874 <.0001	-0.17538 <.0001	0.07939 <.0001
Full_EMR5	-0.02174 0.0879	0.12041 <.0001	0.26113 <.0001	0.20206 <.0001	0.58219 <.0001	0.62940 <.0001	0.32573 <.0001	0.73341 <.0001	0.72550 <.0001	1.00000	0.07678 <.0001	0.06060 <.0001	0.10425 <.0001	-0.14616 <.0001	0.05733 <.0001
NOFBEDS_log NOFBEDS_log	-0.12585 <.0001	-0.01581 0.2147	0.03712 0.0036	0.07931 <.0001	0.11204 <.0001	0.04343 0.0006	0.02557 0.0447	0.03065 0.0161	0.08449 <.0001	0.07678 <.0001	1.00000	0.16590 <.0001	0.73415 <.0001	-0.06454 <.0001	0.33114 <.0001
Age_log Age_log	0.02583 0.0426	0.01121 0.3790	0.03924 0.0021	0.07819 <.0001	0.07960 <.0001	0.03239 0.0110	0.03495 0.0061	0.02053 0.1070	0.08086 <.0001	0.06060 <.0001	0.16590 <.0001	1.00000	0.07853 <.0001	-0.38061 <.0001	0.08660 <.0001
CMI CMI	-0.12116 <.0001	-0.04892 0.0001	0.08422 <.0001	0.09968 <.0001	0.12302 <.0001	0.05357 <.0001	0.06116 <.0001	0.05852 <.0001	0.10874 <.0001	0.10425 <.0001	0.73415 <.0001	0.07853 <.0001	1.00000	-0.03666 0.0040	0.25793 <.0001
proprietary proprietary	0.01899 0.1360	0.09055 <.0001	-0.05946 <.0001	-0.11294 <.0001	-0.21728 <.0001	-0.07341 <.0001	-0.02168 0.0888	-0.03611 0.0046	-0.17538 <.0001	-0.14616 <.0001	-0.06454 <.0001	-0.38061 <.0001	-0.03666 0.0040	1.00000	-0.11547 <.0001
academic academic	-0.06578 <.0001	-0.04042 0.0015	-0.01113 0.3823	0.04622 0.0003	0.12662 <.0001	0.04984 <.0001	-0.01268 0.3195	0.03885 0.0023	0.07939 <.0001	0.05733 <.0001	0.33114 <.0001	0.08660 <.0001	0.25793 <.0001	-0.11547 <.0001	1.00000

PNR Measure (Mortality_ReadM_Rate)

