ABSTRACT

Title of Dissertation:	INFORMATION TECHNOLOGY AND ITS TRANSFORMATIONAL EFFECT ON THE HEALTH CARE INDUSTRY
	Corey M. Angst Doctor of Philosophy in Information Systems, 2007
Dissertation directed by:	Professor Ritu Agarwal Decision and Information Technologies Department

This dissertation examines the adoption of health IT by addressing the barriers to adoption from the perspective of multiple stakeholders. I examine three different phenomena using alternative methodologies and theoretical lenses.

Essay 1: The Impact of Firm Characteristics and Spatial Proximity on the Diffusion of Electronic Medical Records: A Hazard Modeling Analysis.

This study, positioned at the inter-organizational level, draws upon adoption and diffusion literature to predict the likelihood of EMR adoption by hospitals. I theorize that adoption is driven by factors such as the concentration and experience with complementary HIT and an environmental factor, spatial proximity. Using a hazard model fitted to data from a sample drawn from almost 4,000 hospitals, I find support for a positive relationship between IT concentration and likelihood of adoption. I also

find that spatial proximity explains variance in adoption and that its effect diminishes as distance increases.

Essay 2: Isolating the Effects of IT on Performance: An Empirical Test of Complementarities and Learning.

An issue at the organizational level is whether benefits result from investment in HIT. I apply a knowledge-based lens to the examination of IT adoption and process-level value, incorporating the effects of learning occurring through complementary IT adoption. I test hypotheses using data from almost 400 nationally-representative hospitals matched with quality and financial performance data and find that learning associated with more experience with IT leads to superior performance.

Essay 3: Adoption of Electronic Medical Records in the Presence of Privacy Concerns: The Elaboration Likelihood Model and Individual Persuasion.

At the individual level, privacy concerns can inhibit the adoption of EMRs. I draw from literature on attitude change to develop hypotheses that individuals can be persuaded to support the use, and ultimately opt-in to EMRs, even in the presence of significant privacy concerns if compelling arguments about the value of EMRs are presented. Using a quasi-experimental methodology, I find that privacy concerns interact with argument framing and issue involvement to affect attitudes toward the use of EMRs. In addition, results suggest that attitude towards EMR use and CFIP directly impact the likelihood of adoption of EMR technology.

INFORMATION TECHNOLOGY AND ITS TRANSFORMATIONAL EFFECT ON THE HEALTH CARE INDUSTRY

by

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Dissertation submitted to the Faculty of the Graduate School of the
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SYNOPSIS: INFORMATION TECHNOLOGY AND ITS TRANSFORMATIONAL EFFECT ON THE HEALTH CARE INDUSTRY

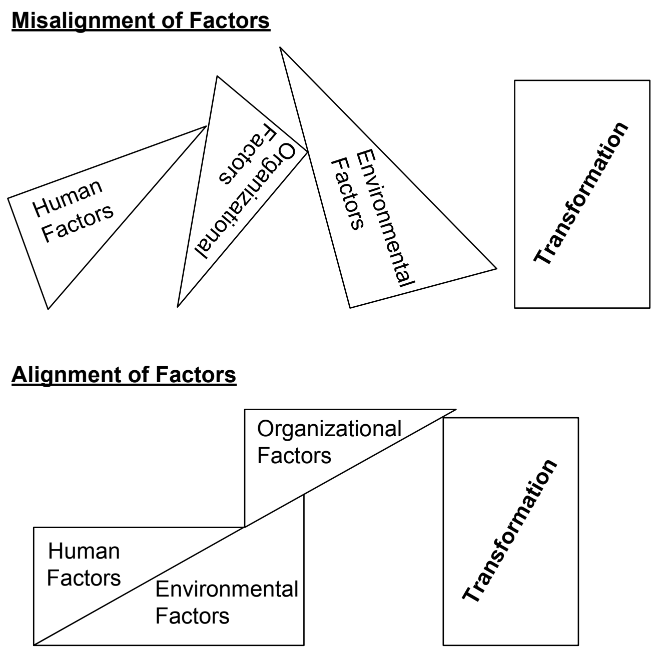
"…the system as we know it today is in need of fundamental change--transformational change--to survive into the next decade and century."

-- Paul H. Keckley in Saving Lives & Saving Money, by Newt Gingrich, 2003

Transformation – A marked change, as in appearance or character, usually for the better. -- Webster's Dictionary

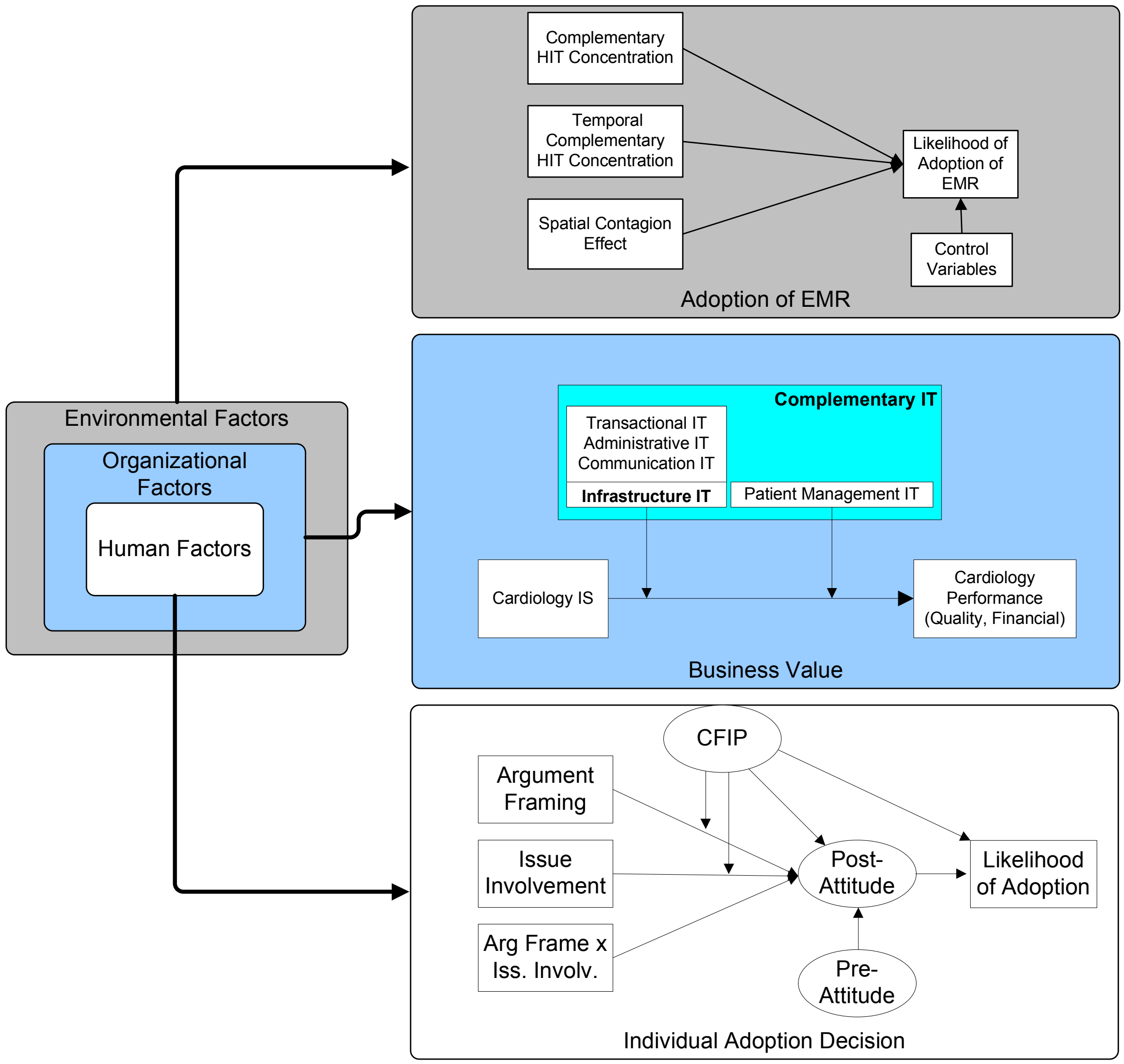
This dissertation seeks to quantify various aspects of the transformation of the health care industry as a result of information technology use. It is divided into three distinct, yet inter-related essays that approach the issue of barriers to adoption in markedly distinct ways. Due to the multi-faceted impact of IT – particularly in health care – I have chosen to examine three different phenomena using alternative methodologies and theoretical lenses. Although researchers frequently investigate the impact of technology in a monocratic fashion; much richness is sacrificed with such an analysis. Consider the following example that illustrates an episode in health care that is likely to occur in the near future. When a patient begins using an electronic personal medical record, the impact of the use of this technology will be realized at multiple levels. It will affect the record-keeping in the doctor's office, which is in turn influenced by HIPAA regulations. Access to the electronic record will also have a bearing on the information that the doctor has, which is likely to affect the treatment that the patient receives. Indeed, it has been demonstrated that medical errors, ordering of tests and treatments, and responses to reminders have a relationship with usage of electronic records (Hunt et al. 1998; Overhage et al. 1997). In addition, the health system itself will experience the greatest impact from the usage of HIT. The use of HIT will alter work processes, impact financial performance (either positively or negatively), disrupt the dynamics of the system, and possibly subject the institution to changes in levels of risk. For these reasons and several others, the transformation should be studied in the context of a multi-level framework. The three essays comprising this dissertation represent building-blocks that collectively extend understanding of the transformation process. This metaphor suggests that each block supports others and is supported by them, and when they are aligned, the process of transformation can occur (see Figure 0.1.).

Figure 0.1. Building-Blocks of Transformation



The common thread in the three essays is that each represents a distinct barrier to adoption. At the individual level, it has been acknowledged that privacy concerns can inhibit the adoption of electronic medical records. A primary issue at the organizational level is whether there is a payoff from investment in HIT. Finally, at the inter-organizational level, I investigate factors that may contribute to the likelihood of adoption of EMRs. The diagram below provides a schematic overview of the three essays in this dissertation (see Figure 0.2.).

Figure 0.2. Overview of Three Essays



Recent discourse in both academic and practitioner literatures (Birkmeyer et al. 2004; Kohn et al. 2000; Lazarou et al. 1998; Mullaney 2005; Pear 2003) suggests that the delivery of health care in the US is significantly challenged in regard to efficiency, quality of care, and patient safety. To the extent that HIT can alleviate some of these challenges and that the US health care system has been slow to adopt new HIT, there is a compelling need for rigorous analyses that can inform processes of adoption and diffusion of HIT. This dissertation represents an attempt to shed light on these issues.

Interestingly, the findings from these individual studies provide insights that may not have been discovered had they been conducted in isolation. For example, in essay one, the *a priori* proposition was that learning through early acquisition of HIT would be a strong determinant of likelihood of adoption. In essay two, I similarly posited that learning was a critical element in studying HIT, but that it would directly influence performance when it was associated with application-specific IT. The results suggest that learning is a much stronger determinant of performance than it is of future adoption. Findings from each of the studies also suggest that the implementation of HIT into the health care system truly is a multi-faceted, multi-level phenomenon in that significant relationships related to adoption were found at all levels. This work is timely in that there are intense debates and general discourse surrounding the application of HIT with individual stakeholders seeking to advance their interests. Probably the most salient issue for consumers is the topic of privacy and security of personal medical information. Some have argued that the general public does not want his/her medical information digitized; which, if true, could halt the diffusion of information-based systems such as the electronic medical record. My work suggests otherwise. In particular, the results from the third essay conclusively demonstrate that people's attitudes toward the use of EMRs can be altered in a positive way with appropriate value-based messages. The question then becomes, how much perceived privacy will one 'compromise' and in exchange for what? Much work remains to be done related to this topic but to the extent that better and timelier information (through the digitization of medical records) leads to better health, one could strongly assert that many people would favor the use of electronic medical records and other information-based systems. Without evidence from essay three – suggesting that there is hope for being able to convince the public that there is value in EMRs – the other two studies may not be relevant. Likewise, demonstrating that both financial value and quality of care are influenced by the use and learning associate with cardiology information systems provides more justification for the value-based arguments provided in essay three.

Finally, the title of this dissertation references the ‘transformational’ effect of health information technology. While the goal of this research is not to determine whether a transformation has occurred, it is valuable to provide a current-state report based on the findings from this work. Romanelli and Tushman (1994) argue that a revolutionary transformation has occurred if there are changes in three major organizational conditions; strategy, structure, and power, within any two-year time period. While it can be conclusively stated that this has not occurred in the health care industry, factors are beginning to align. For example, this work provides some evidence for what the drivers of EMR adoption are. It also suggests that the business value of HIT is quantifiable – both from financial perspective and quality of care. Most importantly, in my opinion, is the finding that privacy concerns can be alleviated through proper messaging and education of consumers. This is not to say that other barriers do not exist. It is a well-known fact that physicians have a strong, historical culture and that they can be resistant to changes, such as those that surface when a new disruptive technology is being implemented. There are also significant financial constraints related to the investment in HIT at not only the small/medium/large practice level but also at the hospital level. Finally, it is becoming increasingly more apparent that special-interest groups are gaining momentum in their endeavor to bring privacy concerns associated with electronic medical records to light. All of these challenges provide exciting opportunities for intriguing research.

DOMAIN OVERVIEW: HEALTH INFORMATION TECHNOLOGY

"The archaic information systems of our hospitals and clinics directly affect the quality of care we receive."

-- Newt Gingrich and Patrick Kennedy, NY Times, May 3, 2004

Throughout the history of information technology, there has not been a more concerted effort put forth for embracing technology than the one currently being orchestrated in the health care industry in the USA. Directives are being given from the very highest echelons of the federal government (Bush 2004a; Bush 2004b). It is hardly presumptuous to state that the health care industry may be the most fertile ground for research in the information sciences and one that begs for rigorous analysis. Recent federal initiatives have allocated significant funds for health information technology (HIT) demonstration and research projects. The Agency for Health Research and Quality (AHRQ) alone has allocated over $200 million dollars over the next five years (White et al. 2005) in grant monies for implementation, research, and planning related to HIT. On November 10, 2005, the Department of Health and Human Services awarded four contracts totaling $18.6 million to health care and HIT organizations to develop prototypes for a Nationwide Health Information Network (NHIN) architecture (NHIN Awards 2005). Each of these projects has the goal of demonstrating that an interoperable, standards-based network can be used at a national level for the secure exchange of health care information.

A quote from the Bush Administration's Health Information Technology Plan illustrates the commitment and unambiguous belief that HIT can change the way that medicine is practiced in the United States:

> *"I believe that innovations in electronic health records and the secure exchange of medical information will help transform health care in America - improving health care quality, preventing medical errors, reducing health care costs, improving administrative efficiencies, reducing paperwork, and increasing access to affordable health care (Bush 2004c)."*

Health care is not unlike other industries in that there are significant barriers to adoption of IT. Other industries have had to address challenges related to adoption and implementation, but the health care industry has problems unique to itself. For example, the budget for HIT often competes with those of treatment technologies (Burgelman et al. 2004). A typical discussion of technology and health care would most often conjure visions of Magnetic Resonance Imaging (MRI) units, X-ray machines, ultrasounds, and Electro-Cardiograms (EKG). Not often do people entertain thoughts of electronic charts, personal health records, computerized practitioner order entry, or PDAs. One plausible explanation for this perspective is that most individuals tend to think about the technologies that directly affect their treatment – not the information technologies for which they have less direct contact. For much the same reason, doctors and practitioners have focused most of their attention on understanding technologies that directly influence patient care and diagnosis. Likewise, extending this argument all the way to the top of the health care food-chain; the administrators and executives that run the hospital are often hard-pressed to justify the purchase of the latest hospital-wide Electronic Medical Record (EMR) when it is competing with a neonatal heart monitor.

The deficiency in computer technology usage by health care professionals may be explained by the reasons provided above; however it could be due to the simple fact that these individuals lack training and exposure to computer systems. This may be due in part to the lack of IT training received while in medical school (Ford et al. 2006). Most physicians are trained by accessing patient information from a paper chart and they become adept at using color-coded tabs and quickly finding relevant information. When EMRs are offered as substitutes for the paper record, the physicians often struggle with the steep learning curve (Lapointe et al. 2005). One could argue that this is no different than other disciplines; however, based on informal discussions with former medicals students, I believe that other students – such as those in business and engineering schools – receive significantly more computer training than do medical students. In addition, much of the workload in business and engineering school is accomplished by using a computer, therefore students learn by doing. Business school students, out of necessity, are forced to familiarize themselves with spreadsheets, word processors, and presentation software, among other applications. In much the same way, engineering students need to use technology and are given in depth training on various software packages for specific analyses. It has been demonstrated in numerous studies that a link between training and personal innovativeness will lead to long-term adoption of technology (e.g. Bostrom et al. 1990; Compeau et al. 1995a; Raymond 1988; e.g. Venkatesh 1999). On the other hand, fear of technology and lack of use will lead to low self-efficacy and unfaithful usage in the future (Compeau et al. 1995b; Thatcher et al. 2002).

In spite of these obstacles, there are some positive signals related to a growth in the use of HIT, albeit at a slow rate. Using data from an annual survey from the HIMSS Analytics℠ Database (derived from the Dorenfest IHDS+ Database™), I calculated that the adoption of EMR systems by hospitals has been increasing at an average rate of 25% per year since 1990. However, the average growth rate from 1995 to 2004 was only 15%, indicating that adoption rates in more recent years are trending downward. In addition to wider diffusion, several recent studies have demonstrated a link between HIT and value – either in terms of improved patient outcomes or increased efficiencies (e.g. Barlow et al. 2004; Dexter et al. 2001; Hunt et al. 1998; Overhage et al. 1997). While technology adoption is accelerating in the medical field, it still lags other industries by a considerable gap. Thus, health care represents an ideal context for IS researcher to actively examine and study the transformation of an entire industry sector from a nascent stage progressing through to faithful adoption.

ESSAY 1: THE IMPACT OF FIRM CHARACTERISTICS AND SPATIAL PROXIMITY ON THE DIFFUSION OF ELECTRONIC MEDICAL RECORDS: A HAZARD MODELING ANALYSIS

1.1 ABSTRACT

Electronic medical records (EMRs) offer the promise of addressing many problems confronting the health care industry, yet their adoption by hospitals has been slow. In this paper I draw upon research in the adoption and diffusion of innovations, and metaphors from epidemiology related to the spread of diseases through a social system, to predict the likelihood of EMR adoption by hospitals. I theorize that the likelihood of EMR adoption is driven by two organizational factors: the presence and concentration of complementary health information technologies, and the level of experience that the hospital has with these technologies. I further investigate the effects of an environmental factor, spatial proximity, reflecting the presence of contagion, on EMR adoption. I use a hazard model fitted to data from a sample drawn from a multi-year survey spanning 1970 to 2004 of almost 4,000 hospitals across the USA to test the hypotheses. Results provide strong support for the proposed relationships and yield interesting insights into the drivers of EMR adoption. Theoretical and practical implications are discussed.

1.2 INTRODUCTION

"I just invent, then wait until man comes around to needing what I've invented."
--R. Buckminster Fuller

The popular press vociferously argues that the time for the health care industry to adopt information technology (IT) has long since passed. The health care system in the United States is broken, and by some accounts, the only way for it to be repaired is by transforming it through information technology (Gingrich et al. 2003; Mullaney 2005). Evidence suggests that in spite of the value potential of IT, institutions in the health care sector have been slow to adopt it (Ash et al. 2005; Bates 2000; Bower 2005; England et al. 2000). To the extent that significant problems in health care such as patient safety, medical errors, and escalating costs can be addressed through IT, accelerating its diffusion throughout the system is an important public policy issue (Bower 2005; Bush 2004a; Bush 2004c; Gingrich et al. 2003; Pan et al. 2004).

In this essay I study the adoption and diffusion of a specific technology artifact called the electronic medical record (EMR). It is widely acknowledged that the EMR is one of, if not the most significant innovation to impact the health care industry in recent years. Many thought-leaders in this domain consider the EMR to be, "the most important thing happening in health care," (Lohr 2006). The EMR offers the promise of unifying fragmented data and applications, providing a repository of patient information, and allowing the practice and administration of medicine to incorporate more evidence-based decision making (Andrew et al. 2003; Elson et al. 1995; Elson et al. 1997; Smith et al. 2005; Tang et al. 1994). Yet it also raises concerns related to physician control, privacy (Gostin et al. 2002; Harris Poll: EMRs Pose Risks 2005), and implementation costs (Hartley et al. 2005; Ventres et al. 2006). Therefore, it is not surprising the diffusion of EMRs across the United States has been slow (Ash et al. 2005; Bower 2005; England et al. 2000).

Drawing upon theory related to the adoption and diffusion of innovations and the spread of epidemics I study the phenomenon of EMR adoption by a health-care facility. Prior research has suggested that firm characteristics such as size and structure, and environmental factors such as the actions of competitors are important determinants of innovation adoption (Debruyne et al. 2005). Using a survival analysis technique, I model the likelihood of EMR adoption as a function of three new constructs – *Complementary HIT Concentration, Temporal Complementary HIT Adoption, and Spatial Contagion Effect.* The first two represent internal firm characteristics that capture the availability of complementary technologies, and a temporal component reflecting the cumulative learning and experience that the firm has with information technologies. In order to isolate the effects of these variables, I control for other structural characteristics such as size and facility type that may affect the likelihood of adoption.

Prior research has also suggested that firms tend to mimic the behaviors of “similar” others, where similarity is typically assessed along dimensions such as size and industry (Acs et al. 1994; Debruyne et al. 2005; Haveman 1993). The diffusion of innovations literature argues that that diffusions spread through a social system via a contagion effect, although it does not specify the mechanism through which such contagion occurs. I model contagion using a spatial construct reflecting the effect of local knowledge spillovers that can occur among firms that are geographically proximate (Acs et al. 1994; Breschi et al. 2000, p. 1).

Using data from a sample drawn from a multi-year survey spanning 1970 to 2004 of almost 4,000 hospitals across the USA, I find that the likelihood of EMR adoption is positively related to the presence and concentration of complementary health information technologies. In addition, results show that the likelihood of EMR adoption is much higher when hospitals are spatially located close to other hospitals with EMRs. This contagion effect will be discussed in detail in the following sections.

The remainder of this paper is structured as follows. In the next section, I define key terms and present the literature review. This is followed by a description of the research model and development of hypotheses. Next, I discuss the methods employed, including data collection, subjects, and analyses. Finally, I present and elaborate upon the results and end with a discussion of limitations, conclusions, and directions for future research.

1.3 LITERATURE REVIEW

I first describe the various ways in which innovations have been conceptualized in prior research, and argue that the EMR constitutes a radical, disruptive innovation, which is one plausible explanation for its slow diffusion. Then I present a brief review of the literature on innovation adoption and diffusion, describing the factors that have been used to predict adoption. I draw a parallel between diffusion of innovations and epidemiology, concluding that both theories have important implications for the study of EMR adoption. Finally, I discuss the concept of local knowledge spillovers and a contagion effect in innovation adoption.

The Nature of Innovations

Studies of diffusion of innovations are of central concern to disciplines ranging from organizational sciences, information systems, to marketing, and others. Researchers seek to classify innovations in various categories (Damanpour 1991) such as: administrative and technical (Daft 1978; Damanpour 1987); radical and incremental (Dewar et al. 1986; Nord et al. 1987); stage of adoption (Marino 1982; Zmud 1982); or product and process (Daft 1978; Utterback et al. 1975). More recent work suggests that some innovations can be highly *disruptive* (Christensen 1997). Although scholars have used various definitions to describe disruptive innovations, central tenets of these types of innovations are that they introduce new performance dimensions to an industry and are inferior – at least in the short term – to the traditional technology on measures that are important to the consumer (Adner 2002; Christensen 1997; Debruyne et al. 2005; King et al. 2002), and they can transform markets through the disruptions they create (Han et al. 2001).

Descriptions of EMR systems in extant literature (Acs et al. 1994; Ash et al. 2005) and studies of EMR systems in practice (Als 1997; Greatbatch et al. 1995; Warshawsky et al. 1994) suggest that as an innovation, they are radical in that they cause major shifts in the work practices of clinicians and other personnel in health care facilities (Makoul et al. 2001; Overhage et al. 2001; Patel et al. 2002). They are both technical innovations, because they alter the underlying technology used in the delivery of patient care, as well as administrative innovations, because of their effects on the billing, insurance, and other administrative practices. EMRs incorporate new "products" such as an electronic repository of patient information that is portable, as well as new processes around patient-clinician interaction.

The medical informatics literature also identifies characteristics that suggest that EMRs constitute a disruptive innovation. First, studies of the implementation of EMR systems find that the adoption of these systems is highly complex and involves multiple stakeholders (Goh et al. 2005; Koch 2003; Lapointe et al. 2005). Sánchez et al. (2005) further elaborate this point by noting that EMR implementations must be successful on several dimensions: effectiveness, efficiency, organizational attitudes, user satisfaction and patient satisfaction. Thus, the scale and scope of EMR effects is substantial, and creates an inherent source of complexity. Second, EMR systems introduce new dimensions and methods for performance evaluation. In some instances, both hospitals (e.g., CMS HQID 2005; Gebhart 2003) and doctors (DoBias 2005; DOQ-IT 2006) are assessed based on performance measures that are captured via EMR systems. Such evaluations were infeasible in the past because there was no systematic or standardized ways to collect the data. In contrast, EMRs allow near real-time transfer of data.

Third, it can be argued that EMR systems are inferior to the traditional paper-based technology and/or multiple independent technology infrastructures, particularly when viewed from the perspective of the clinician as the primary user of the technology. Research suggests that clinicians, especially physicians, are resistant to EMR use (Bodenheimer et al. 2003; Johnston et al. 2003; Krall 1995). One explanation for this resistance is that because of managed care and fee-for-service insurance, the metric that is most important to clinicians is quantity rather than quality of care (MD NetGuide 2005). Thus, some clinicians suggest that EMRs slow them down (Krall 1995; Lee et al. 1996; Overhage et al. 2001; Tierney et al. 1993) and restrict their decision choices (Garg et al. 2005); although this is believed by many to be temporary until the EMR is fully adopted. Physicians also have become very accustomed to the paper chart and often find the learning curve of EMR use to be daunting (Lapointe et al. 2005).

Finally, studies have shown that EMR use can create disruptions in workflow ("Cardiology Practice and EMR Workflow" 2001; Safran et al. 2000). The users of the EMR are not limited to well-trained administrators, but also include those who use the system only occasionally and to different degrees than others (Sánchez et al. 2005). A clinician will use an EMR in the presence of a patient very differently than an administrator will at a front desk.

With all of the opportunities for failure present in a disruptive innovation, why would a firm choose to adopt one? When firms decide to adopt disruptive innovations, they are accepting risk and uncertainty in hopes of capitalizing on a new market opportunity (Adner 2002; Christensen 1997; King et al. 2002). Disruptive innovations are attractive because they offer the promise of efficiency, quality improvements, and cost reductions, but they are also known to impact business processes (positively and negatively), create fear and uncertainty amongst users, and cause management to lose its focus on competitive actions.

As might be expected, the adoption of disruptive innovations is a complex and multi-faceted organizational decision that is likely to be made based on a variety of factors. For instance, EMR adoption could be driven by societal pressures (Bush 2004a; Bush 2004b; Gingrich et al. 2004; "Harris Poll: EHRs to grow rapidly 2004; Mullaney 2005) to performance impacts (Bates 2000; Bates et al. 1998; Leapfrog 2004), and finally to performance oversupply (Christensen 1997). Performance oversupply exists when the demands of consumers are met with the current technology but they decide to implement new technology because some secondary benefits may exist (Christensen 1997). Finally, public policy concerns such as privacy and security of health information are also likely to weigh heavily on the decision to adopt EMRs (Alpert 1998; Angst et al. 2006; Detmer 2000; Watson et al. 2006). I discuss the literature that has examined the drivers of innovation adoption next.

Adoption and Diffusion of Innovations

Firms innovate because innovation has been shown to lead to competitive advantage (Barney 1991). The literature in the organizational sciences offers significant evidence that the adoption of innovations by firms is a function of not just intra-firm characteristics, but also external influences (for meta-analysis see Vincent et al. 2004). In very broad terms, organizational factors such as strategic orientation (Srinivasan et al. 2002), IT capabilities (Bharadwaj et al. 1998; Wade et al. 2004), organizational resources (Barney 1991; Bharadwaj 2000; Meyer et al. 1988; Rao et al. 2002; Teece et al. 1997), and structure (Camisón-Zornoza et al. 2004; Russell 1990; Wolfe 1994), have been shown to influence the adoption of innovations. Prior research has also identified key environmental factors such as competition (Kimberly et al. 1981; Tsai 2001), industry (Meyer et al. 1988; Pelham et al. 1996), urbanization (Goes et al. 1997), etc. as drivers of innovation (Meyer et al. 1988).

While research on the adoption of innovations attempts to model the factors that drive the behavior of a single entity such as a firm, diffusion models are typically used to describe the adoption of an innovation by a target population over a specific period of time (Fichman 2000; Mahajan et al. 1979; Mahajan et al. 1990b). The process itself must incorporate an innovation, communication channels, time, and a social system

(Rogers 1995). Diffusion studies are useful because they can be used to predict increases in number of adopters and project future trends.

In the context of EMRs, a recent article by Bower (2005) analyzes data from several thousand health facilities in the US and compares the diffusion of EMRs with other technologies. His findings suggest that EMR diffusion is still in a period of slow adoption growth and will not reach 80% acceptance until roughly 2016 if it continues at a pace matching the diffusion curves of other, similar innovations. Seminal work in the field of diffusion by Rogers (1995) notes that the slow growth period is typically followed by a sudden period of rapid adoption and then a gradual leveling off, thus forming the familiar S-shaped diffusion curve. Rogers' work shows that the period of rapid expansion occurs when social and technical factors align to create an environment conducive to growth. Drawing from the popular press, one must acknowledge the tremendous amount of media attention devoted to health care and in particular, health information technology in recent times. It is well accepted that messages about technology innovations are transferred via mass media and/or by word of mouth; though some debate the impact of each relative to the other (Bass 1969; Fourt et al. 1960; Mansfield 1961). Most popular diffusion models account for these social factors by incorporating estimation coefficients derived from the diffusion of other similar technologies that assess the impact of internal and external influences (Bass 1969; Rogers 1995). In the health IT domain, Bower (2005) fits a diffusion function (Geroski 2000; Teng et al. 2002) to his data and using a cluster analysis method of assessment, chooses internal estimation coefficients based on several characteristics of technologies, such as innovation objective, network externalities, complexity, and whether the innovation is a device or a system. He concludes that EMRs fit into a cluster defined as large-scale relational database innovations (LSRD) and are very similar to Enterprise Resource Planning (ERP) systems (Bower 2005 pp. 38-42).

However, my goal is not to project adoption into the future or to assess diffusion at a population level. Rather, I seek to predict a hospital's likelihood of adoption in the next time period, given its actions and choices in the past. Further, as argued earlier, EMRs are a unique technology involving highly complex routines resulting in radical changes to workflows. The societal and public policy implications of adoption make this innovation somewhat unique in that it does not closely resemble other technologies from which estimation coefficients have been derived. In this study I therefore adopt a variance-based approach by examining the historical diffusion of EMRs (see Figure 1.1).

Insert Figure 1.1 about here

There are several confounding variables which can impact the shape of the diffusion curve. For example, Rogers (1983) suggests that adoption can be affected by the population in a region and others argue that it is not only the population, but also the distance between centers of population that are key factors (Attewell 1996). It has been observed that diffusion models are not appropriate when advanced technologies are applied simply because the complexity of the systems does not allow for adoption decisions by a single entity (Eveland et al. 1990, p. 123). Therefore, the assumption that diffusion is a result of individual decisions and social interaction may not be valid

(Attewell 1992). Here, a second theoretical perspective from the bio-informatics field that has striking similarities to DOI but offers additional unique insights is informative.

An epidemic has traditionally been defined as the occurrence of a disease in clear excess of normalcy within a specific geographic region (Gerstman 2003; Last 2001). The field of epidemiology studies the factors underlying the diffusion of disease and extends into causes, transmission, incidence, prevalence, distribution in populations, and factors that influence this distribution (Gerstman 2003; Gordis 2000; Last 2001). While the primary goal of epidemiology is to improve human health by altering the natural course of disease (Gordis 2000), there are other important research foci such as: identifying the etiology (causes) and risk factors (factors that increase a person's risk for getting the disease), identifying subgroups in the population who are at high risk for disease, exploring how the disease is transferred from person to person or non-human reservoir to a human, and identifying those who are at high risk so they can be evaluated to determine which factors put them at risk and ultimately modify those factors (Gerstman 2003; Gordis 2000).

Epidemiology thus provides a theoretical rationale for 'diffusion' through a population. In fact, other researchers have drawn from epidemiology literature to explain the diffusion of health innovations at the individual level (Anderson et al. 1985) and have concluded that social interaction amongst physicians is an independent driver of adoption. Table 1.1 maps the constructs in epidemiology to those found in the diffusion of innovations literature. The essence of epidemiology is the presence of a contagion effect caused by close contact between entities that is posited to be a primary driver of the spread of a disease. In a similar vein, in this study I am interested in the causes underlying the diffusion of EMRs at the firm level. Specifically, my goal is to identify the *risk factors*[1] as they relate to the adoption of EMRs and the *modes of transmission*[2] through which contagion manifests itself.

Insert Table 1.1 about here

The Contagion Effect in Innovation Adoption

Prior research has established that firms tend to model their practices, business processes, and procedures after successful peer firms (e.g. Abrahamson 1991; Abrahamson et al. 1993; DiMaggio et al. 1984). The innovation adoption literature suggests that such mimetic behavior is most likely to be observed between firms that are similar in characteristics such as size, industry, product, culture, etc. (Debruyne et al. 2005; Haveman 1993). Although mimetic behavior arising as a result of geographic proximity has been alluded to in the literature (Porter 1990; Pouder et al. 1996), no study that I am aware of specifically incorporates the effects of the spatial distribution of the adopting population on adoption decisions. Scholars have documented the emergence of industry clusters in specific regions, such as the high-tech clusters in the US (Piore et al. 1984; Saxenian 1994; Storper 1995), however, as Breschi and Lissoni (2000) note, researchers have "avoid[ed] studying the specific mechanisms through which [geography and innovation] are linked," but instead have simply noted that the process (knowledge spillover) exists because the results are evident.

[1] The reader should not interpret my choice of terminology to mean that I view EMR adoption as harmful. Epidemiology and survival analysis have their roots in the biological sciences and therefore have been burdened with negative connotations associated with morbidity and harmful illnesses. I use this framework and nomenclature because it is useful for this discussion.
[2] Similar to what Rogers (1995) refers to as 'information flows'.

I argue that the presence of a specific mimetic phenomenon known as localized knowledge spillover (LKS) is one reason firms in geographic proximity begin to resemble each other from a technology infrastructure standpoint. LKS has been defined as "knowledge externalities bounded in space, which allow companies operating nearby the knowledge sources to introduce innovations at a faster rate than rival firms located elsewhere," (Breschi et al. 2000, p. 1). The LKS literature argues that the adoption of highly complex information systems requires specific knowledge that is fundamentally tacit knowledge (Audretsch 1998; Zander et al. 1995). Because this knowledge is not codified, the geographic proximity to other adopters is very important (Breschi et al. 2000; Zander et al. 1995). The tacit knowledge can be spread through face-to-face interaction, personal relationships, or simply because there is knowledge transfer when knowledge workers leave one firm for another: all of which tend to occur with greater frequency when distance between entities decreases (Breschi et al. 2000).

Summary

I have argued that EMRs are an instance of a radical, disruptive innovation and that the EMR adoption decision is complex. I provided a brief review of the literature that has examined the antecedents of innovation adoption, noting that both firm characteristics and environmental influences explain the adoption decision. Finally, I described a contagion effect in innovation adoption and suggested that localized knowledge spillover arising as a result of geographical proximity plays an important role in the innovation adoption decision.

1.4 RESEARCH MODEL AND HYPOTHESES

Drawing upon the theoretical foundations described above, the overall research model underlying the study is shown in Figure 1.2. The focal dependent variable of interest is the likelihood of EMR adoption in the next time period, given the choices and decisions made by the adopting entity (i.e., the hospital) in previous time periods. Using an epidemiology metaphor, this likelihood is influenced by two risk factors or adoption determinants: complementary HIT concentration, temporal complementary HIT adoption; and a mode of transmission determined by spatial proximity. The *adoption of innovation* literature provides the framework for the covariates that must be controlled (e.g. organizational structure, resources, strategic orientation, etc.) in order to isolate the focal effects.

Insert Figure 1.2 about here

Risk Factors

Complementary HIT Concentration. EMR systems are often used as the conduit that links and aggregates the data within isolated legacy systems within hospitals. Recent work suggests that successful implementation of a technology requires an already existing robust IT infrastructure (Broadbent et al. 1999; Sambamurthy et al. 2003). Other research has shown that the presence of complementary information technologies can enhance the diffusion of the focal technology (Bucklin et al. 1993; Mitropoulos et al. 2000; Nambisan 2002). Ray and colleagues (2004; 2005) demonstrate that the use of generic technologies moderates the relationship between shared knowledge and performance. In all of these examples, the common theme is that successful implementations of a focal technology are reliant upon the presence of complementary IT infrastructure. In the case of HIT, there is not one specific information system that is known to be the primary integrator or complementor to the

EMR (Sánchez et al. 2005). In fact, by some accounts, hospitals have more than 200 different IS applications, few of which are interoperable ("EMR Interoperability 2005). Some have argued that CPOE (Computerized Practitioner Order Entry) and electronic prescribing are key elements (Briggs 2006), while others simply point to the necessity of an up-to-date and reliable IT infrastructure. At the other extreme, some CIOs believe EMRs should integrate all information systems, including clinical, financial, and environmental (Briggs 2006). To conceptualize the Complementary HIT Concentration metric, I developed a measure of that incorporates a large subset of various information systems used within hospitals.

Diseases are known to strike those who have less immunity resistance, especially when opportunities for transmission are prolific (Gordis 2000). Thus, drawing from epidemiology literature, I view the concentration of HIT as creating an environment conducive to adoption of EMRs. I model this variable as time-invariant such that it influences the event across the entire span of the analysis (Singer et al. 2003, pp. 388-390). This leads to my first hypothesis.

H1: The likelihood of EMR adoption will be positively associated with Complementary HIT Concentration.

Temporal Complementary HIT Adoption. In the previous hypothesis, I posit that complementarities will influence adoption of the EMR. It is not merely the presence of the complementary technologies, however, that influences the propensity to adopt an innovation; what is also important is the point in time at which the complementary HIT's are adopted. An extensive body of literature ranging from learning-by-doing (Epple et al. 1991; Glaser et al. 1989; Zollo et al. 2002) to organizational learning (Argote 1999; Argote et al. 2000; Levitt et al. 1988; Tyre et al. 1997) to absorptive capacity (Cohen et al. 1990; Zahra et al. 2002) suggests that the amount of experience with an IT affects the success and ultimately, the likelihood of future adoption. Studies have shown that early information system adoption fosters an environment for later adoption of technologies (Lai et al. 1997; Swanson et al. 1997). Organizations place more strategic importance on later use of information technology when they have been early adopters of other innovations (Fletcher et al. 1997; Zaltman et al. 1973). I argue that hospitals who have more experience with HIT and have learned over time, will exhibit a higher likelihood of adoption of EMRs and test:

> H2: The likelihood of EMR adoption will be positively associated with the time-weighted adoption of Complementary HIT Concentration.

Modes of Transmission

Spatial Contagion Effect. As discussed earlier, previous research suggests that firms – especially those firms that serve the same industries, are comparable in size, and/or in age – exhibit a tendency towards isomorphism over time. This isomorphism can take the form of similarities in the innovations that have been adopted. The next hypothesis investigates the contagion effect of EMR adoption. I draw from localized knowledge spillover and epidemiology literatures to suggest that adoption will spread through the health care industry – hospital-to-hospital, or hospital-to-environment-to-hospital (Gordis 2000) through the increased likelihood of interaction among entities located close to each other. I extend prior literature that has posited that structural similarities are the primary determinants of mimetic behavior and hypothesize that spatial proximity explains variance above and beyond structural similarities.

> H3: Spatial proximity explains variance in the likelihood of EMR adoption above and beyond that explained by structural characteristics of hospitals.