	MORTALITY_READM_RATE	OE	CDSS	CDR	CPOE	PD	Basic_EMR	Basic_PD	Full_EMR4	Full_EMR5	NOFBEDS_log	Age_log	CMI	proprietary	academic
MORTALITY_READM_RATE MORTALITY_READM_RATE	1.00000	0.01809 0.2064	-0.00791 0.5807	-0.04659 0.0011	-0.02293 0.1093	0.03190 0.0258	-0.01243 0.3856	0.01755 0.2202	-0.03443 0.0162	-0.00913 0.5237	0.06133 <.0001	-0.03838 0.0073	-0.11285 <.0001	0.02969 0.0381	0.12355 <.0001
OE OE	0.01809 0.2064	1.00000	0.10402 <.0001	0.16371 <.0001	0.05787 <.0001	0.10439 <.0001	0.38112 <.0001	0.17213 <.0001	0.17532 <.0001	0.12837 <.0001	-0.00758 0.5964	0.00756 0.5977	-0.05008 0.0005	0.08264 <.0001	-0.03283 0.0218
CDSS CDSS	-0.00791 0.5807	0.10402 <.0001	1.00000	0.38607 <.0001	0.19560 <.0001	0.23069 <.0001	0.80087 <.0001	0.36170 <.0001	0.36840 <.0001	0.26976 <.0001	0.03934 0.0060	0.04452 0.0019	0.07771 <.0001	-0.08222 <.0001	0.00511 0.7211
CDR CDR	-0.04659 0.0011	0.16371 <.0001	0.38607 <.0001	1.00000	0.16360 <.0001	0.20137 <.0001	0.61938 <.0001	0.27974 <.0001	0.28492 <.0001	0.20863 <.0001	0.07942 <.0001	0.08434 <.0001	0.09808 <.0001	-0.13138 <.0001	0.04656 0.0011
CPOE CPOE	-0.02293 0.1093	0.05787 <.0001	0.19560 <.0001	0.16360 <.0001	1.00000	0.40567 <.0001	0.21376 <.0001	0.35733 <.0001	0.81384 <.0001	0.59592 <.0001	0.10111 <.0001	0.09070 <.0001	0.11392 <.0001	-0.23766 <.0001	0.11831 <.0001
PD PD	0.03190 0.0258	0.10439 <.0001	0.23069 <.0001	0.20137 <.0001	0.40567 <.0001	1.00000	0.26598 <.0001	0.85613 <.0001	0.38804 <.0001	0.63850 <.0001	0.04514 0.0016	0.02944 0.0398	0.05211 0.0003	-0.08771 <.0001	0.06094 <.0001
Basic_EMR	-0.01243 0.3856	0.38112 <.0001	0.80087 <.0001	0.61938 <.0001	0.21376 <.0001	0.26598 <.0001	1.00000	0.45164 <.0001	0.46000 <.0001	0.33683 <.0001	0.02556 0.0742	0.04476 0.0018	0.05122 0.0003	-0.05374 0.0002	0.00193 0.8930
Basic_PD	0.01755 0.2202	0.17213 <.0001	0.36170 <.0001	0.27974 <.0001	0.35733 <.0001	0.85613 <.0001	0.45164 <.0001	1.00000	0.49511 <.0001	0.74580 <.0001	0.03476 0.0152	0.01879 0.1895	0.05777 <.0001	-0.05226 0.0003	0.05006 0.0005
Full_EMR4	-0.03443 0.0162	0.17532 <.0001	0.36840 <.0001	0.28492 <.0001	0.81384 <.0001	0.38804 <.0001	0.46000 <.0001	0.49511 <.0001	1.00000	0.73223 <.0001	0.08222 <.0001	0.08947 <.0001	0.09514 <.0001	-0.19803 <.0001	0.08547 <.0001
Full_EMR5	-0.00913 0.5237	0.12837 <.0001	0.26976 <.0001	0.20863 <.0001	0.59592 <.0001	0.63850 <.0001	0.33683 <.0001	0.74580 <.0001	0.73223 <.0001	1.00000	0.07978 <.0001	0.06354 <.0001	0.10133 <.0001	-0.16433 <.0001	0.07575 <.0001
NOFBEDS_log NOFBEDS_log	0.06133 <.0001	-0.00758 0.5964	0.03934 0.0060	0.07942 <.0001	0.10111 <.0001	0.04514 0.0016	0.02556 0.0742	0.03476 0.0152	0.08222 <.0001	0.07978 <.0001	1.00000	0.15940 <.0001	0.73507 <.0001	-0.05713 <.0001	0.32054 <.0001
Age_log Age_log	-0.03838 0.0073	0.00756 0.5977	0.04452 0.0019	0.08434 <.0001	0.09070 <.0001	0.02944 0.0398	0.04476 0.0018	0.01879 0.1895	0.08947 <.0001	0.06354 <.0001	0.15940 <.0001	1.00000	0.07611 <.0001	-0.38749 <.0001	0.09055 <.0001
CMI CMI	-0.11285 <.0001	-0.05008 0.0005	0.07771 <.0001	0.09808 <.0001	0.11392 <.0001	0.05211 0.0003	0.05122 0.0003	0.05777 <.0001	0.09514 <.0001	0.10133 <.0001	0.73507 <.0001	0.07611 <.0001	1.00000	-0.03131 0.0287	0.25558 <.0001
proprietary proprietary	0.02969 0.0381	0.08264 <.0001	-0.08222 <.0001	-0.13138 <.0001	-0.23766 <.0001	-0.08771 <.0001	-0.05374 0.0002	-0.05226 0.0003	-0.19803 <.0001	-0.16433 <.0001	-0.05713 <.0001	-0.38749 <.0001	-0.03131 0.0287	1.00000	-0.11030 <.0001
academic academic	0.12355 <.0001	-0.03283 0.0218	0.00511 0.7211	0.04656 0.0011	0.11831 <.0001	0.06094 <.0001	0.00193 0.8930	0.05006 0.0005	0.08547 <.0001	0.07575 <.0001	0.32054 <.0001	0.09055 <.0001	0.25558 <.0001	-0.11030 <.0001	1.00000

APPENDIX F: The synergistic Impact using all Variables

The following tables show the result of the regression test before omitting full EMR-No PD and basic EMR-PD portfolios from our model:

Table A. Estimation of the effects of the synergy between the portfolios of EMR capabilities on healthcare quality outcomes at U.S. Hospitals (Unbalanced Panel; 2008-2012)

Variable	**HAM**	**HAR**	**HFM**	**HFR**	**PNM**	**PNR**	**PS**
Order Entry	-0.01	0.20**	-0.04	0.20	-0.19*	0.18*	-0.45
CDSS	-0.22**	0.05	0.01	-0.02	0.07	0.24**	-0.89**
CDR	-0.08	-0.20**	0.01	-0.01	0.004	-0.13	0.01
CPOE	0.25**	0.04	0.24***	-0.09	-0.05	0.01	-0.61
Physician Documentation	-0.06	-0.23**	0.004	-0.27*	0.09	-0.10	0.37
The Synergy Between Basic EMR Capabilities							
Basic EMR-No PD	0.14	-0.11	0.08	-0.15	0.08	-0.28**	0.18
Basic EMR-With PD	0.07	0.22**	-0.02	0.20	-0.08	0.25	-1.05**
The Synergy Between Full EMR Capabilities							
Full EMR-With PD	-0.03	-0.02	-0.01	0.12	-0.10	-0.15	1.57***
Full EMR- No PD	-0.40***	-0.04	-0.27***	0.01	0.13	0.07	-0.07
Hospital size (log)	0.24	0.12	0.21	0.23	0.18	0.28*	-0.87
Case mix index	-0.74***	-0.55*	-0.69***	-1.89**	-0.91***	-1.0***	3.87**
For-Profit Hospitals	0.13	-0.25 *	0.14	0.27*	0.16	-0.01	0.01

Hospital Age (log)	0.10	-0.11	0.09	-0.08	0.15	-0.01	0.87**
Academic Hospitals	0.18	0.19	-0.18	0.52**	0.07	0.85***	-0.52
R-Square F Value Cross Sections #	0.71 7.12*** 1308	0.77 7.35*** 1079	0.73 8.54*** 1470	0.82 9.65*** 1401	0.74 8.66*** 1484	0.80 9.00*** 1408	0.86 15.15*** 1941
* = significance at p < 0.10, **=p < 0.05, and ***=p < 0.01							

Table B. Estimation of the effects of the synergy between the portfolios of EMR capabilities on healthcare quality outcomes at U.S. Hospitals (Balanced Panel; 2008-2012)

Variable	**HAM**	**HAR**	**HFM**	**HFR**	**PNM**	**PNR**	**PS**
Order Entry	-0.04	0.19*	-0.04	0.45***	-0.03	0.37***	-0.94*
CDSS	-0.29**	0.05	-0.01	0.12	0.24*	0.13	-0.77*
CDR	-0.21*	-0.19	-0.07	0.03	-0.06	-0.21*	-0.21
CPOE	0.30***	-0.11	0.20*	-0.11	0.02	-0.14	0.51
Physician Documentation	-0.12	-0.28**	0.07	-0.63***	-0.08	-0.18	0.17
The Synergy Between Basic EMR Capabilities							
Basic EMR- No PD	0.14	-0.13	0.09	-0.36*	-0.02	-0.28*	0.45
Basic EMR- With PD	0.12	0.24**	-0.10	0.48**	-0.3	0.18	-0.36
The Synergy Between Full EMR Capabilities							
Full EMR- With PD	-0.04	0.11	0.01	0.23	-0.02	-0.08	1.10**
Full EMR- No PD	-0.43***	-0.09	-0.21*	-0.02	0.04	0.13	-0.94

Control Variables							
Hospital size (log)	0.03	0.12	0.09	0.21	0..06	0.23	0.13
Case mix index	-1.01***	-1.02***	-0.51*	-2.21***	-1.36***	-4.01***	4.10***
For-Profit Hospitals	0.09	-0.40***	0.30**	0.17	0.28*	0.08	0.30
Hospital Age (log)	0.14	0.01	-0.01	-0.21	0.03	-0.02	0.51
Academic Hospitals	0.29	0.17	-0.21	0.44**	0.15	0.86***	-1.43**
R-Square F Value Cross Sections #	0.67 7.88*** 689	0.76 8.29*** 657	0.71 9.30*** 820	0.81 10.19*** 899	0.71 9.27*** 825	0.79 9.77*** 906	0.83 15.11*** 810
* = significance at p < 0.10, **=p < 0.05, and ***=p < 0.01							