Both LKS and epidemiology note that proximity is a critical component of diffusion. As mentioned earlier, some researchers suggest that specific structural characteristics – such as the size of the firm – interact with spatial proximity to influence diffusion (Acs et al. 1994). Essentially these authors argue that small firms do not have the research capabilities to be highly innovative and therefore, they mimic the technology adoption patterns of other hospitals that are in close proximity. Following in the tradition of Audretsch (1999) and others (Lazerson et al. 1999), I suggest that firms will actively seek to capture knowledge beyond their boundaries by luring key knowledge workers, conducting informal information gathering, and through personal friendships – particularly within close spatial proximity. Proximity is an important factor in spillover, which typically occurs because tacit knowledge becomes diluted with distance, and knowledge workers tend to switch jobs locally due to risk aversion, localized sunk costs, and personal issues (Breschi et al. 2000; Jaffe et al. 1993). Although some researchers have argued that knowledge between highly competitive firms does not spillover; even they acknowledge that localized job transfers will still occur, thus allowing for the transfer of knowledge (Almeida et al. 1999; Audretsch 1999; Breschi et al. 2000). Finally, a study of engineers in Silicon Valley (Saxenian 1994), found that knowledge workers often transferred between companies within a small geographic region. To the degree that there are multiple hospitals in every medium to large city in the USA, this creates the opportunity for even greater mobility amongst knowledge workers.

The epidemiology metaphor is appropriate for explaining such a geographical contagion effect. Researchers such as Jacquez et al. (1988) and Kaplan (1991) show that the types of interactions taking place and the patterns of contact are critical to understanding the diffusion of a disease (Jacquez et al. 1988). In this literature, face-to-face contact and proximity to high concentrations of 'infected' carriers will increase propensity for the focal individual to become infected (Gordis 2000), providing further support for the importance of spatial proximity. I therefore hypothesize that hospitals within a tightly coupled geographic cluster of other EMR-adopting hospitals will be more likely to adopt an EMR than hospitals in a loosely coupled geographic cluster.

H4: The influence imparted by other hospitals to adopt an EMR decreases as the distance between the focal hospital and other adopters increases.

1.5 METHODOLOGY

Electronic Medical Record System

In this study, a hospital is the unit of analysis and the EMR system is the focal technology artifact. Drawing from recent definitions, I conceptualize an EMR system as an application environment that is typically composed of the clinical data repository, clinical decision support, and the computerized patient record (Bower 2005). Some researchers have included several other technologies in an EMR system such as a controlled medical vocabulary, order entry, computerized physician order entry, and clinical documentation applications. For the purposes of this study, I suggest that the EMR system supports the patient's electronic medical record across the continuum of care, and is used by health care professionals to document, monitor, and manage health care delivery (Angst 2006; Garets 2005; Shortliffe 1999; Stead et al. 2005). Below, I discuss in greater detail how the presence of the EMR is operationalized.

Estimation Methods

I use a hazard model to predict the likelihood of EMR adoption. This is a well-known method of analysis in the engineering and medical fields, where it is traditionally used to assess the likelihood of failure (or death). The choice of this estimation approach is based on the fact that recent methodological developments allow for investigation of covariate effects on the hazard rate. OLS is not appropriate here due to the high likelihood of multi-collinearity between independent variables. More importantly, since I use discrete time-series data in this analysis, OLS does not perform adequately because it estimates a continuous model, and the use of a maximum likelihood estimation (MLE) procedure to overcome these problems is recommended (Schmittlein et al. 1982). Although MLE also has limitations in that it considers only sampling errors and ignores all other errors, I chose MLE because of its advantages when working with discrete-time data.

Hazard is the quantity used to assess the likelihood of an event occurring in each discrete time period assuming that it did not previously occur (Singer et al. 2003), while diffusion is a representation of growth (Rogers 1995). Hazard is typically described by a probability density function – the probability that individual or firm *i* will experience the event in time period *j*, $\Pr[T_i=j]$. This is extended by explaining that each firm *i* can experience the event in time period *j* if, and only if, it was not experienced in any prior period, hence: $h(t_{ij})=\Pr[T_i=j|T_i \geq j]$. This is a discrete-time hazard function. Each hospital has its own hazard function describing its likelihood of adopting the EMR. Discrete-time hazard is more simply represented as the number of hospitals who adopt in a time period divided by the number of hospitals at likelihood of adoption during the experienced same time period. Both of these descriptions assume homogeneity of subjects.

$$\hat{h}(t_{ij}) = \frac{n\ \ events_j}{n\ \ at\ risk_j} \quad \text{vs.}$$

$$\hat{S}(t_j) = \frac{n\ who\ have\ not\ \text{exp}erienced\ the\ event\ by\ end\ of\ time\ period\ \ j}{n\ \ in\ the\ dataset}$$

If the population is heterogeneous – the subjects are distinguished on the basis of their values of selected predictors – then each subject may have a different hazard function as described by the following equation:

$h(t_{ij})$=Pr[$T_i = j | T_i \geq j$ *and* $X_{1ij} – x_{1ij}$, $X_{2ij} = x_{2ij}$,…$X_{Pij} = x_{Pij}$]; (*observed heterogeneity*)

This represents the probability that each subject will experience the event in a specified time period, conditional on no prior event occurrence and each subject's particular values for the P predictors in that time period.

$$\text{logit } h(t_{ij}) = [\alpha_1 D_{1ij} + \alpha_2 D_{2ij} + \ldots + \alpha_J D_{Jij}]$$
$$+ [\beta_1 X_{1ij} + \beta_2 X_{2ij} + \ldots + \beta_1 X_{Pij}].$$

α - *each intercept represents the value of log odds of event occurrence in that time period for each subject in the 'baseline' group.*
β - *each slope assesses the effect of a one unit difference in that predictor on event occurrence, statistically controlling for the effects of all other predictors in the model.*
D = discrete time periods
X = unique predictors

Using this logit function, I calculate the likelihood of EMR adoption in the final time period, 2005, based on the above referenced heterogeneous firm factors.

Censored Data

In this study, I have *a priori* knowledge that by most accounts, more than 2/3rds of the hospital population in the US has not experienced the event. This is a very important subset of the data that is not randomly distributed because by definition, they are least likely to experience the event. Much information can be gleaned from these non-adopters and this would be lost if these cases were ignored, as is required in most analytical methods including regression analysis (Mitchell 1991; Tuma et al. 1984). These cases are said to be right censored in that: 1) the hospital will never experience the event; or 2) the hospital will experience the event but not during the time in which the data are collected (Singer et al. 2003).

One solution is to assign the censored cases the event time associated with the end of the data collection (e.g., Frank et al. 1984) but this biases the data by changing non-events to events. In addition, it makes the false assumption that all censored cases occurred at the same time – the last date in the time period (Singer et al. 2003). Event-history methods, such as the accelerated event-time statistical model, incorporate the information that an observation is censored and weight the influence of the case accordingly (Mitchell 1991). This method accounts for time-dependent aspects of entry (Debruyne et al. 2005). I model entry – or in this case, implementation – as a dichotomous event using hazard analysis.

The Sample

The empirical analysis and hypothesis tests are based on secondary data set collected via a survey. The data came from a nationwide, annual survey of Care Delivery Organizations (CDO) in the USA, conducted by HIMSS Analytics™. The 2004-2005 HIMSS Analytics Database (derived from the Dorenfest IHDS+ Database™)

provides information for almost 27,000 CDO's including 3,989 hospitals. By some assessments, this represents approximately 85% of the total number of hospitals and 65% of the Ambulatory and Sub-Acute facilities in the entire USA.

Variable Operationalization

Complementary HIT Concentration. In the survey, the CIO or other IT executive responded to the question, "Do you have xyz application at your facility?" The next question asked what year the xyz application was contracted (choices given were: Live and Operational, Installation in Process, Contracted but Not Yet Installed, To Be Replaced, Not Yet Contracted, and Not Automated). The automation question was asked because the researchers wanted to assure that the facility was using an application-specific software tool rather than a basic program (e.g. if the facility was using Excel to manage their payroll, this was not considered an application-specific tool and therefore was not categorized as automated).

For this analysis, I classify a facility as not having adopted the application if it is "Not Yet Contracted" or "Not Automated." In cases where the system is "To Be Replaced," I select the older contract and eliminate the newer (e.g. Facility A stated they contracted a CPOE in 1994 and classified it as "To Be Replaced" in 2002 but they also stated they have a CPOE at "Installation in Process" for 2002 – in this case, I would log the CPOE as being adopted in 1994). An EMR event occurrence is defined here as the year in which all three information systems' components (CDR – Clinical Data Repository; CDSS – Clinical Decision Support System; CPR – Computerized Patient Record) are contracted (Bower 2005). For example, if a CDR was contracted in 1999, CDSS in 1987, and CPR in 1987, then the EMR event occurrence year would be 1999.

Complementary HIT Concentration (CHITC). I conducted a literature review and discovered 52 HIT applications which are commonly used in hospitals (Appendix A1 includes a partial list of the applications). These technologies were chosen because they are well-known amongst health care providers and often discussed in conjunction with EMRs. For the most part, they also have diffused to a greater extent than EMRs[3]. The CHITC measure is simply the sum total of HIT applications implemented of the 52 HIT applications during the timeframe referenced.

Temporal Complementary HIT Concentration (TCHITC). This metric is a temporal assessment of both the number of HIT applications adopted *(CHITC)* and the experience (length of time) the hospital has had with the technology in use. After investigating if the hospital had adopted a specific technology, I then found the year in which each technology was adopted by each hospital and subtracted that year from the year 2006, thus yielding an experience value. If a hospital did not adopt said technology, the hospital received a zero value for that technology. Finally, I summed the experience values to yield a weighted concentration. I subsequently calculated a second weighted value which incorporated the number of HIT applications adopted and multiplied this value times the experience value. I found that the second value was highly correlated with the first; therefore I used the original value in my model. The hazard model I use does not allow me to include this variable as time-variant; however, the operationalization of it as a time-weighted variable indirectly assesses this aspect.

Spatial Contagion Effect (SCE). Using an Excel® add-in program ("Zip Code Tools 2004) that calculates Euclidian distance between two zip codes, I calculated the

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[3] This is not a co-diffusion process: my assumption is that these technologies have been implemented prior to the EMR; however all do not have to be present for the EMR to be implemented.

total number of hospitals within three radii – 5 miles, 50 miles, and 100 miles. I again used the HIMSS Analytics database to cross-reference zip code with those hospitals that had an EMR and also the total number of hospitals in a zip code radius. Modifications were made to the program (Franco 2006) allowing me to first input a database of all hospitals and, second, input a database with all hospitals with an EMR. From this, I was able to extract all hospitals that met the criteria and was able to perform a count (see Figure 1.3). To operationalize EMR adoption, I used a dichotomous variable (i.e., adopted/not-adopted) as described above. The variable is operationalized as a 0 or 1 related to either the absence or presence of an EMR in any year between 1970 and 2004. I make the assumption that once the EMR is adopted, it remains in place throughout the timeframe sampled.

Insert Figure 1.3 about here

Control Variables. I use several control variables in this analysis. The size of the hospital is used because it has often been shown to influence technology adoption in organizations (e.g. Chandrashekaran et al. 1995; Hannan et al. 1984; Lai et al. 1997). Size is operationalized as the number of beds that are staffed. I also controlled for the type of hospital by classifying a hospital as a teaching/research hospital or not. Finally, I control for resource characteristics such as profit versus not-for-profit and age of the hospital. Event-history methods are very useful for controlling for 'other' possible influences and allow the use of dummy coded dichotomous variables (Mitchell 1991).

1.6 ANALYSIS AND RESULTS

Descriptive Statistics

Descriptive statistics for the hospitals are presented in Table 1.2. The total sample size is 3,989. The sample shows that most hospitals reside in urban areas as expected. All other variables that were used in the analysis are also shown.

Insert Table 1.2 about here

In Figure 1.4, I present several HIT applications on a diffusion graph. The earliest adoption of an EMR system is 1975 and the latest is 2004. The graph should be interpreted with caution with regard to year 2004. The research organization collects data on a rolling, monthly basis, but only once per year per facility. Because of this, the data from 2004 will not be entirely complete until December 2005. For example, if Facility A was surveyed in July 2004, they will have reported data only up through July 2004. If Facility A contracted for an EMR system in August 2004 to be installed before the end of 2004, that data will not show up in our analysis until we re-survey Facility A in July 2005. Therefore, the graph is depicting less than one half of the actual diffusion from 2004. In some cases, there was also an issue with a facility reporting that it had adopted a technology but the year was not known. I describe in Appendix B1 how this was situation was handled.

Insert Figure 1.4 about here

Power

Initially I used all 3,989 hospitals in the analysis. Because I investigated 30-years of adoption data, this created a matrix of data that included 119,670 cases (3,989 x 30). This posed problems related to the significance of coefficients in that most variables were found to be highly significant simply because of the large statistical power. I then randomly selected 335 hospitals (roughly 10,000 cases) from the population and conducted the analysis. I selected several different sample sizes and sub-samples and found similar results in all cases. My final sample matched closely the descriptive ratios shown for the full sample. What I describe below in the hazard model results is a sub-sample of 335 firms but all of the descriptive data and spatial data are based on all 3,989 hospitals.

Hypothesis Testing

Table 1.3 presents the results of fitting a hazard model to the data. In the first hypothesis, I test the relationship between the presence of Complementary HIT's (CHITC) and the likelihood of EMR adoption. In H2, I posited that a time-weighted CHITC would also be associated with the likelihood of EMR adoption. The $\hat{\beta}$'s, which assess the effects of the predictors (CHITC, TCHITC, etc.) estimate the main effect of the time invariant variables to the main effect of time (year). In both cases, the hypotheses are supported (see Table 1.3, Model 2), however, the explanatory power of TCHITC is quite low (0.190, $p<.000$; 0.005, $p<.000$). The coefficient on CHITC in Model 2, when antilogged ($e^{0.190}=1.21$), suggests that in every year measured, the likelihood of EMR adoption is 21% greater for hospitals whose HIT concentration is one standard deviation greater (Mean CHITC = 34.43, Standard Deviation = 6.56). Even though the coefficient of TCHITC is significant, the effect is very small ($e^{0.005}=1.005$), suggesting that a one standard deviation increase in TCHITC will result in only a 0.5% increase in the likelihood of EMR adoption (Mean TCHITC = 224.16, Standard Deviation = 124.33).

Insert Table 1.3 about here

Spatial Proximity. First I present descriptive statistics highlighting some interesting findings related to geographic clusters of hospitals adopting EMRs (see Tables 1.4, 1.5, 1.6). It is intriguing that when standardizing by using characteristics of the entire distribution and controlling for the number of hospitals, I find that some cities emerge as very highly concentrated in EMR adoption. I controlled for the number of hospitals within each radius so as to eliminate bias present in highly-concentrated regions (e.g. HOSP_5, HOSP_50, and HOSP_100).

Insert Tables 1.4, 1.5, 1.6 about here

The next two hypotheses investigated whether spatial proximity affected the likelihood of adoption. By controlling for size, type, profit/not-for-profit, and age of the hospital, I was able to show that spatial proximity explained variance above and beyond that explained by structural characteristics, thus supporting H3 (see Table 1.3, Model 3, 4, and 5). The change in R^2 is significant when the spatial variables are added to the model.

With H4, I test whether the localized influence from hospitals having adopted an EMR is greater than dispersed influence. In Table 1.7, I present data showing the dispersion of hospitals with an EMR relative to the total number of hospitals within a specific radius. I next tested the influence imparted at increasing radii and found that indeed the strongest influence came from those hospitals within a 5-mile radius, rather than 50 or 100-mile radii. Therefore, H4 was also supported.

Insert Table 1.7 about here

Because the decision to adopt is hospital-specific, all potential adopters do not have the same probability of adopting the product in a given time period (Mahajan et al. 1990a). During any time period, the hospital assesses the uncertainty (ROI, implementation challenges, error reduction, etc.) surrounding the implementation of the EMR. It also factors in information received through negative word of mouth (Mahajan et al. 1984) and then makes the decision to purchase when the perceived value outweighs the current state (Mahajan et al. 1990a). Because these perceptions change over time due to the internal and external influences, I incorporated a time-varying variable which measures the adoption of EMRs in each year.

The results show that the likelihood of adoption is increasing over time. The parameter estimates for the time-variant variables, $\hat{\alpha}$'s, (Y1975, Y1980, Y1985, Y1990, Y1995, Y2000, and Y2004) provide estimated values of the baseline logit hazard function. The $\hat{\alpha}$'s, which as a group are maximum likelihood estimates of the baseline logit hazard function, are steadily increasing in size from 1975 to 2004 and they are all significant suggesting that the likelihood of a hospital adopting an EMR increases over time.

1.7 DISCUSSION

Bower (2005, p. 22) speculates that the work conducted by Anderson and Jay (1985) related to an epidemic or contagion effect between physicians could be extrapolated to multiple levels of analysis. He also notes that no work has investigated the spread of HIT at the firm or industry level. My research addresses this gap. At a conceptual level, I argue that contagion can be viewed as localized knowledge spillover between institutions and it takes place irrespective of the structural characteristics of the firm. Rogers (1995) work alludes to the contagion effect specifically in the form of social influences, but there is no consensus regarding its operationalization (Debruyne et al. 2005). The results of this study illustrate that in isolation, size, profit/not-for-profit, age, and type of hospital have almost no measurable effect on the likelihood of adoption (see Table 1.3, Model 1; Note: In some cases the coefficient is statistically significant, yet its explanatory power is very low). This is significant because most prior research suggests that similarities in structural characteristics are the primary drivers of mimetic behavior, i.e. firms adopt processes and practices from similar others. My findings, by contrast, show no significant relationships between structural variables and likelihood of adoption. In the presence of the spatial proximity variables; however, the type of hospital and profit/not-for-profit do become significant. Yet, size and age, two very popular measures of structural similarity, are not significant.

An important objective of this study was the investigation and operationalization of the contagion effect. LKS provided the theoretical justification for positing the existence of highly concentrated regions of adoption and DOI and epidemiology provided conceptual reasoning for how this transmission could occur. The results of this study demonstrated that indeed, geographic clusters of high-concentration EMR adoption are emerging, and that spatial proximity explained variance above and beyond that explained by structural characteristics. The presence of localized knowledge spillover is one explanation for this result. In addition, I found that the influence from EMR-adopting hospitals decreases as the distance between the hospitals increases. The influence from hospitals within a 5-mile radius was much greater than either the 50- or 100-mile radii (CNT_5 > CNT_50 > CNT_100). If contagion were not occurring through LKS, this result would not be present.

When standardizing by the number of hospitals, and choosing only those cities that have three or more hospitals, I find that some cities emerge as highly concentrated in EMRs. Surprisingly, these are typically not the cities that have been known to be highly innovative. One possible explanation for this phenomenon is that some health systems in specific geographic regions have been notably active in the movement to make their information systems infrastructure highly interoperable so they can exchange patient data. For example, in Salt Lake City, Utah, Intermountain HealthCare and a network of physician practices and other stakeholders have collaborated to form a Regional Health Information Organization (RHIO) as a means of sharing data between sites. This data share would not be possible without EMRs so it stands to reason that there is a high degree of contagion between sites – a fact that is confirmed by my empirical analysis.

Another important contribution of this work is the identification of EMR adoption determinants. I am not aware of any prior work that has identified any firm-level determinants of EMR adoption. Because at this point in time, EMRs require the presence of existing technological infrastructure, it is important to determine which prior innovations are the most predictive of EMR adoption. This study takes the first step by identifying that the concentration of complementary technologies is an important antecedent of the likelihood of EMR adoption. Though, the experience that hospitals have with the complementary technologies does not appear to be a strong predictor of the likelihood of EMR adoption, suggesting that the learning occurring as result of prior technology use is of less consequence. One plausible explanation for this finding is that EMRs are so significantly different from prior HITs that the prior accumulated experience does not facilitate the learning that has to occur in the EMR context.

Other findings from the hazard analysis show that diffusion is taking place even in the presence of competitive forces and in spite of the fact that EMRs are a radical, disruptive innovation. The α coefficients increase steadily from 1975 to 2004 in all cases, indicating that the likelihood of adoption is increasing in each successive time period. From this analysis I cannot assert with certainty that this trend will continue. Many other factors come into play such as government involvement at the state and federal level, the possibility for incentives, the propagation of RHIOs, the announcement of potentially harmful or negative effects, and the push for interoperability.

In summary, this study makes three primary theoretical contributions. First, I extend DOI literature by drawing from disruptive innovation literature and explore and operationalize the social spread of an innovation. Second, I demonstrate that contagion through localized knowledge spillovers is a measurable phenomenon as it relates to the adoption of EMRs, and that it explains variance above and beyond structural characteristics. I believe this is an important perspective on how innovations diffuse and one that merits further investigation. Finally, this is the first study to identify firm-level antecedents of likelihood of EMR adoption.

This work also makes several practical contributions. The investigation of EMR diffusion is a new topic of interest; however, all prior work is concerned with projecting what the diffusion curve will look like in future years. Yet, policy makers, hospital executives, physician practices, vendors and others are seeking practical guidance on how to encourage the adoption of EMRs not in the next decade but in the coming days, weeks, or months. To be able to provide this answer, researchers must examine path-dependence in the use of HIT by hospitals and be able to isolate the effects of specific variables. This study takes a step towards identifying specific factors important for adoption and suggests that local influence may be one of the most important means of spreading the innovation. Thus, an implication is that state-level and possibly even county-level initiatives are more important for rapid diffusion of EMRs than federal-level initiatives. Grass-roots efforts by respected organizations within localized regions are likely to be the most influential in determining the subsequent adoption by other hospitals within a small region, while the influence imparted by geographically distal hospitals (and, by implication, other entities that are at a distance) is almost negligible.

Limitations

Before concluding this manuscript, I acknowledge the limitations of this work and also suggest areas for extension. One weakness of the empirical analysis is the use of a dichotomous variable for EMR adoption which may artificially inflate diffusion. Some hospitals may own the EMR but not use it or use it to varying degrees. As discussed, I also reduced the sample size in order to identify truly significant relationships. However, I randomly sampled hospitals and confirmed that the sub-sample was similar in descriptive characteristics to the full sample. In addition, as I systematically decreased the sample size, the overall results did not vary except that the smaller coefficients approached insignificance or became insignificant. When examining the unused data, the same phenomenon was present and the results were consistent.

There are other potentially important covariates that I have not addressed in this study. For example, I was not able to tap into any management-level data such as the propensity to innovate or other aspects of the hospitals, such as their decision-making model (e.g. centralized, decentralized, federal, etc.). I also cannot ascertain whether the effects of spatial proximity will be enduring over time. Finally, I believe there are important findings yet to be uncovered in this rich dataset. For example, a next step would be to investigate the timing of EMR adoption. Specifically, it would be valuable to know if the majority of the innovating originated first in large metropolitan areas and then diffused outward.

1.8 CONCLUSION

Technology innovations do not always diffuse rapidly even when the advantages are obvious (Rogers 1995, p. 10); e.g. the QWERTY keyboard (Dvorak 1936). Prior research also finds that rewards and sanctions in the form of government incentives or fines are not always effective in getting full conformance. For example, seat belt use in the USA is still below 80% even though penalties began to be enforced in 1996 ("Seat Belt Use Rate Up Since Mobilizations Began 2003). Prior epidemiological research suggests that there is ‘safety in numbers,’ also known as Herd Immunity (Gerstman 2003; Gordis 2000; Last 2001). If large, like-minded groups of potential adopters cluster together, the likelihood of resisting the event (disease or implementation) is greatly increased, especially if a large proportion of the members of the group are immune (Gordis 2000). If a large proportion of hospitals resist the spread, those who are undecided are likely to be influenced by those hospitals that they interact with the most and less likely to come into contact with those that would promote adoption. The converse of this is true as well, as the results of this study highlight.

EMR systems have not diffused rapidly. First implementations date back to the early 1970's, yet growth has been very slow and only recently has it increased (Bower 2005). Bates (2000) and England (2000) suggest several reasons for the slow diffusion ranging from lack of evidence showing the impact of EMRs, to providers' fragmented internal structure, to poor funding for research, to lack of demand from the healthcare industry, and finally to financial constraints. In order to rapidly accelerate diffusion, it is essential to increase social contagion factors that influence adoption decisions (Ford et al. 2006). This study yields important insights into what factors increase the likelihood of adoption of EMRs, which will not only be useful for practitioners, but will also offer researchers directions for future investigations.

1.9 FIGURES

Figure 1.1. Visual Representation of the Portion of Diffusion Curve Studied

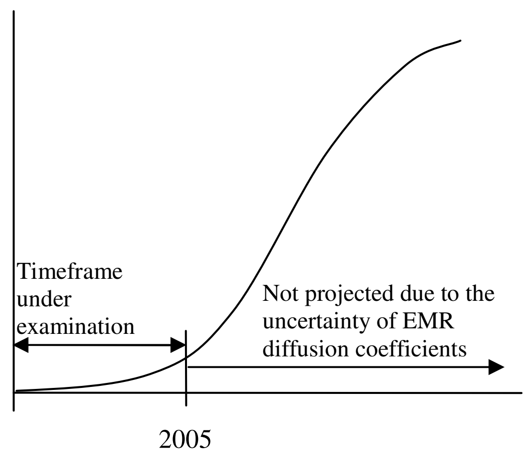


Figure 1.2. Conceptual Model – Antecedents of Likelihood of Adoption of EMR

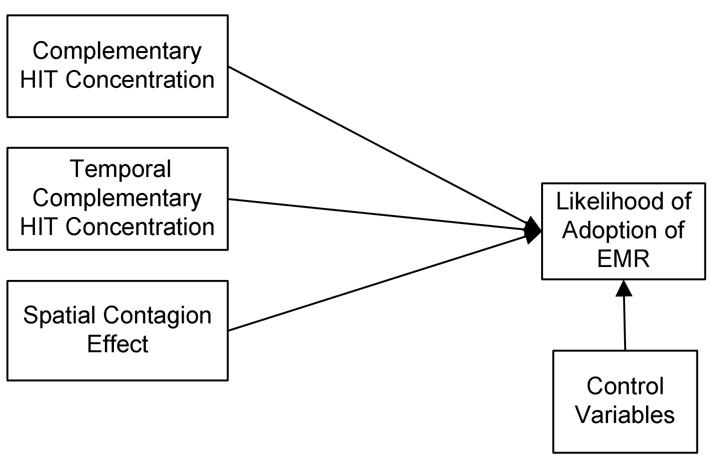
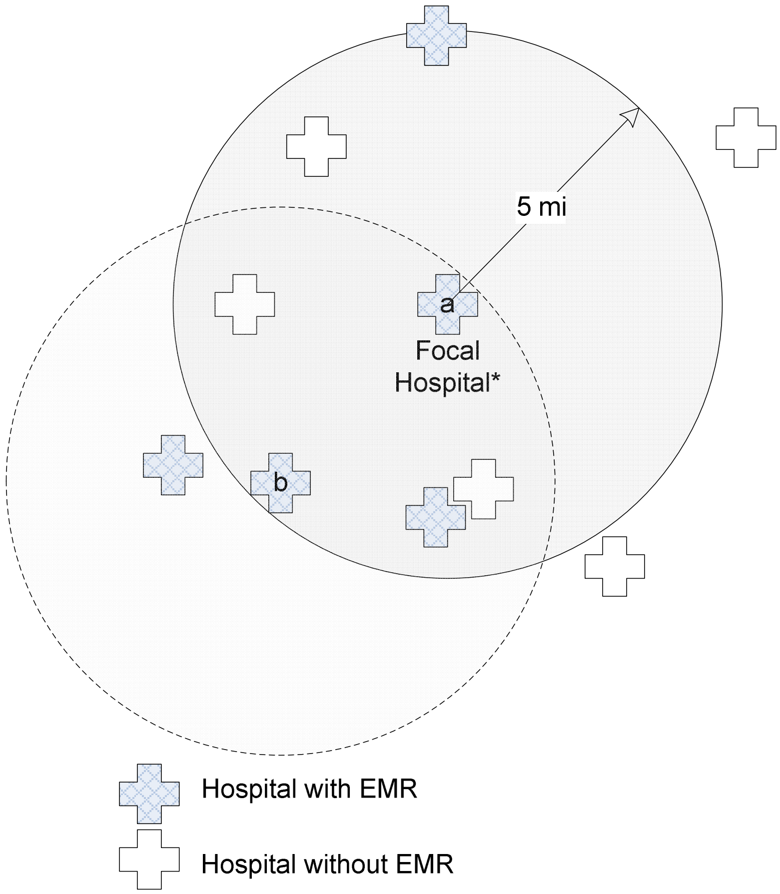
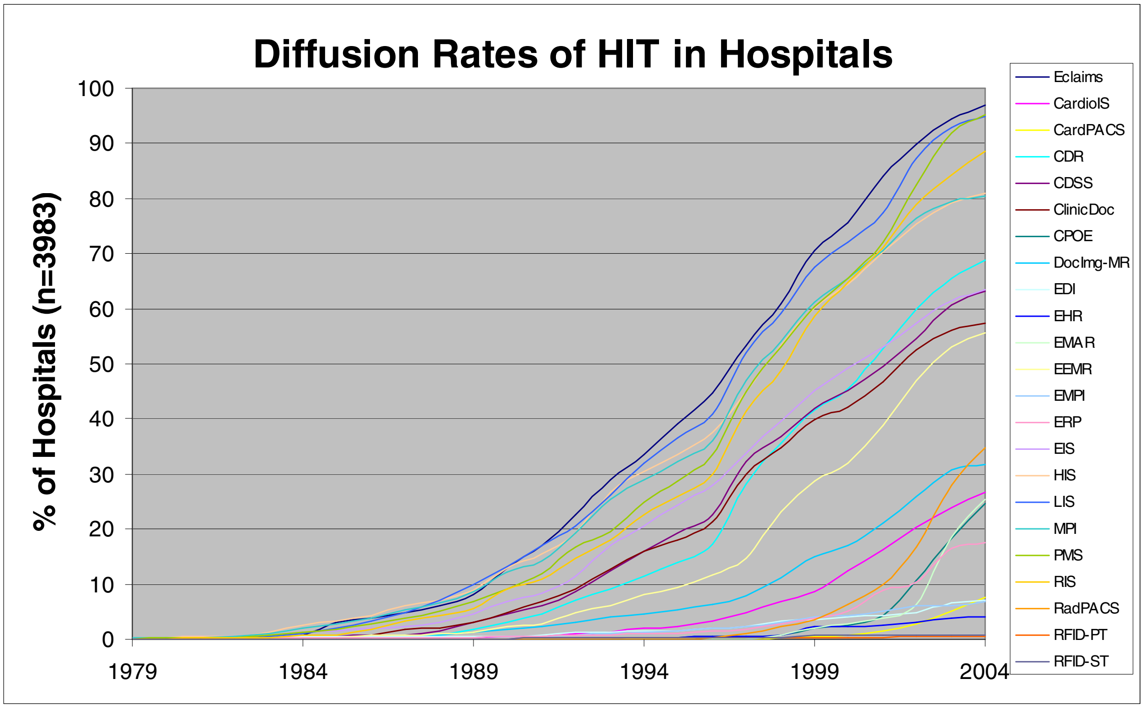


Figure 1.3. Hospital Count and EMR Count within 5-Mile Radius



Note: The EMR Count (n_5) for the focal hospital 'a' is 3, and the hospital count (m_5) is 6.
Assuming all hospitals within the darker gray area are in the same city, it is apparent that these hospitals can have markedly different values of (n) and (m). For example, as noted, hospital 'a' has values of n=3 and m=6, and hospital 'b' has values of 3 and 5, respectively.

Figure 1.4. Diffusion of Various Health Information Technologies



1.10 TABLES

Table 1.1. Epidemiological Metaphors for Informing EMR Diffusion

Item Description	Epidemiology	EMR Diffusion
Event	Presence of a disease	Presence of an EMR in hospital
Event Presence	Clinical Disease – Characterized by signs and symptoms.	Implementation – Characterized in our study as the year the EMR was contracted.
Modes of Transmission	Direct – person to person via direct contact Indirect – occurs through a vehicle such as a common water supply (Gordis 2000). Interaction between humans and environment (Gerstman 2003).	Internal – organizational innovativeness, word of mouth External – imitation, media (Bass 1969; Burt 1987; Greve 1998; Lekvall et al. 1973; Mahajan et al. 1990a)
Event Distribution	Not randomly distributed in a population. Humans have specific characteristics – genetic or environmental – that protect them from a variety of diseases (Gordis 2000).	Not randomly distributed in a population. Hospitals have specific characteristics – genetic or environmental – that predispose them to implementation.
Rapid and Extensive Event Distribution	Epidemic – Sometimes refers to the rapid and extensive spread of an infectious disease within a geographic region. More recently used to describe any disease or health-related condition that occurs in excess of normal expectancy (Gerstman 2003; Last 2001)	Rapid Diffusion – Occurs when social and technical factors align to create an environment conducive to growth (Rogers 1995).
Identifying Cause of Event	Epidemiologic Reasoning – Determining whether an association exists between a factor (environmental exposure) or a characteristic of a person and the development of the disease in question. However, if an association is found, it does not necessarily mean it is causal. The next step after association is to derive inferences about causal relationships from the associations (Gordis 2000).	Investigation of antecedents of EMR adoption.
Objective	Prevent or halt the diffusion of the event.	Promote and encourage the diffusion of the event.
Metrics	Attack Rate: $\hat{a}(t_{ij}) = \frac{n\ \ who\ develop\ disease_j}{n\ \ at\ risk_j}$	Hazard rate: $\hat{h}(t_{ij}) = \frac{n\ \ events_j}{n\ \ at\ risk_j}$

Table 1.2. Hospital Descriptive Data

Variable	Description	Count (% of Total)
Region*	1= Urban	2437 (61.1%)
	2= Other Urban	174 (4.4%)
	3= Large Rural Core	617 (15.5%)
	4= Other Large Rural	24 (0.6%)
	5=Small Rural Core	448 (11.2%)
	6= Other Small Rural	44 (1.1%)
	7= Isolated	238 (6.0%)
	Total	3989
	Range	Mean (Stdev)
Complementary HIT Concentration (CHITC)	4 – 52	34.43 (6.56)
Temporal CHITC (TCHITC)	0 – 803	224.16 (124.33)
Number of Staffed Beds (SIZE)	3 - 1757	183.31 (163.62)
Year Hospital Opened (AGE)	1818 - 2004	1975.63 (34.09)
No. of Hospitals with EMR within 5-mi Radius (CNT_5)	0 – 7	0.76 (1.49)
No. of Hospitals with EMR within 50-mi Radius (CNT_50)	0 – 68	12.56 (15.13)
No. of Hospitals with EMR within 100-mi Radius (CNT_100)	0 – 121	30.16 (26.87)
Adopted EMR (EMR_YES)		1,365 (34.2%)
For-Profit Hospital (PROFIT)		665 (16.7%)
Teaching/Research Hospital (TEACH)		334 (8.4%)

* Seven Category Rural Urban Commuting Area (RUCA) codes from the University of Washington Rural Health Research Center

Table 1.3. Results of Hazard Model Logistic Regression

Variable	Model 1	Model 2	Model 3	Model 4	Model 5
Y1975	-6.596 (0.223)	-6.626 (0.184)	-6.640 (0.181)	-6.631 (0.178)	-6.640 (0.171)
Y1980	-6.596 (0.223)	-6.626 (0.184)	-6.640 (0.181)	-6.631 (0.178)	-6.640 (0.171)
Y1985	-1.818 (0.000)	-1.960 (0.000)	-1.974 (0.000)	-1.992 (0.000)	-2.022 (0.000)
Y1990	-0.785 (0.011)	-0.864 (0.007)	-0.870 (0.007)	-0.885 (0.006)	-0.901 (0.006)
Y1995	0.386 (0.041)	0.430 (0.033)	0.432 (0.033)	0.442 (0.031)	0.452 (0.029)
Y2000	1.197 (0.000)	1.374 (0.000)	1.386 (0.000)	1.422 (0.000)	1.464 (0.000)
Y2004	1.571 (0.000)	1.828 (0.000)	1.846 (0.000)	1.895 (0.000)	1.961 (0.000)
SIZE	0.001 (0.018)	0.000 (0.058)	-0.001 (0.045)	-0.001 (0.024)	0.000 (0.188)
PROFIT	-0.039 (0.427)	-0.056 (0.727)	-0.267 (0.104)	-0.585 (0.001)	-0.668 (0.000)
AGE	-0.001 (0.000)	-0.006 (0.000)	-0.005 (0.000)	-0.005 (0.000)	-0.005 (0.000)
TEACHING HOSP	0.123 (0.310)	0.192 (0.113)	0.564 (0.000)	0.714 (0.000)	0.819 (0.000)
CHITC		0.190 (0.000)	0.186 (0.000)	0.179 (0.000)	0.185 (0.000)
TCHITC		0.005 (0.000)	0.006 (0.000)	0.006 (0.000)	0.006 (0.000)
EMR-Adopting Hospitals within 5-mi radius (CNT_5)					0.323 (0.000)
Total number of hospitals in 5-mi radius (HOSP_5)					-0.273 (0.000)
EMR-Adopting Hospitals within 50-mi radius (CNT_50)				0.122 (0.000)	0.091 (0.000)
Total number of hospitals in 50-mi radius (HOSP_50)				-0.041 (0.000)	-0.022 (0.000)
EMR-Adopting Hosp. within 100-mi radius (CNT_100)			0.007 (0.085)	-0.036 (0.000)	-0.025 (0.000)
Total number of hospitals in 100-mi radius (HOSP_100)			-0.010 (0.000)	0.006 (0.040)	-0.002 (0.444)
-2 Log likelihood	4941.3	4194.5	4148.5	4046.6	3902.1
Cox & Snell R^2	0.592	0.621	0.623	0.627	0.632
Nagelkerke R^2	0.790	0.829	0.831	0.836	0.843
ΔR^2		0.039	0.002	0.005	0.007

Table 1.4. City Rankings by Spatial EMR Adoption (25 Largest US Cities)

City, State	(a) # Hospitals in City	(b)* Mean # of Hosp with EMR within 5-mi Radius	(c) Standard Deviation of (b)	(d)** Standardized Mean # of Hospitals with EMR within 5-mile Radius	(e) Standard Deviation of (d)
Boston, MA	12	6.33	0.78	1.41	0.29
New York, NY	22	5.77	2.16	0.76	1.03
Philadelphia, PA	28	4.96	2.20	0.83	0.51
Baltimore, MD	15	4.40	1.99	1.81	1.09
Los Angeles, CA	24	4.33	1.86	0.89	0.65
Chicago, IL	36	4.03	2.25	0.72	0.58
Denver, CO	11	3.73	1.35	0.97	0.50
Seattle, WA	10	2.50	1.27	0.48	0.42
Houston, TX	30	2.43	2.22	0.36	0.62
Columbus, OH	9	2.11	1.90	0.57	0.87
Phoenix, AZ	14	1.93	1.38	0.25	0.47
San Antonio, TX	20	1.85	1.23	0.34	0.30
Dallas, TX	18	1.61	1.24	0.19	0.37
San Diego, CA	9	1.44	1.24	0.05	0.60
Indianapolis, IN	12	1.25	1.14	0.24	0.40
Austin, TX	8	1.25	0.89	0.07	0.29
Fort Worth, TX	12	1.08	0.90	-0.04	0.28
San Francisco, CA	10	0.90	0.57	-0.06	0.27
San Jose, CA	6	0.83	0.75	0.04	0.17
Charlotte, NC	6	0.83	0.98	0.00	0.34
Memphis, TN	10	0.80	0.63	-0.02	0.21
Jacksonville, FL	6	0.67	0.52	-0.04	0.14
El Paso, TX	6	0.67	0.52	-0.08	0.18
Milwaukee, WI	11	0.55	0.82	-0.39	0.39
Detroit, MI	9	0.00	0.00	-0.59	0.20

* Sorted in descending order by column (b)

** Column (d) is standardized by the number of hospitals in a city as shown below:

$$Z = \frac{X - \mu}{\sigma}$$

$X = Number\ of\ Hospitals$

$\mu = arithematic\ mean\ of\ distribution$

$\sigma = std.deviation\ of\ distribution$

Table 1.5. City Rankings by Spatial EMR Adoption (cities with 3 or more hospitals)

Rank by Mean (b)	City, State	(a) # Hospitals in City	(b) Mean # of Hospitals with EMR within 5-mi Radius	(c) Standard Deviation of (b)
1	Boston, MA	12	6.33	0.78
2	Jamaica, NY	3	6.33	0.58
3	Camden, NJ	3	6.00	0.00
4	New York, NY	22	5.77	2.16
5	Brooklyn, NY	18	5.72	1.71
6	Philadelphia, PA	28	4.96	2.20
7	Bronx, NY	11	4.91	1.64
8	Albuquerque, NM	11	4.45	2.02
9	Honolulu, HI	7	4.43	0.79
10	Baltimore, MD	15	4.40	1.99
11	Los Angeles, CA	24	4.33	1.86
12	Chicago, IL	36	4.03	2.25
13	Loma Linda, CA	3	4.00	0.00
14	Birmingham, AL	11	3.82	1.47
15	Denver, CO	11	3.73	1.35
16	Jersey City, NJ	3	3.67	2.08
17	Salt Lake City, UT	9	3.44	2.35
18	Lexington, KY	8	3.38	1.51
19	Washington, DC	8	3.38	1.51
20	Akron, OH	4	3.25	0.50
21	Grand Rapids, MI	5	3.20	0.45
22	Jackson, MS	6	3.17	0.41
23	Pittsburgh, PA	13	3.15	1.91
24	Portland, OR	8	3.13	1.64
25	Augusta, GA	5	3.00	0.00
….				
Lowest rank by Mean				
144	Detroit, MI	9	0.00	0.00
145	Rochester, NY	6	0.00	0.00
146	Fort Myers, FL	5	0.00	0.00
147	Ann Arbor, MI	4	0.00	0.00
148	Dayton, OH	4	0.00	0.00
149	Green Bay, WI	4	0.00	0.00
150	Lancaster, PA	4	0.00	0.00
151	Madison, WI	4	0.00	0.00
152	San Angelo, TX	4	0.00	0.00
153	West Palm Beach, FL	4	0.00	0.00
154	Wichita, KS	4	0.00	0.00
155	Coral Gables, FL	3	0.00	0.00
156	Edmond, OK	3	0.00	0.00
157	Greensboro, NC	3	0.00	0.00
158	Hialeah, FL	3	0.00	0.00
159	Huntsville, AL	3	0.00	0.00
160	Irving, TX	3	0.00	0.00

161	Johnson City, TN	3	0.00	0.00
162	La Jolla, CA	3	0.00	0.00
163	Lansing, MI	3	0.00	0.00
164	Lincoln, NE	3	0.00	0.00
165	Monroe, LA	3	0.00	0.00
166	Ocala, FL	3	0.00	0.00
167	Pontiac, MI	3	0.00	0.00
168	Saginaw, MI	3	0.00	0.00
169	Sioux Falls, SD	3	0.00	0.00
170	Springfield, MO	3	0.00	0.00
171	Wichita Falls, TX	3	0.00	0.00

Table 1.6. City Rankings *Standardized* Spatial EMR Adoption (3 or more hospitals)

Rank by Standardized Mean (d)	City, State	(a) # Hospitals in City	(d) Standardized Mean # of Hospitals with EMR within 5-mile Radius	(e) Standard Deviation of (d)
1	Jamaica, NY	3	2.41	0.06
2	Loma Linda, CA	3	2.21	0.00
3	Baltimore, MD	15	1.81	1.09
4	Honolulu, HI	7	1.74	0.47
5	Akron, OH	4	1.70	0.34
6	Albuquerque, NM	11	1.62	0.85
7	Winston-Salem, NC	4	1.53	0.00
8	Davenport, IA	3	1.53	0.68
9	Salt Lake City, UT	9	1.53	1.34
10	Boston, MA	12	1.41	0.29
11	Lexington, KY	8	1.36	0.86
12	Portland, OR	8	1.31	0.85
13	Grand Rapids, MI	5	1.27	0.28
14	Brooklyn, NY	18	1.24	0.59
15	Augusta, GA	5	1.23	0.17
16	Colorado Springs, CO	4	1.19	0.39
17	Camden, NJ	3	1.19	0.00
18	Jackson, MS	6	1.14	0.33
19	Birmingham, AL	11	1.02	0.48
20	Bronx, NY	11	0.97	0.51
21	Denver, CO	11	0.97	0.50
22	Washington, DC	8	0.92	0.53
23	Providence, RI	4	0.91	0.71
24	Los Angeles, CA	24	0.89	0.65
25	Alexandria, LA	3	0.85	0.00
….				
Lowest rank by Standardized Mean				
144	Monroe, LA	3	-0.23	0.06
145	Ann Arbor, MI	4	-0.25	0.10
146	Green Bay, WI	4	-0.25	0.10
147	Greensboro, NC	3	-0.30	0.00
148	Huntsville, AL	3	-0.30	0.00

149	Johnson City, TN	3	-0.30	0.00
150	La Jolla, CA	3	-0.30	0.00
151	Lansing, MI	3	-0.30	0.00
152	Lincoln, NE	3	-0.30	0.00
153	Ocala, FL	3	-0.30	0.00
154	Pontiac, MI	3	-0.30	0.00
155	Saginaw, MI	3	-0.30	0.00
156	Springfield, MO	3	-0.30	0.00
157	Wichita Falls, TX	3	-0.30	0.00
158	Miami, FL	12	-0.32	0.58
159	Dayton, OH	4	-0.33	0.10
160	Hialeah, FL	3	-0.33	0.06
161	Irving, TX	3	-0.33	0.06
162	San Angelo, TX	4	-0.35	0.06
163	Wichita, KS	4	-0.35	0.06
164	Milwaukee, WI	11	-0.39	0.39
165	Lancaster, PA	4	-0.40	0.00
166	Madison, WI	4	-0.40	0.00
167	Rochester, NY	6	-0.43	0.16
168	St. Louis, MO	16	-0.48	0.48
169	Newark, NJ	6	-0.49	0.56
170	Detroit, MI	9	-0.59	0.20
171	Coral Gables, FL	3	-1.03	0.12

Table 1.7. Geographic Dispersion of Hospitals

# hospitals relative to focal hospital	Hospitals with EMR within radius | Total No. of Hospitals within radius					
	5 mile radius		50 mile radius		100 mile radius	
0 hospitals	n_5=2725	m_5=653	n_{50}=362	m_{50}=29	n_{100}=80	m_{100}=11
1	563	1659	292	60	76	2
2	267	507	231	78	105	7
3	161	260	284	107	84	9
4	89	191	256	84	57	16
5	58	135	250	67	67	29
6	70	99	232	86	56	17
*7**	55	72	232	114	77	27
8	0	78	160	117	84	25
9	0	95	168	121	59	25
10	0	45	110	113	80	35
11	0	30	127	110	94	23
12	0	15	105	121	71	25
13	0	14	119	103	78	18
14	0	15	113	122	107	28
15-19	0	71	194	471	616	113
20-24	0	29	124	406	372	74
25-34	0	21	162	433	779	311
35-49	0	0	210	399	276	540
50-74	0	0	258	303	451	884
75-99	0	0	0	216	100	680
100-149	0	0	0	178	220	477
150-200	0	0	0	150	0	613
	3988	3989	3989	3989	3989	3989

*Note: The information in the table can be interpreted using the following example: There are 55 cases (focal hospitals) in the sample that have 7 hospitals with an EMR within a 5-mile radius. There are 72 cases (focal hospitals) in the sample that have 7 hospitals within a 5-mile radius, either with or without an EMR. In both cases, the focal hospital is not counted toward the totals.

ESSAY 2: ISOLATING THE EFFECTS OF IT ON PERFORMANCE: AN EMPIRICAL TEST OF COMPLEMENTARITIES AND LEARNING

2.1 ABSTRACT

Recent literature suggests that firms realize performance benefits through the possession of valuable and rare IT resources. An alternative knowledge-based perspective argues that firms which can more efficiently generate, transfer, and apply IT knowledge internally will outperform their rivals. In this study, I apply a knowledge-based lens to the examination of IT adoption and process-level value, incorporating the effects of the learning that occurs through complementary IT adoption. I build on prior work which acknowledges the importance of complementarities in IT-value research by proposing a knowledge-based operationalization. Using a rich historical IT implementation dataset of almost 400 nationally-representative hospitals in the US, matched with both quality and financial performance data, I examine a specialty IT application related to cardio care within hospitals and explore the condition-specific relationship to performance metrics. Of particular interest is the effect that complementarities in the form of IT infrastructure learning and patient management IT learning have on the relationship between cardiology IT and performance.

The use of detailed historical data allow for an operationalization of IT infrastructure that goes beyond basic counts of hardware, software, and personnel and represents a proxy for IT learning. Overall, results show that when a temporal learning component is introduced into the model as a complementary effect, the IT-Performance link becomes stronger, thus suggesting that it is unique knowledge and learning associated with more experience with the IT that creates superior performance and not

simply presence or absence of IT. From a pragmatic perspective, the findings suggest that although it is not feasible for a firm to increase the length of time it has possessed an IT resource, there is the possibility that knowledge stock can be accumulated through other means. These, along with theoretical contributions are discussed.

2.2 INTRODUCTION

A recent article by Jaan Sidorov (2006) argues that the use of the highly publicized and controversial electronic medical record (EMR; see Appendix A for a list of acronyms used in this article) system may not actually reduce health care costs. Sidorov courageously challenges conventional wisdom and observes that the EMR is not an information technology that will yield the much desired outcome of a reduction in the immense national expenditure on health care. Rather, he suggests that the value created by EMRs will be unanticipated, and perhaps indirect such as that gained through supporting patient-centric health care, disease management, and possibly as a mechanism for health care transformation (2006, p. 1083). Sidorov's assertions are supported by some recent empirical studies that illustrate that under certain circumstances, the use of health information technology (HIT) can result in unintended consequences and negative or inconclusive impacts (Garrido et al. 2005; Han et al. 2005; Koppel et al. 2005; Miller et al. 2005).

A robust body of research in information systems (IS) has examined the link between IT and multiple conceptualizations of value in different industries. One broad conclusion that emerges from this literature is that the process of value generation through IT involves several intermediate steps, and that distal connections between IT and value are tenuous. In the early to mid 1990s, a spirited debate waged amongst IS researchers, economists, practitioners regarding what came to be known as the 'productivity paradox,' (Brynjolfsson 1993; Brynjolfsson et al. 1996; Im et al. 2001; Lucas 1999; Pinsonneault et al. 1998). Researchers sought to demonstrate that there was measurable value in using IT, and more importantly, that it was not a negative effect. By the early 2000's, it became evident that some of the equivocal findings in early IT-value research were attributable to the methods employed (Brynjolfsson et al. 1996) and the attempt to make distal connections (Ray et al. 2004; Ray et al. 2005) such as the assertion that the presence of an EDI system increases firm profits. In other words, these studies underscored the need to relate IT investments and use to outcomes that are more proximal to the specific technology under investigation.

This paper focuses on the business value of health IT. Given the challenges confronting the health care sector and the pressing need to contain costs and improve service quality (*Crossing the Quality Chasm* 2001; Kohn et al. 2000), policy makers are increasingly turning to IT to alleviate some of the problems. In an attempt to appease eager policy makers and interested stakeholders, HIT researchers are rushing to draw connections between the adoption of HIT and distal outcomes such as reduced mortality rates. Building upon the cumulative findings from IT value research, I suggest that such relationships have to be theorized and empirically assessed with care. I draw from several streams of literature – including the knowledge-based view of the firm, complementarities, and organizational learning – to inform the topic of IT and value. I argue that the performance benefits of IT are enhanced when there is greater learning associated with not only the focal IT, but also with other IT including infrastructural IT. I propose that IT infrastructure learning acts in a complementary way in its effect on the

IT-value link. Finally, I model this relationship at the organizational process level as a means of isolating its effects.

Using cardiology information systems as the focal HIT, I test my hypotheses using a robust longitudinal dataset consisting of approximately 400 randomly selected hospitals in the US, matched to a second cross-sectional database of lagged performance metrics. I find a positive relationship between application-specific IT adoption and performance. More importantly, to the extent that increased years of experience with IT equate to additional process-level learning, the results suggest that learning associated with infrastructural and other application-specific IT accentuates the relationship between IT use and value. This is a striking finding and suggests the need for research in the IS domain to focus more on experiential factors associated with IT adoption and less upon simple counts of presence/absence.

Findings from this study also have important pragmatic implications. Empirical evidence establishing the business value of IT in the healthcare industry is sparse and business leaders are increasingly being called upon to demonstrate return on investment. Results from this study can be used to more fully elaborate the important mechanisms for achieving superior performance. Although it is not feasible for a firm to increase the length of time it has possessed and learned from an IT resource, there is the possibility that knowledge stock can be accumulated through other means. Even though IT implementations are but one mechanism for learning, certain aspects of this work can be generalized to other learning mechanisms such as new project initiatives and diversification.

The remainder of this paper is structured as follows. I first provide an overview of the core theoretical foundations for the study including the knowledge-based view of the firm, the business value of IT, and the notion of complementarities. This is followed by a discussion of the research model and the research hypotheses. In the methodology section, I present the study design, data collection, and analyses. Next I discuss the results and reflect on the key findings. I conclude with a discussion of implications for practice and theory.

2.3 THEORETICAL BACKGROUND

The theoretical foundations for this study draw from three streams of literature: the knowledge-based view of the firm that uses knowledge as the fundamental rationale for why firms exist, the literature on the business value of IT that contains a rich body of theoretical and empirical research relating investments in and use of IT to various outcomes, and research on complementarities that illustrates how the presence of synergistic factors accentuates the relationship between IT and business value. I briefly summarize relevant findings from these three literatures below.

The Knowledge-Based View of the Firm

Theories of the firm attempt to explain the emergence and existence of organizations as an alternative to market mechanisms for conducting transactions. Seeking theoretical explanations for the formation of firms has been an ongoing concern in the economics and strategy literatures, and the discourse has traditionally been multidisciplinary in nature. The existence of firms has been explained by the possession of valuable and rare resources (Barney 1991; Barney 1996), economic behavior (Foss 1996a; Foss 1996b; Oxley 1995; Williamson 1975; Williamson 1979; Williamson

1985), employment contracts (Coase 1937; Conner et al. 1996; Simon 1951), and the possession and utilization of knowledge (Kogut et al. 1992; Kogut et al. 1996).

Recent theories of the firm that have gained significant support for the study of a wide variety of organizational phenomena include the resource-based perspective (Bharadwaj 2000; Ray et al. 2004; Ray et al. 2005) and the knowledge-based view (Grant et al. 1995; Kogut et al. 1992; Kogut et al. 1996). While the resource-based perspective posits that the competitive advantage of firms accrues as a result of heterogeneously distributed rare, valuable, and inimitable resources, the knowledge-based view (KBV) of the firm suggests that knowledge is the most valuable resource possessed by firms. As Ray and colleagues (2004, p. 26) note, "resources can only be a source of competitive advantage if they are used to 'do something.'" In this view, firms exists because of the inherent complexities associated with the generation, transfer, and application of knowledge via market mechanisms (Barney 1991; Conner et al. 1996; Grant 1996; Grant et al. 1995; Kogut et al. 1996). It associates the competitive advantage of firms with their ability to create, store, and apply knowledge (Grant et al. 1995; Kogut et al. 1992; Kogut et al. 1996). Indeed, Kogut et al. (1996, p. 503) note that 'a firm can be understood as a social community specializing in the speed and efficiency of creation and transfer of knowledge.'

I use the KBV as the foundation for this study because health care organizations are, arguably, fundamentally knowledge-based. Many have observed that the delivery of health care services is more appropriately characterized as an art (non-codified processes) than a science (codified processes; Eddy 2005; Mendelson et al. 2005), and that not enough has been done to convert the tacit knowledge to process and procedures, which make it useful for others (Kogut et al. 1996). Hospitals are unique because on the one hand, they are a collection of 'free-agents' in that although most doctors utilize the services of the hospital, they are not exclusively tied to that facility as employees. On the other hand, hospitals also employ a large number of knowledge workers, including nurses, technicians, and other clinicians. Between the active employees and the free agents, few would disagree that hospitals are social communities rich in knowledge. With roots in varied research streams such as epistemology, organizational learning, and the resource-based view of the firm (Grant et al. 1995), the knowledge-based view incorporates elements of valuable and rare resources, learning, and organizational capabilities.

Learning processes are a fundamental element of the KBV (Kaplan et al. 2001; Levitt et al. 1988; March et al. 1958). Knowledge exists within firms in the form of a stock, but it is not static or unchanging. Firms update and refresh existing knowledge, acquire new knowledge, forget knowledge (Leonard-Barton 1992) and willfully destroy knowledge (Kaplan et al. 2001) that is no longer relevant through a series of learning processes (Nelson et al. 1982). Learning occurs in the day-to-day activities, processes, organizational routines, and the decisions of organizational actors that modify and extend this knowledge stock (Cyert et al. 1992). It has been suggested that the performance of firms is closely related to the quality of the learning that occurs and the integration of this knowledge into work processes (Grant 1996; Grant et al. 2000; Pavlou et al. 2005). Finally, scholars contend that prior experience with IT provides a mechanism for organizational learning (Woiceshyn 2000) but only to the extent that its use is codified in standard operating procedures, toolkits, or manuals (von Hippel 1994).

Business Value

The business value of information technology (IT) literature argues that the use and management of IT can yield competitive advantage (Mata et al. 1995) and can influence the performance of a firm (Barua et al. 2000). In this context, a robust body of literature has examined the relationship between firm performance and IT investments (Bakos et al. 1992; Barua et al. 1991; Barua et al. 1995; Brynjolfsson et al. 1996; Lucas 1993; Lucas 1999), types of IT applications (Barua et al. 1997; Lucas et al. 1999; Mukhopadhyay et al. 1995), the role of co-specialized assets (Dos Santos et al. 1995; Duliba et al. 2001), organizational complementarities (Davern et al. 2000), IT capabilities (Bharadwaj 2000; Mata et al. 1995; Sambamurthy et al. 1999), and the indirect influence of IT (Chen et al. 2004; Kauffman et al. 1989; McKeen et al. 1993).

One important insight that emerges from research in the business value of IT is that although studies have found a positive relationship between IT investments and various measures of firm performance, the effects of IT are best isolated and measured at a process-level of analysis rather than at the macro firm level. The logic for focusing on processes is predicated on the observation that IT is typically deployed to serve a specific function (often, within specific departments) and an outcome metric associated with this function is most representative of reality (Aral et al. 2006a; Barua et al. 1995; Ray et al. 2004; Tallon et al. 2000). For example, Ray et al. (2005) found that customer service IT positively influence customer service quality when coupled with firm-specific resources. Likewise, Banker and colleagues (2006) found that manufacturing capabilities mediate the impact of information systems on plant performance.

A second important insight from the business value of IT literature is that the same system can yield different outcomes in differing contexts. To the extent that IT systems are introduced into organizational environments of considerable heterogeneity, variations in performance will likely result (Byrd et al. 1996). For instance, Krumbholz and Maiden (2001) found that a firm's culture affects ERP implementation success. Brynjolfsson and Hitt (2000) noted that an IT system does not yield value in and of itself but rather, distinct benefits result when IT systems are coupled with complementary technologies and reinforcing organizational changes (Milgrom et al. 1990). And finally, Ray et al. (2005) contend that the context in which an IT is adopted is more important than the IT itself, relative to performance benefits.

IT Adoption as an Opportunity to Learn

As noted earlier, organizational learning is a fundamental component of the knowledge-based view of firms. The term organizational learning (OL) began appearing in literature in the early 1960's (e.g., Cyert et al. 1963) and has generated a robust body of research in the past four decades. Huber (1991) subdivides OL into four components: knowledge acquisition, information distribution, information interpretation, and storing and retrieving information to/from organizational memory. More recently, these components have been combined into a more succinct definition that conceptualizes OL as "the process of creating, transferring, and institutionalizing knowledge that drives competitive advantage" (Snell et al. 1996). Thus, learning is valuable because it has a positive influence on performance. Indeed, the relationship between organizational learning and performance has been documented, both theoretically and empirically, in an extensive body of literature (see Table 2.1).

Insert Table 2.1 about here

Arguably, organizations learn – through changes in individual learning – when their structure, business processes, and/or rules change (Argyris et al. 1996; Cyert et al. 1992; Holmqvist 1999; Polanyi 1966) and an action outcome occurs (Crossan et al. 1999; Dodgson 1993). To the degree that the use of IS constitutes an organizational routine (March et al. 1988) because it includes forms, rules, procedures, conventions, strategies, and technologies around which organizations are constructed and through which they operate (Levitt et al. 1988, p. 320), one important mechanism for instituting learning is the adoption and implementation of new information system (Woiceshyn 2000).

The implementation of systems constitutes a decision making process in which intentional learning results from reacting and responding to feedback received from constituents (Huber 1991). The feedback arises from users and stakeholders after the systems have been put into service. This intentional learning process has been described in prior literature as "successive limited comparisons," (Lindblom 1959), and it involves *proposing* movement to some condition or position other than the present undesirable condition or position, and obtaining feedback from those affected by the proposed movement. If implementing a new information system creates operational disruptions and changes workflows (e.g., Adner 2002), then organizational learning is likely to occur under these conditions. Despite its importance to organizational performance, surprisingly, the importance of IT learning has only recently been incorporated into models of IT value (Pavlou et al. 2005). In this paper I redress this important gap in the literature.

Complementarities

Prior literature argues that there is a performance benefit when complementary resources are coupled (e.g., Barney 1992). For example, Song et al. (2005) found that complementarities between technology and marketing related capabilities positively influence joint venture performance. Scholars have noted that even if a resource itself is valuable, rare, and inimitable, it may not result in a competitive advantage unless it is bundled with complementary resources (Amit et al. 1993; Barney 1992; Teece et al. 1997). Particularly when resources are tacit, socially complex, or cognitively challenging, bundling has been demonstrated to be more effective (Barney 1992; Coff 1997; Penrose 1959) than deploying a resource in isolation. In the case of organizational IS implementations, which are known to be highly complex and disruptive, research has shown that the presence of similar or supportive information technologies is beneficial for more comprehensive appropriation (Bucklin et al. 1993; Mitropoulos et al. 2000; Nambisan 2002; Zhu 2004). For example, the adoption of an electronic medical record system may yield significantly greater returns if an infrastructure technology such as enterprise-wide wireless connectivity is already implemented. In this case, the presence of the wireless system makes the EMR more valuable and at the same time increases the importance of the wireless system; thus generating a complementarity (Wernerfelt 1984).

Summary

Establishing the business value of information technology is an enduring question that has challenged both IT researchers and practitioners for decades. Enough evidence now exists to conclude that IT impacts are more accurately modeled and observed at the process level of analysis. To the extent that health care delivery organizations are heterogeneous in not only the systems they adopt, but also the internal makeup of the organization, it is expected that considerable variation will exist in the performance realized through IT adoption. Finally, research suggests that an organization's prior experience with IT generates an opportunity for organizational learning, and the presence of complementary technologies can enhance the IT-performance link.

2.4 RESEARCH MODEL AND HYPOTHESES

Drawing upon the theoretical foundations described above, I propose the research model shown in Figure 2.1 in which the adoption of an application-specific IS directly influences application-specific performance. The focal IS in this model is a system known as a cardiology information system (CIS). The CIS is deployed exclusively for cardiac care and is used by cardiologists, nurses, technicians, and administrative personnel to automate functions in the cardiology department. A robust CIS can manage functions as disparate as maintaining and indexing images and other clinical data to providing reminders for medication administration.

Insert Figure 2.1 about here

In addition to the direct relationship proposed in the model, I posit the existence of complementarities that enhance the IT-performance link. I further argue that this effect is influenced by the learning that takes place through IT implementations over time. These complementarities, as I define them, consist of other information technologies that are heterogeneously distributed among hospitals, and the length of time for which the hospitals have had the systems in place. Each of the constructs and relationships is further elaborated upon below.

Conceptualizing Performance

The traditional information systems' literature most often uses some form of financial outcome to operationalize firm performance. For example, some of the more novel methods employed are the use of Tobin's q, which assess a firm's future value (Bharadwaj et al. 1999); the use of real options, which considers the value of waiting to invest (Benaroch et al. 1999); and financial market share (Dos Santos et al. 1995). More traditional financial metrics operationalize value either as a reduction in cost or a growth of revenue (Mithas et al. 2006); however, the relationship of such outcomes to IT investments has been tenuous (Hitt et al. 1996; Rai et al. 1997). Firm profits have not traditionally been used as a proxy for performance or at least two reasons. First, prior research suggests that there is a tradeoff between cost reductions and revenue growth (Rust et al. 2002b), which ultimately impacts profits; and second, extensive challenges exist in isolating effects of IT use when taking into account all of the covariates that exist at the firm level (Brynjolfsson 1993).

In the healthcare domain specifically, other challenges emerge which preclude the use of profits as a dependent variable. More than 75 percent of the hospitals are not-for-profit, thus profit maximization may not be a management objective. Irrespective of the industry under investigation, operating costs at the process level may provide a more precise operationalization of performance simply because there are less covariates which could potentially confound the results.

Beyond financial measures, quality outcomes constitute a key performance metric in the healthcare domain (e.g., McGlynn et al. 2003). Quality of care is defined as "the degree to which actions taken or not taken maximize the probability of beneficial health outcomes and minimize risk and other untoward outcome, given the existing state of medical science and art," (Quality of Care 2006). Prior research has shown that IT use in hospitals can impact quality of care delivered. For example, in one study, error rates were reduced by 55 percent (Bates et al. 1998) when computerized practitioner order entry (CPOE) systems that reminded clinicians to follow a protocol of care were used. In another study, the use of a CPOE system was credited with reducing errors of omission and improving adherence by reminding clinicians to order the recommended tests and treatments, resulting in a 24.4 percent improvement over a control group (Overhage et al. 1997).

IT Adoption, Learning, and Performance

As argued earlier, the introduction of an information system that is specifically designed to assist with a specific procedure or process should generate condition-specific learning and result in condition-specific performance benefits. To the degree that learning is a complex, knowledge-based activity that takes time to unfold, the greater an actor's experience with a specific IT, the more opportunities the actor has to learn from it and the higher the expected performance benefits. Thus, drawing from the resource-based perspective that treats an IT system as a resource, and the KBV that argues for the importance of learning in improving performance, I formalize these expectations in the following proposition:

P1: Implementation of an application-specific IS (Cardiology IS - CIS) will influence application-specific performance (Cardiology performance),

> especially when this resource is coupled with organizational learning about IT.

I treat the length of time an organization has possessed an IT resource as its "window of learning opportunity." As discussed earlier, prior work has demonstrated that there is a link between IT use and cost reductions. Specifically in the context of healthcare, some research has shown that use of IT can result in reduced length-of-stay, lowered patient charges, and reduced hospital costs (Tierney et al. 1993). The primary drivers of these benefits are attributable to efficiency gains in work process flow, information retrieval, and scheduling (Chin 1998; Hillestad et al. 2005; Tierney et al. 1993). To the extent that more experience results in the use of more features of the technology, greater understanding of its benefits, and more efficient operation, I argue that greater performance impacts will result and operationalize this proposition in the following hypotheses:

> H1a: Earlier adoption of a CIS will be positively associated with a reduction in cardiology *cost* outcomes (i.e. the more years of experience with the CIS, the lower the cost).

Prior research has not explicitly examined *experience* with IT as a predictor of quality performance – with the exception that some work has show that there can be a short-term detrimental learning effect (Hunt et al. 1998). Under the assumption that automated procedures will enhance data accuracy and quality and help overcome clinicians, nurses, and other health care workers' bounded rationality, the effect of system presence on quality should be positive. However, to the extent that more experience translates into greater learning about the features and capabilities of the system and results in expanded use, possessing the system longer intensify its effect on quality. I test this in the following hypothesis:

> H1b: Earlier adoption of a CIS will be positively associated with an improvement in cardiology *quality* outcomes (i.e. the more years of experience with the CIS, the greater the quality).

IT Complementarities

It has been suggested that information technology is a commodity, but that value can be derived from firm-specific implementations to solve business problems (e.g., Powell et al. 1997). Earlier, I argued that the implementation and use of IS results in organizational learning. Researchers suggest that learning occurs in two ways – by integrating diverse knowledge and by building upon related knowledge (Kaplan et al. 2001). Thus, too much diversity will dilute the knowledge stock and prevent knowledge transfer from one implementation to the next (Levitt et al. 1988). Too much uniformity will decrease absorptive capacity and hinder innovation (Cohen et al. 1990; Jansen 2005; Levitt et al. 1988). As Levitt and March (1988, p. 333) note, "Ordinary learning tends to lead to stability in routines, [which] extinguish[es] the experimentation that is required to make a learning process effective." However, IT is multi-faceted and many different types of instantiations exist. To the extent that an IS is purely administrative and task-oriented, it may yield significantly less learning than one that is rich in information and requires cognitive effort to yield value (Levitt et al. 1988). Thus, different types of IS are likely to have different effects on the relationship between application-specific technology and application-specific performance, i.e. as I argue below, the relationship between application-specific performance and application-specific IT use is moderated by the use of complementary IT.

Classifying HIT. Nenonen et al. (2002) propose that hospital systems can be classified as either clinical systems or administrative/statistical systems. Although this classification is reasonably comprehensive, one shortcoming is that it does not incorporate the patient management systems such as electronic medical records and cardiology information systems. These systems were likely not included in the original classification because prior to 2002, they were not widely discussed in the published literature. Nenonen and colleagues do acknowledge the importance of clinical databases and electronic patient indices, however, the link between the clinical and business system that patient management systems such as EMRs often provide is absent.

Weill's (1992) work suggests that IT is often adopted in order to fulfill management objectives such as transactional, informational, and strategic. Menon et al. (2006) adopt this taxonomy and disaggregate health IT into IT investments by management objective. In table 2.2, using Menon's classification, I provide *HIT Categories* and identify the applications which make up the categories. The hospital systems are categorized as 1) transactional IT, 2) administrative IT, 3) communication IT, and 4) patient management IT (see Table 2.2).

Insert Table 2.2 near here

Classification by management objective is a well-documented and accepted means of categorizing information systems and has been used extensively in other industries (Laudon et al. 2004; Weill 1992). Yet, from a *functional* standpoint (O'Brien 2002), while transactional, communication, and administrative IT serve different management objectives, they all support the *infrastructural* needs of a facility. IT infrastructure has been defined as the physical facilities, IT hardware, software, IT services, IT personnel, and data processing within an organization (Broadbent et al. 1999; O'Brien 2002; Rainer et al. 2007; Zhu 2004). Not surprisingly, prior research has shown that the presence of existing IT infrastructure complements the value that can be realized from future IS implementations (Zhu 2004). This value is reflected in the system classifications and the complementarities between them. For example, a *transactional* IT (TrIT) system is primarily used to improve productivity through automation (Menon et al. 2006). These systems are adopted in an effort to gain efficiencies in data storage, retrieval, and reporting, or for planning and forecasting. They are typically utilized for task-based processes and often used by line operators, technicians, and clerical workers to perform such functions as accounting, clinical procedures, inventory control, and human resources. The data generated from transactional systems feeds into administrative systems.

An *administrative* IT (AIT) system provides information in the form of analytics and reports to middle level managers with the goal of reducing costs and/or increasing yield (Menon et al. 2006). Most decision support systems (DSS) would be classified as administrative systems as would utilization review and risk management systems (Rosow et al. 2003). The AIT systems rely extensively on the data captured in transactional systems to provide information for such things as management dashboards, which present graphical and tabular information to managers for decision making purposes (Rosow et al. 2003). The presence of AIT systems suggests that the hospital has processes in place to extract greater value from digital data through the application of decision support features.

Finally, a *communication* IT (CIT) is primarily used for conveying messages between individuals, both internal and external to the firm (Menon et al. 2006). As noted in table 2.2, communication technologies include applications such as e-mail, Intranet portals, and other highly ubiquitous technologies including the telephone, facsimile, and computer networks. More advanced technologies such as customer relationship management systems (CRM) are also included in this category because the service they provide is essentially one of streamlining communication. Those technologies which are found in every hospital in the US such as telephones and fax machines were not included in this analysis.

Indirectly, Broadbent and colleagues (1999, p. 163) suggested that infrastructure was in fact, more services-based than technology-based. Building on their study, I classify AIT, TrIT, and CIT as belonging to the infrastructure category. I find that their twenty-three 'Prototypical Firm-Wide IT Infrastructure Services' (Broadbent et al. 1999, p. 170) map closely upon Menon's et al.'s classifications (2006). Specifically, Broadbent et al. identify communication network services, messaging services, executive information systems, data management services, and others as components of IT infrastructure.

The core proposition of this research is that learning associated with these infrastructure technologies has a complementary effect on the process-level link between IT and value. There are four reasons why this is likely to be true. First, research finds that prior computer-based skills (Compeau et al. 1995a; Johnson et al. 2000) and beliefs about computer self-efficacy (Agarwal et al. 2000; Bandura 1986; Compeau et al. 1995a; Compeau et al. 1995b; Compeau et al. 1999) will transfer from one application to another, suggesting that users who have experience with other IT will be more efficient in their use of the CIS. Second, based on my interviews with CIS users and reviews of manufacturers' literature, it is apparent that more value can be derived from the CIS when it draws data from other information systems within the hospital. One simple example of this is the cross-population of patient admittance and discharge records. If the CIS is already fully populated with the patient's admittance data, this eliminates the need for re-entry of data which can result in errors.

A third explanation for why the presence of infrastructural IT enhances the value derived from CIS is related to management decision-making. Data generated by the CIS can be processed and responded to from the management level in a way that effectively allocates time to value-enhancing activities. If the CIS operated in isolation with no links to other IT, it can be assumed that actions would be taken to maximize the effectiveness of the CIS unit at the expense of broader goals. In much the same way, data from the infrastructural IT's can populate the CIS. Therefore, when decision support is coupled with the benefits of CIS use, the effect will be amplified.

Finally, the learning associated with a communications IT system should also complement the relationship between the CIS and value. Conceivably, the use of customer relationship management – whether it is in the form of email, patient-portals, or direct marketing – should generate relationship capital (Dyer et al. 1998; Sambamurthy et al. 2003) between patients and the hospital. Others have suggested that a strong interface between customer-facing applications and backend infrastructure reduce time and distance constraints (Smith et al. 2000; Zhu et al. 2002). However, one would not expect to find a direct link between process/department-level performance and communications IT use because of the distal connection and variations in use of IT at the process-level (i.e. as previously argued, application-specific IT use is most closely associated with application-specific performance). In fact, I contend that the benefits of customer relationships must act in a complementary, rather than direct way. Therefore, to the extent that learning associated with CIT use generates firm-level relationship capital and this translates into increased patient retention, the trickle-down effect should persist at the process level and enhance the relationship between IT and value. Based on these arguments, I expect the relationship between CIS learning and CIS performance to be complementary and positive and test the following hypotheses:

H2a: Infrastructural IT learning enhances the relationship between CIS learning and CIS *Financial* Performance

H2b: Infrastructural IT learning enhances the relationship between CIS learning and CIS *Quality* Performance

Patient Management IT. Of particular interest in this study is the *patient management* IT (PMIT) system. Both the EMR and CIS would be classified as PMIT systems under Menon's categorization. PMIT systems are used for, or are directly related to, treating patients and/or managing their care. In many cases, the utilization of the system takes place in the presence of the patient. However, there are other applications that fit into the PMIT category that are used 'behind-the-scenes,' such as those that support the value chain in departments including medical records, central administration, and the pharmacy.

Menon et al. (2006) argue that PMIT reduces costs in the short term – although this was not supported in their results. Their logic was that a direct relationship existed between the adoption of PMIT and performance. In contrast, while acknowledging the possible existence of a direct relationship, I posit that only *application-specific* PMIT will directly influence application-specific performance. In fact, my contention is that the moderating relationship between PMIT learning and IT-value is more nuanced than the infrastructural IT learning relationship described above, and may lead to offsetting effects. For example, there is very limited evidence in the health IT domain demonstrating a discernible link between adoption and financial value (Hillestad et al. 2005; Taylor et al. 2005) and results are mixed (Johnston et al. 2003; Poon et al. 2004). The adoption of complementary PMIT in the short-term may diminish the effect of CIS learning on financial performance due to the disruptions in workflow and business processes that are known to take place when PMIT systems are adopted (Als 1997; Greatbatch et al. 1995; Ventres et al. 2006; Warshawsky et al. 1994) – although a specific cardiology practice found this not to be the case ("Cardiology Practice and EMR Workflow" 2001). A second reason for a negative short-term return is that some research has shown that the financial benefits of PMIT adoption do not accrue to hospitals, but instead to payers or others (Doolan et al. 2002; Johnston et al. 2003). Because my study focuses on learning, I argue that increased understanding of PMIT use will be beneficial to the CIS-performance link. If PMIT were operationalized simply as a dichotomous variable (yes/no), one would not be able to isolate this learning effect, which may result in spurious conclusions. Framing this using a knowledge-based lens, I maintain that the learning associated with the use of a properly designed PMIT will enhance the learning associated with CIS use. For example, PMIT use – such as EMR and CPOE use – has been shown to reduce redundant tests and other duplications and lead to a reduction in errors (Bates 2000; Bates et al. 2004; Bates et al. 2003; Bates et al. 1999; Overhage et al. 1997), with the caveat that some recent research suggests otherwise (Ash et al. 2004; Koppel et al. 2005). To the extent that the CIS interfaces with the EMR and other PMIT, it is reasonable to assume that accurate information in one system will translate and transmit into the other and that more experience with these systems will equate to richer and more complete data. For example, reminders may be set in an EMR system such that nurses are prompted to give all patients who are admitted with a cardiac-related issue an aspirin. Therefore, I expect the existence of a complementary relationship between PMIT learning and CIS learning such that PMIT learning will positively enhance the relationship to performance, and test:

H3a: Patient Management IT learning enhances the relationship between CIS learning and CIS *Financial* Performance

H3b: Patient Management IT learning enhances the relationship between CIS learning and CIS *Quality* Performance

To summarize the research model, building upon prior research I have identified the existence of several types of IT in hospitals, one of which (CIS) is theorized to directly impact performance (cardio cost and quality) through the learning associated with its use, while others enhance this relationship through a complementary learning role. The role that application-specific IT fulfills is one of making it possible to execute a specific process better. This differs from infrastructural IT which provides the mechanisms for how work gets done. I argue that different kinds of learning result from each and that a more complex, enriched learning process takes place when interfacing with application-specific IT.

2.5 METHODOLOGY

Cardiology Information Systems

HIMSS Analytics defines the HIT under investigation in this study – the cardiology[4] information system (CIS) – as

> "An application that specifically automates functions in the cardiology department. The application must provide some of the following: order processing, permanent patient history index maintenance, image and EKG tracing storage, transcribing and distributing results, clinical documentation, prep instruction cards maintenance, appointment scheduling, and management reporting."

The CIS is diffusing quite rapidly across the US and is following the diffusion trajectory set by the EMR, a widely-discussed HIT, quite closely (see Figure 2.2). It is used exclusively for a specific subset of patients who require some form of cardiac care. The systems themselves are rare, with less than a 30% adoption rate. They are also valuable: a review of pricing for some commonly used CIS applications, manufactured by well-known firms such as GE, McKesson, and Siemens suggests that a CIS equipped with standard features will retail for approximately one million dollars for a 200- to 500-bed hospital. However, this cost is small considering that by some estimates more than 400,000 new heart failure cases are diagnosed each year with 39,000 of those resulting in death (Heart Failure 2006). It is estimated that expenditures for heart failure, which accounts for five million U.S. hospital days each year, are between $10 and $25 billion annually (Heart Failure 2006).

Insert Figure 2.2 near here
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[4] The study of the heart and blood vessels and related disorders and treatments – http://heart.kumu.org/hhglossary.html

Because information systems are oftentimes envisioned in different ways at the practice level, I interviewed several doctors[5] and asked them how they conceptualized a CIS. Interestingly, most of them defined the CIS relative to the EMR. The consensus was that in many ways, the EMR and the CIS were similar, but the primary difference revolved around the specific features of a CIS which are used to capture, store, and retrieve complex cardiac imaging, which includes: echocardiography, electrocardiography, catherization imaging, stress test imaging, along with pertinent periprocedural and hemodynamic data (e.g., vital signs, timing, use of materials, dye injection/medication administration, etc.). One interviewee stated, "[A CIS] probably is much more data intense than most text-based EMRs, but similar in complexity to a Radiology PACS." Also of note, the doctors suggested that some of the complexity inherent in the CIS is a result of the multitude of personnel who use it. For example, they noted that technicians collect data from procedures performed by physicians, such as data from real-time catherizations, and then input this information through a laboratory interface. Registered nurses and other clinicians interface with the CIS, both from a data entry and access standpoint and through their responses to reminders for medication administration and patient safety. Finally, there are others who retrieve data after the procedure, such as other physicians requesting tests or general patient information.

Finally, it is not clear from the literature and interviews whether a Cardiology Picture Archiving and Communication System (CPACS; see Appendix A2 for a list of

[5] Interviews conducted with the Director, Cardiothoracic Anesthesiology, large mid-Atlantic university medical school; Cardiologist, Director Healthcare Informatics, large pharmaceutical company; Chief Medical Information Officer, large mid-Atlantic health system

HIT acronyms) is typically included as a primary component of the CIS. In the data set used for this study, the CPACS is a separate component and in fact, has diffused at a much slower rate than the CIS. Therefore, while there are some elements of a CPACS described in the definition I provide for the CIS, I assumed that it was not mandatory for a hospital to adopt a CPACS to have adopted a CIS.

The Sample

The data for this study come from a nationwide, annual survey of hospitals in the USA, conducted by HIMSS Analytics™. The 2004-2005 HIMSS Analytics Database (derived from the Dorenfest IHDS+ Database™) provides detailed information for almost 4,000 of the roughly 6,000 hospitals in the US, using statistics from the year 2004. The HIMSS Analytics data includes information on the types of information systems used by hospitals, the year in which the systems were deployed, and the vendor who provided the system. I match this data to performance metrics for each hospital. The research sample consists of a longitudinal dataset consisting of 388 randomly selected (through random number generation) hospitals in the US, matched to a second cross-sectional database of lagged performance metrics[6]. This random selection closely mirrors the full population of US hospitals. In table 2.3, I report descriptive statistics for both the random sample and the total population of hospitals in the US and compare the two for statistical significance using a 2-tailed t-test. In all cases, the random sample was not significantly different than the US population of hospitals. Finally, I was able to obtain complete performance data from publicly available data sources. Assuming the

[6] The American Hospital Directory (AHD) was one source for the performance metrics. AHD provides online data for over 6,000 hospitals. Their database of information about hospitals is built from both public and private sources including Medicare claims data (MedPAR and OPPS), hospital cost reports, and other files obtained from the federal Centers for Medicare and Medicaid Services (CMS).

total population of hospitals to be 6,000 and response distribution of 50%, results from my sample represent a **5% margin of error with a 95% confidence level.**

Insert Table 2.3 about here

Variable Operationalization

Application-Specific Performance. To account for the temporal nature of the relationships in the IT-value link (Goh et al. 2005; Im et al. 2001; Menon et al. 2006), I use lagged performance indicators. Performance metrics are assessed for each hospital at the completion of the federal government's fiscal year 2005[7]. The data I use related to IT learning was collected during the calendar year 2004. Because the HIMSS Analytics data is collected on a rolling basis and each case does not specify the date of survey completion, the lag between each hospital's adoption data and performance data is between 9 months and 21 months. The IT adoption data extends back to 1970 with the earliest year of adoption for the CIS being 1987 and the earliest of any IT's used in this analysis being 1975.

<u>Financial Performance.</u> I use an objective measure of financial performance commonly used to assess hospital outcomes related to costs. This metric – *case mix adjusted cost* – takes into account the variations in types of procedures conducted by hospitals. For example, a head-to-head comparison of a surgical hospital versus a general medicine facility would not be possible if the case mixes were not normalized since surgical procedures are far more expensive than most general medical treatments.

[7] The US Federal Government fiscal year runs from August 1 to September 30.

The CMI Adjusted Average Cost[8] is the case mix adjusted average cost divided by the case mix index. Since medical service categories are based on groupings of patient Diagnosis Related Groups (DRG)[9], the average value reported for a DRG is the total allocated cost divided by the number of discharges. In this study, I use the Medicare *Cardiology* case mix index (CMI_{cardio})[10], which is based on the Medicare Hospital Inpatient Prospective Payment System for the corresponding federal fiscal year, which extracts only those procedures and treatments associated with cardiac care. This allows me to isolate the financial component of cardiac treatment from the general hospital costs. Hence, this is what I refer to as *application-specific financial performance.* In simple terms, the lower the CMI_{cardio} adjusted cost, the more efficiently the hospital is assumed to operate, i.e. *ceteris paribus*, lower cost translates into greater profits.

Quality Performance. As mentioned above, unlike other industries, a key factor related to the performance of a hospital is its service quality. Outside of health care – and with the exception of specific departments, such as customer service or manufacturing departments –quality metrics are rarely reported for units within firms. This is not the case with hospitals where nearly every department within a hospital is assessed on its quality and the data are made public. In fact, there are many specialty

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[8] The CMI is very useful in analysis since it indicates the relative severity of a patient population and is directly proportional to DRG (Diagnosis Related Group; see footnote 9) payments. When making comparisons among various hospitals or patient groups, the case mix index can be used to adjust indicators such as average charges. (Case mix adjusted average charges would be actual charges divided by the CMI). The CMI is the average DRG weight for all of a hospital's Medicare volume. The DRG payment for a Medicare patient is determined by multiplying the relative weight for the DRG by the hospital's blended rate: DRG PAYMENT = WEIGHT x RATE.

[9] The Medicare Prospective Payment System (PPS) is based on paying the average cost for treating patients in the same DRG. Each patient (except outliers) is classified into a DRG on the basis of clinical information and the hospital is paid a flat rate for the DRG, regardless of the actual services provided.

[10] All financial information is taken from the Medicare Provider Analysis and Review (MedPAR) file which is updated annually by CMS based on the federal fiscal year. The file includes billing data for 100% of all Medicare fee-for-service claims for discharges during the twelve months ending September 30.

firms in existence whose function is to assess the quality of hospitals based on numerous criteria. I used publicly available data related to the performance of cardiac procedures to assess the quality performance of hospitals ("Hospital Compare 2005).

The quality metrics that I chose are directly related to functions and services that a CIS can provide. For example, a CIS provides reminders to nurses to administer medications, to warn patients about the dangers of smoking, and to provide arrival and discharge information. In addition, I chose quality metrics that are uniformly captured across most hospitals and treatments that are common (see Appendix B2). These quality metrics have been used in prior research, but primarily at the hospital level of analysis. For example, recent research suggests that these hospital performance metrics are predictive of differences in hospital risk-adjusted mortality rates (Bradley et al. 2006; Werner et al. 2006), however the differences are very small and viewed by some as inconsequential (Horn 2006; McNamara et al. 2006). Of note in these studies is that the *process*-level quality metrics are used to assess *hospital*-level performance metrics. Therefore, it is not surprising that the correlations are weak due to the distal connection being drawn between application-level technologies and firm-level performance. Because my goal is to isolate the effects of cardio-quality, I exclude firm-level quality indicators such as the number of routine discharges and morbidity data. These metrics can be biased by the type and size of the hospital and the region it serves.

I performed factor analysis on seven cardio-quality measures[11] and discovered that two factors emerged. One factor ($Qual_1$) was strongly related to the administering of medication, while the other factor ($Qual_2$) related to providing instructions, advice, and counseling to patients (see Appendix C2). In both cases, one role that the CIS plays is providing reminders to the clinician to complete these tasks. I aggregate the individual items within $Qual_1$ and $Qual_2$ to form composite measures for use as dependent variables. All of the quality metrics are operationalized as the 'percentage of times that the function is performed.' For example, if the question is, "Heart attack patients given aspirin at arrival," the metric used to assess this is the percentage complete, e.g. "65% of the time." This data is primarily captured through analysis of insurance claims; however it can be collected from the output of EMRs and CISs as well.

Application-Specific IT Learning. The focal application under investigation is the CIS. The HIMSS Analytics data identifies whether the system was: *Live and Operational, Installation in Process, Contracted But Not Yet Installed, To Be Replaced, Not Yet Contracted,* or *Not Automated*. I categorize the CIS as *present* if it was either *'live or operational'* or *'to be replaced.'* If it is present, I incorporate the learning component by including the year in which the CIS was adopted. For example, if a hospital adopted a CIS in 1980, I subtract the year 1980 from 2005, to get a value of 25 years of experience. To the extent that earlier adoption creates more experience with IT

[11] Quality data obtained from *Hospital Compare*, a website created through the efforts of the Centers for Medicare & Medicaid Services (CMS), an agency of the U.S. Department of Health and Human Services (DHHS) along with the Hospital Quality Alliance (HQA). The HQA is a public-private collaboration established to promote reporting on hospital quality of care. The cardio metrics chosen are related to heart attacks (acute myocardial infarction – AMI) and heart failure which are the leading causes for hospital admission for Medicare beneficiaries, age 65 and older. Substantial scientific evidence indicates that the metrics used represent the best practices for treatments.

and more learning will result, this is a time-weighted metric incorporating the learning effect.

Complementary IT Learning. With few exceptions (e.g., Broadbent et al. 1999), prior work has operationalized IT infrastructure as a count of infrastructure-related components including the number of PCs, software, LANs, etc. (e.g., Hitt et al. 1997; Mukhopadhyay et al. 1995; Zhu 2004). It is easy to see that there are two problems with this metric. First, PCs have become ubiquitous to the point that the size of the firm (number of personnel) would be as reasonable a proxy. Further, even if the number of servers is used, there are significant challenges with operationalizing this metric. For example, the rapidly declining cost of computing power coupled with improved memory-chip performance has led to an order of magnitude decrease in the number of servers needed to perform specific functions, thus a firm with a bank of servers may have the same amount of computing power as a firm with a single server.

The second problem with using a count of infrastructure-related components is that there is no accounting for the amount of experience the firm has with its technology. Even in those studies that incorporate lagged performance measures, infrastructure count assumes that all components were adopted at the same point in time. It is well-established that learning results from increased usage of an IS, thus I argue that to the extent that complementarities can be affected by learning, a time-dependent aspect should be included in the operationalization. Therefore, accurately assessing the success of any single IS implementation is contingent not only upon the incorporation of complementary IT infrastructure but also on a learning-based operationalization that reflects heterogeneity that is not simply a function of the firm's size or computing technology counts.

In much the same way as described above, complementary IT learning is operationalized as an aggregate measure of years of experience. I compute a mean value of experience based on the year of adoption of all other IT's from the same group because multiple information technologies are included in each category of Complementary IT. A close examination of Menon et al.'s (2006) classification reveals that the four categories – TrIT, AIT, CIT, and PMIT – map very closely upon the categories that HIMSS Analytics uses in their database schema. However, HIMSS Analytics goes deeper into the functional applications and thus, I aggregate up to a level that aligns with the Menon et al. classification. For example, Communication IT (CIT) includes two high-level groups – CRM and Information Sharing (see Table 2.2). HIMSS Analytics breaks these groups down one more level into functional components, e.g. a CRM is made up of two components, a Marketing CRM and Customer Service CRM. Table 2.2 shows a breakdown of the categories (column 1), the groups identified which make up the category (column 2), and the number of applications that make up the groups (column 3). Therefore, I first use a count (based on presence/absence) of each system present within each category to assess the number of applications adopted relative to the total number available within each hospital. Then, to capture the learning component, I calculate an average year of adoption for each HIT category. Again, I reverse code the year by subtracting the average year from the year 2005 to give a measure of *years of experience*.

Control Variables. Firm characteristics have been shown to be important correlates of performance outcomes. Therefore I control for variables related to a firm's characteristics (e.g., size, age, type of hospital, IS budget) that are likely to influence performance. The size of the hospital is used because it has often been shown to influence technology adoption in organizations (e.g. Chandrashekaran & Sinha, 1995; Hannan & McDowell, 1984; Lai & Guynes, 1997). Size is operationalized as the number of beds that are staffed. I also control for the type of hospital by classifying a hospital as a teaching/research hospital or not, for profit or not-for-profit, age of the hospital (year it was founded), and IS budget as a percentage of overall budget. Finally, when using the quality-based dependent variable, it is important to control for state-level average quality metrics to eliminate bias related to geographic region.

2.6 ANALYSIS AND RESULTS

Descriptive Statistics

Descriptive statistics related to the hospital characteristics are given in Table 2.3. In Table 2.4, I report means, standard deviations, minimum, and maximum values for the dependent variables (CMI_{cardio}, $Qual_1$, $Qual_2$), the independent variable (CIS_{learn}), and the moderators ($InfraIT_{learn}$, $PMIT_{learn}$). Because the dependent variables have different quantities of missing data, the sample size varies from a minimum of 363 to a maximum of 388. Prior to performing the moderated analysis, checks of bivariate correlations between the moderating variables and the independent and dependent variables are conducted (see Table 2.5). Scatter plots were constructed as means of visually inspecting the data for outliers and broad trends. For both the quality and cost data, I did not remove outliers unless they fell outside of the range of values at 0 years of experience (see Figure 2.3 and 2.4). For optimal interpretation of the interaction term, Baron and Kenny (1986, p. 1174) suggest that the moderating variables should be uncorrelated with both the independent and dependent variables. In all cases, the moderating variables are not significantly correlated with these variables.

Insert Tables 2.4 and 2.5 about here

Insert Figures 2.3 and 2.4 about here

Hypothesis Testing

CIS Learning and Financial Performance. In hypothesis 1a, I test the relationship between application-specific IT learning and application-specific performance. In particular, I investigate the influence that CIS-associated learning has on cardiology cost outcomes. Using ordinary least squares regression, I regress CMI_{cardio} cost on the amount of experience with the CIS (CIS_{learn}), while controlling for the hospital-level variables referenced above. In all models tested, only the size of the hospital was found to be statistically significant, i.e. the larger the size the greater the cost. To simplify the reporting of the findings, I list only the variables of interest (see Table 2.6). The results show that more years of experience with the CIS do not translate into a reduction in cardio costs ($F(6,381)=11.139$, $p=.000$; $\beta_{1aCISlearn}=-.006$, $p=.902$; Adj. $R^2=.136$, $\Delta R^2=0.0$).[12,13] Therefore, H1a is not supported.

[12]The change in R^2 reported in Models 1 and 2 in Table 2.6 are the difference between variance explained by the control variables only and variance explained by the control variables and the variables of interest. In models 3 and 4, the ΔR^2 is the difference between the full models (3 and 4) and the partial models (1 and 2), respectively.
[13] Significance test for ΔR^2 was a comparison of F_{calc} to $F_{critical}$ using this formula:

Insert Table 2.6 about here

CIS Learning and Quality Performance. Using the same process as described above, I test the relationship between quality metrics and adoption and learning associated with CIS implementation. Recall that two quality factors emerged from the factor analysis. Upon analyzing the data, I found that in all cases, models using $Qual_1$ (e.g. administering of medication upon arrival and discharge) provide a better fit for the data than do models using $Qual_2$ (e.g. providing instructions, advice, and counseling) as the dependent variable. Subsequent interviews with clinicians suggested that some CIS's may not be programmed to provide instructions/advice, but all would likely provide reminders for medication administering. Therefore, in the remainder of this paper, I report findings using $Qual_1$ only[14].

In this analysis, other than a change to a quality-based dependent variable, the only departure from the model used to test H1a is the use of more control variables. I normalize the data for geographic differences by controlling for state-level average quality metrics. Again, for simplicity of presentation, I report data only for the variables of interest. In regressing $Qual_1$ on CIS learning, I find that the relationship between the year of adoption and quality is significant ($\beta_{1bCISlearn}$=.191***, p=.000; Adj. R^2=.121, ΔR^2=0.035***). Therefore, hypothesis 1b is supported.

Complementary IT Learning and the Moderating Effect on Performance. I follow in the tradition of other IS researchers who have created interaction terms by multiplying the

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$$F_{calc} = \frac{(R_2^2 - R_1^2) \div (k_2 - k_1)}{(1 - R_2^2) \div (N - k_2 - 1)}$$

[14] Contact the author for results pertaining to models incorporating $Qual_2$.

independent variable by the moderating variable[15] (Mishra et al. 2006; Zhu 2004). The significance of these interaction terms determines whether the hypotheses are supported or not (Baron et al. 1986, p. 1174). The analysis itself follows the methods suggested by Baron and Kenny (1986). The regression was conducted in blocks such that control variables were included first, followed by main effects, and finally interaction terms.

Model 3 includes CMI_{cardio} as the dependent variable and each of the independent variables in isolation as well as each interacted with CIS_{learn}. As hypothesized both the interaction term including infrastructural IT (CIS_{learn} x $InfraIT_{learn}$) and patient management IT (CIS_{learn} x $PMIT_{learn}$) are marginally significant and in the hypothesized directions (see Table 2.5 for detailed statistics; ($\beta_{2aCISlearnxInfraITlearn}$ =-.124†, p=.078; $\beta_{3aCISlearnxPMITlearn}$ =-.195†, p=.091). There is also a significant increase in R^2 (ΔR^2=1.0%†), when the interaction terms are included in the model with the final total variance explained being 14.6%. Therefore, both H2a and H3a are supported.

In Model 4, I replace the financial dependent variable with the quality variable ($Qual_1$) and as previously discussed, I include the state-level quality metrics to control for geographic variations. In this model, both interaction terms are significant and in the correct direction as hypothesized. Therefore, both H2b and H3b are supported (F(17,370)=6.049***, $\beta_{2bCISlearnxPMITlearn}$ =.143**, p=.004; $\beta_{3bCISlearnxInfraITlearn}$ =.156**, p=.002);. There is also a significant increase in variance explained when the interaction terms are included in this model (ΔR^2 =6.2%***) with a final total variance explained of 18.3%. A discussion of these findings is presented in the next section.

[15] Milgrom et al. (1990) propose a series of mathematical methods that can be used to incorporate complementarities into empirical models; however, while this work is impressive in its rigor, to employ these methods in this study is not plausible.

2.7 DISCUSSION

IT use in health care is emerging not only as a strategic advantage but also as a quality of care and financial imperative. Health information technology has been identified as the single most important component of the plan to reduce escalating costs and quality of care shortcomings. Yet studies of value and quality improvement have been sparse and findings mixed. Evidence from other industries suggests that value and IT use are positively related, leading one to believe that these results may also be present in the health care industry. This study begins to unravel the complexities associated with isolating the effects of IT use in health systems. I suggested that distal connections between HIT use and value were not likely to be readily evident. I argued that for value to be understood and measurable, a process-level of analysis was warranted along with an appreciation for the complementarities that must be present to enhance the link between application-specific IT and application-specific performance. Despite a few surprising results, overall, the findings support the existence of a relationship between HIT and hospital performance. Consistent with prior research, I find that variance in process performance is explained by process-level IT (e.g., Ray et al. 2004), and that infrastructural IT and learning enhance this relationship. While I am not suggesting that IT infrastructure is the only moderator to IT value – others have shown that decision rights, knowledge work and inputs, and incentives are complementary (e.g., Hitt et al. 1997) – my work specifically focuses on *other* information systems present within a firm including infrastructural, general purpose, and application specific.

***Financial* Performance Findings**

In H1a, I hypothesized a negative relationship between years of experience and cost such that greater learning translates into reduced costs. This relationship was not supported. One plausible explanation for this is that the relationship between CIS experience and cost is far more complex and is not appropriately modeled as a direct relationship in isolation. As I discuss next, it appears that the benefits of learning associated with application-specific technologies, such as the CIS, are most apparent when coupled with other IT learning.

Proceeding to the interaction results, the first finding of note is that the main effect of CIS_{learn} becomes negative and significant ($\beta_{CISlearn} = -.193^{\dagger}$, p=.096) in the presence of the interactions, suggesting that more learning equates to cost reductions. With this understanding, I then can state that both InfraIT and PMIT intensify the effect that CIS_{learn} has on CMI_{cardio} costs. Simply put, when there is more experience with InfraITs and PMITs, learning associated with the CIS has a greater effect on cost reductions. The significance of these moderating relationships is important. For example, while the objective of patient management IT is, by definition, to better manage patients, results suggest that PMIT can also enhance the relationship to cost. From a practical standpoint, this finding is encouraging due to the tremendous diffusion momentum that PMIT systems such as the EMR are undergoing and the concerns that these systems may *directly* impact costs in an adverse way. In fact, what this analysis suggests is that there may be an adverse direct relationship, but that the complementary benefits of PMIT are favorable. Because my study focuses specifically on learning associated with PMIT, an important future research step would be to examine the immediate effect of implementation on costs, and isolate whether the complementary effect is outweighed by the potentially adverse direct aspects.

I also find a negative moderation effect from Infrastructural IT learning. This may suggest that learning is being transferred from other technologies to support the relationship between application-specific IT learning and cost reduction. It is also possible that interoperability and cross-population of data and methods have favorably impacted the relationship between CIS experience and costs. Finally, earlier I discussed the possibility that learning from other systems, such as communication and decision support, may positively affect the relationship to cost. In this study I am not able to isolate the exact mechanism that results in the most salient effect, but I would encourage others to explore these more detailed relationships in the hope of identifying a possible cause and effect.

Quality Performance Findings

Based on my review of the literature related to the use of some patient management systems (again, recall that the CIS is primarily a PMIT), my a priori belief was that CIS experience would have a more profound effect on quality than it would on financials. The financial business case for most patient management systems has not yet been made. In fact, model 2 demonstrates that CIS_{learn} is a better predictor of quality than it is of cost. The quality-based metrics used in this study all rely on some form of reminder to prompt the clinician to perform some task. Therefore, it is not surprising that more experience associated with the use of this system will translate into more compliance with the reminders. On the other hand, there are many external factors which can influence financial outcomes including insurance reimbursement and localized variations, which make the relationship more distal. As I discuss next, there are significant interaction terms in the full model; therefore, one should expect the relationship between learning and quality to be more complex than was just presented.

As hypothesized, learning associated with both forms of complementary IT enhances the relationship between CIS learning and cardio quality. In the specific case of the PMIT, I was able to conduct a post-hoc interview[16] that revealed some additional interesting insights. The technology manager I interviewed suggested that "most hospitals are working towards an *interface* between an EMR [a specific form of PMIT] and a CIS, since they are a long way from *integration* or *interoperability*." He was careful to note the distinction between interface and integration or interoperability. He noted that in most cases the CIS is not integrated with the central EMR – if an EMR exists. He suggested that a first step that some hospitals are taking is simply to port specific information from a CIS to the EMR but that fully populating from one system to another is not yet common. I highlight this point only to illustrate that as integration becomes more prevalent, additional learning benefits should be realized beyond those that have already been identified.

I also hypothesized a positive moderation from infrastructure IT learning and find this to be supported. As noted, relative to quality interventions, the CIS is, in a sense, transformed into a transaction-based IT in that it provides automated prompts for care. Understanding this, other InfraITs that interface with the CIS would be expected

[16] This subject asked to remain anonymous due to potential confidentiality issues.

to enhance the quality link, within the limits of human cognitive capabilities (Simon 1982), and this was empirically supported.

Summary

Even with somewhat small effect sizes and a modest explained variance, the results are encouraging. They indicate that when a temporal learning component is introduced into the model as a complementary effect, the application-specific learning to performance link becomes stronger, thus suggesting that it is unique knowledge and learning associated with more experience with the IT that creates superior performance and not simply presence or absence of IT. Thus, this study empirically shows that both quality and financial performance benefits are realized when learning occurs. In addition, the variance explained increases significantly when the interaction terms are included in the model.

Limitations

The first known limitation of this research is that I cannot explicitly state that performance is reflective of the learning effect. For example, it has been shown that differing learning mechanisms can result in the same outcome (Levinthal et al. 1993). Even though I control for known covariates such as firm size, this does not guarantee that other learning factors are not affecting performance. In addition, I am unable to account for learning loss. A recent study (Pavlou et al. 2005) suggests that *learning time* is a surrogate for output; however, I argue that this operationalization ignores resident or accumulated learning and does not take into account the learning that is destroyed either purposefully or through inactivity. Because my study includes a random sample of hospitals, one can assume that learning (and learning losses) are randomly distributed amongst the hospitals and that the proxy of years of experience subsumes both accumulated learning and losses. Future research is necessary to address the effect of IT learning losses more closely.

Second, I implicitly assume that each unit of time (in this case, year) generates an equal amount of knowledge, independent of the IT type. In fact, this analysis may be picking up some degree of noise relative to variations in the complexity of systems. Attewell (1992) alludes to this when he contends that the adoption of more complex technologies requires a greater degree of organizational knowledge and sophistication due to the intricacies of operation, and that the adoption of these technologies is often delayed until less complex ones are implemented and *learned*. Finally, some firms are much more efficient relative to technology transfer (Oxley 1995), therefore this may in turn provide additional complementary value.

A third limitation is that I do not have data related to actual usage and therefore cannot assess the quantity of learning that has occurred. However, I contend that my operationalization is superior to simple counts in that one can assume that if a system is still in place after several years, the firm must realize some benefit from its use or else it would have been removed. A dichotomous count variable cannot extract this information since the IT may have been installed and removed within a very short period of time that happened to coincide with the data collection timeframe.

Finally, an inherent assumption in this study is that financial- and quality-based goals are pursued on an equal basis, when in fact it is more likely that a tradeoff exists at a higher level such that risk and utilization are managed from a hospital or health system level leaving the cardiology department to compete with other departments for resources. Essentially this suggests that quality initiatives may be undertaken at the unit level while some cost-cutting measures are imparted from a higher level, thus reducing some of the direct process-level effects.

2.8 CONCLUSION AND EXTENSIONS

This study adds to the literature on the business value of IT by investigating the phenomenon in an emerging and consequential context: healthcare. It is encouraging to note that value does result from the adoption of health information technologies when applied appropriately. An important contribution of this work is the unique operationalization of IT infrastructure as an intangible learning-based metric rather than a physical property. Despite a reasonably robust body of research, there are still many unanswered questions about the relationship between IT and firm performance. My objective was to highlight the important insights that can be gained when approaching this research question from a knowledge-based perspective. Few have incorporated organizational learning into models of business value and no work that I am aware of has included IT learning that acts in a complementary fashion or disaggregated its unique effects. From a theoretical perspective, the results of this work point to a potentially new way of conceptualizing IT infrastructure in firms.

However, although this study does include a time-weighted learning aspect, it does not take into account the sequence with which the information systems are adopted. There is reason to believe that the order of adoption factors into the degree of success that a firm has with its IT infrastructure (Aral et al. 2006b). Finally, the possibility exists that there is a U-shaped moderating relationship such that near term adoption may yield detrimental moderating effects while long-term impacts are positive. These are intriguing research questions worthy of exploration.

For practitioners, the key insight that this study offers is the importance of cross-pollination of knowledge. This can be operationalized as the transfer of personnel from one department rich in technology skills to one that is implementing a new system. It could also be the use of best-practices and know-how gained through implementation and learning from other systems. While these results are encouraging from the perspective of demonstrating a link between IT learning and performance, it is important to note that the relationship is far more complex than a simple presence/absence of the system leading to improved performance. Evidence abounds that there is a slow uptake of HIT and this study is important because it takes a step towards identifying how value can be realized by not simply investing in IT, but by learning from IT. In addition, studies showing a connection between the use of HIT and value are lacking and extremely important for policy makers and industry stakeholders.

Although it is not feasible for a firm to increase the length of time it has possessed an IT resource, there is the possibility that knowledge stock can be accumulated through other means. For example, to the extent that it is possible to accelerate the learning process – either with the focal IT or complementary IT – this should translate into performance benefits.

In one sense, the findings from this study are somewhat surprising. Looking deeper into the results, to the extent that improvements in quality – as represented by greater adherence to the quality metrics being assessed in this study – translate into better health outcomes, it can be argued that clinician skill alone is not fully responsible for the final outcomes. Thus, no matter how talented the cardiologist may be, some portion of her/his work is still a function of the system in which s/he operates.

Work remains to be done relative to the interactions of specific information technologies. It is reasonably well-established that complementarities between technologies exist, yet no work has examined the supplementary value of technologies. For example, when data from one system is transferred into another system for additional analysis and decision support, one could argue that supplementary value emerges. With the interfaces and presumed interoperability of health information systems, the supplementary value of systems may become increasingly important.

2.9 FIGURES

Figure 2.1. Conceptual Model

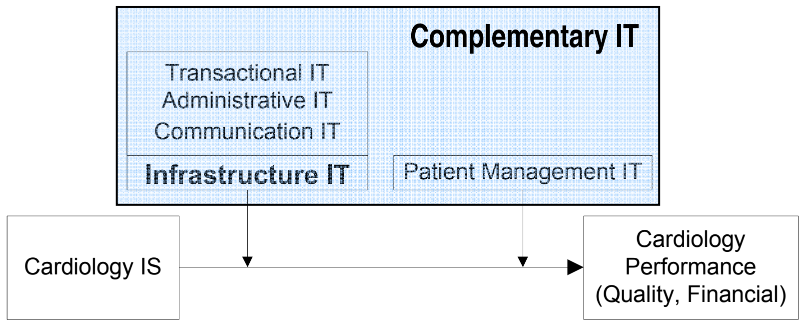

Figure 2.2. Comparison of Diffusion of Various HITs

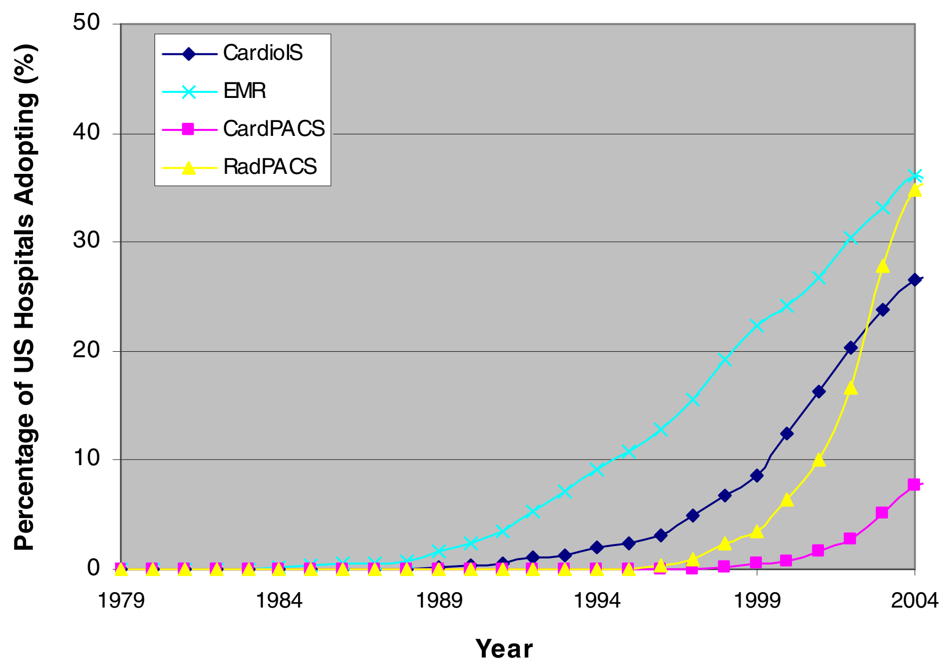

Figure 2.3. Scatterplot Demonstrating Significant Positive Relationship Between Years of Experience with Cardio-IS and Quality Metrics Associated with Cardiology Care

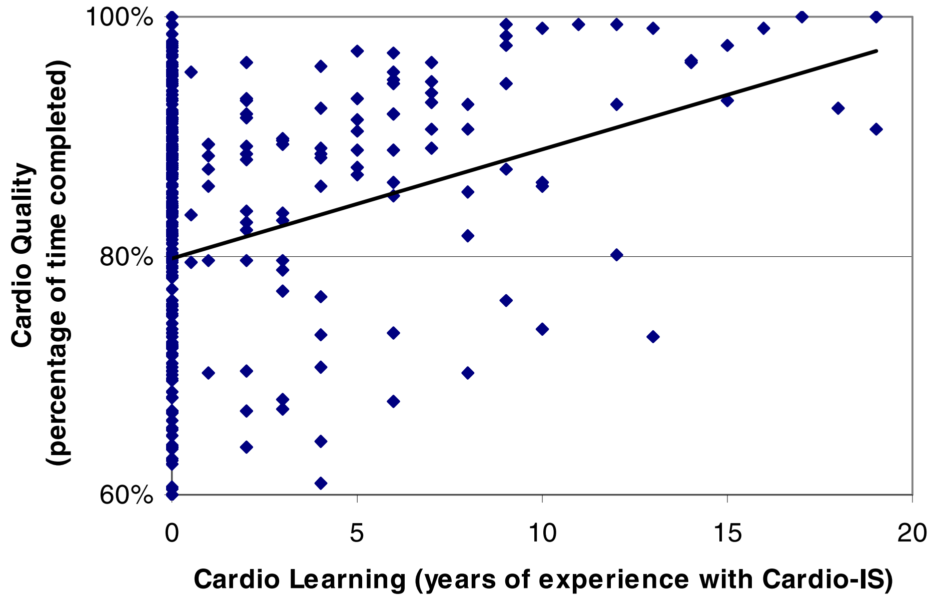

Figure 2.4. Scatterplot Demonstrating Non-Significant Relationship Between Years of Experience with Cardio-IS and Case Mix-Adjusted Cost Metrics Associated with Cardiology Care

2.10 TABLES

Table 2.1. Organizational Learning and Performance Literature Review and Findings

Key Variables	Findings	Reference
Trust, absorptive capacity, learning structures, strategy, training competences. Ability to understand new knowledge, ability to assimilate new knowledge, ability to apply the assimilated knowledge.	Trust between an international joint venture's parent and the JV's relative absorptive capacity with its foreign parent influence its ability to understand new knowledge held by foreign parents. An IJV's learning structures and processes, strategy and training competence only partially influence its ability to assimilate new knowledge from those parents. Trust and management support from foreign parents influence IJV performance but not learning.	(Lane et al. 2001)
Learning effects, joint ventures, contracts	Learning effects are more important in situations characterized by greater contractual ambiguity.	(Anand et al. 2000)
Internal capabilities, external networks, firm performance	Internal capabilities (entrepreneurial orientation, technological capabilities, and financial resources) are important predictors of a start-up's performance. With external networks, only linkages to venture capital companies predicted the start-up's performance.	(Lee et al. 2001)
Knowledge structures (chunks), OL, process improvements	Knowledge can reduce scheduling effort. Chunks provide insight into how learning is accomplished and contributes to process improvements.	(Zhu et al. 1997)
Resource endowments, competencies, strategic change	Organizations possessing greater stocks of historically valuable resources were much less likely to engage in adaptive strategic change. This disinclination towards change tended to have a benign or even beneficial effect.	(Kraatz et al. 2001)
Feedback, relationship quality, procedural issues	Positive feedback loops are critical in the evolutionary process. Procedural issues are critical from the start to foster a climate for positive reinforcement, trust, and confidence in the relationship.	(Arino et al. 1998)
Executive succession, TMT, OL, organization adaptation	Succession exerts a positive influence on organization performance. The positive impact of succession is accentuated when it coincides with strategic reorientation. However, CEO retention is important. Consistently high-performing organizations are managed to sustain a relatively high level of learning.	(Virany et al. 1992)
Personnel turnover, OL, performance, firm structure, and different tasks	Teams in general learn faster and better than hierarchies, hierarchies are less affected by high turnover rates. Institutionalized memory, as embodied in the memories of distributed individuals and in the advisory relationships between individuals, determines the consequences of personnel turnover.	(Carley 1992)
Intelligence generation, business performance	Intelligence generation (OL) is positively related to sales growth, customer satisfaction, product quality and new product success.	(Slater et al. 2000)
OL, product quality, sales growth, customer value	OL was positively linked to relative product quality, sales growth, and enhanced customer value.	(Pelham et al. 1996)
Search-oriented use of e-government services, new business development, time savings, profitability	Search-oriented use of e-gov is positively related to OL, new business development, and time savings. The relationship between use of e-gov and profitability is mediated by firms' intelligence generation.	(Thompson et al. 2005)

Table 2.2. Health Information Technology (HIT) Application Categorization

HIT *Category*	Information Technology *Group* Included in HIT *Category*[17]	No. of Applications Making Up *Group*	% of Hospitals Adopting[18]
Transactional (TrIT)	Supply Chain Management	3	40.9
	Business Office	2	33.5
	General Financials	2	93.5
	Human Resources	7	77.0
	Health Information Mgmt (HIM)	10	67.6
		24	**62.5%**
Administrative (AIT)	Financial Decision Support	7	52.8
	Revenue Cycle Management	8	63.9
	Utilization Review/Risk Mgmt	3	60.3
	Nursing	10	31.6
		28	**52.2%**
Communication (CIT)	CRM	2	3.5
	Info. Sharing (email, portal, etc.)	6	55.2
		8	**29.4%**
Patient Management (PMIT)	Cardiology	6	13.1
	Electronic Medical Record	7	44.0
	Radiology	11	41.0
	Pharmacy	1	79.5
	Laboratory	5	58.1
	ED/Op. Room/Respiratory	6	45.4
		36	**46.9%**

[17] Each broad IT subset is made up of several small information systems. For example, the *Financial Decision Support* system is composed of seven autonomous systems.

[18] This is an aggregated percentage. For example, there are 2 applications that make up a CRM – Marketing CRM and Customer Service CRM. Each application's adoption rate is evaluated individually at the hospital level and then averaged with the other applications that make up the CRM group. If 3.0% of the hospitals adopted a Marketing CRM and 4.0% adopted a Customer Service CRM, the overall percentage having adopted a CRM would be 3.5%, as shown in column four.

Table 2.3. Random Sample of Hospitals and Comparison of Specific Variables with National Statistics

Item Description	**Random Sample**	**Total Population**	**t-test**
Cases (hospitals)	388	3989	
Year hospital opened	1975.0	1975.8	p=.681
Number of beds in hospitals	190.6	182.6	p=.368
Number of facilities in system	99.8	100.0	p=.975
Type of hospital			
General Medical & Surgical	82.0%	80.8%	p=.839
Academic	7.7%	8.4%	
Long-Term Acute	2.6%	3.1%	
Other	7.7%	7.7%	
Not-For-Profit	78.6%	77.9%	p=.754
Have Chief Information Officer (Yes)	95.9%	96.1%	p=.351
IS Budget as % of Operating Budget			
Under 1.0%	11.9%	15.3%	p=.342
1 - 1.49%	23.8	20.9	
1.5 - 1.99%	23.1	21.5	
2 - 2.49%	18.2	19.5	
2.5 - 2.99%	4.9	8.2	
3 - 3.49%	7.0	6.5	
3.5 - 3.99%	1.4	2.8	
4 - 4.99%	4.9	1.9	
5 - 5.99%	2.8	1.9	
Over 6%	2.1	1.4	
Number of states represented	49	50	p=.616
Hospitals with Cardio Info Systems	104 (27.0%)	1,061 (26.6%)	p=.966

Table 2.4. Descriptive Results for Key Variables

Item Description	**N**	**Mean**	**Std. Dev.**	**Min Max**
CMI_{cardio} – Case Mix Adjusted cost of cardiology care	385	$5,200	$1,564	$1,938 $19,303
$Qual_1$ – Administering of medication upon arrival and discharge (% of time completed)	388	80.7%	17.0%	12% 100%
$Qual_2$ – Providing instructions, advice, and counseling (% of time completed)	363	61.8%	24.5%	4% 100%
CIS_{learn} – Average number of years of experience with CIS	388	1.61	3.54	0.0 19.0
$InfraIT_{learn}$ – Average number of years of experience with Infrastructure IT	388	7.10	3.89	0.0 28.9
$PMIT_{learn}$ – Average number of years of experience with Patient Management IT	388	5.44	3.75	0.0 24.8

Table 2.5. Correlation Matrix for Dependent Variables and Moderators

	CMI_{cardio}	CIS_{learn}	$InfraIT_{learn}$	$PMIT_{learn}$
$Qual_1$	.146**	.204***	-.021	-.019
CMI_{cardio}		.041	-.048	.026
CIS_{learn}			.024	-.032
$InfraIT_{learn}$				.674***

* p< .05, ** p< .01, *** p<.001

Table 2.6. Results of Ordinary Least Squares Regressions

	Model 1	Model 2	Model 3	Model 4
IV \ DV	CMI_{cardio}	$Qual_1$	CMI_{cardio}	$Qual_1$
CIS_{learn}	-0.006 (0.902)	0.191*** (0.000)	-0.193† (0.096)	0.184* (0.050)
$InfraIT_{learn}$			-0.027 (0.809)	-0.065 (0.191)
$PMIT_{learn}$			0.141* (0.043)	-0.059 (0.233)
CIS_{learn} x $InfraIT_{learn}$			-0.124† (0.078)	0.143** (0.004)
CIS_{learn} x $PMIT_{learn}$			-0.195† (0.091)	0.156** (0.002)
Number of CVs	5[a]	5	5	12[b]
CVs only	F(5,382) =13.398***	F(5,382) =8.453***	F(5,382) =13.398***	F(12,375) =6.453***
Model Summary	F(6,381) =11.139***	F(6,381) =9.916***	F(10,377) =7.624***	F(17,370) =6.049***
Hypothesis	1a	1b	2a, 3a	2b, 3b
Adjusted R^2	0.136	0.121	0.146	0.183
ΔR^2	0.0 ns	0.035***	0.010†	0.062***
Hypothesis	Not Supported	Supported	2a: Supported 3a: Supported	2b: Supported 3b: Supported

† p< .10, * p< .05, ** p< .01, *** p<.001
[a] =Hospital size, age, type, profit/not-for-profit, IS budget
[b]=Addition of the seven state-level average quality indicators.

ESSAY 3: ADOPTION OF ELECTRONIC MEDICAL RECORDS IN THE PRESENCE OF PRIVACY CONCERNS: THE ELABORATION LIKELIHOOD MODEL AND INDIVIDUAL PERSUASION PRIVACY

3.1 ABSTRACT

Electronic medical records (EMRs) constitute a significant technological advance in the way medical information is stored, communicated, and processed by the multiple parties involved in the delivery of health care. However, there is widespread concern that privacy issues may impede the diffusion of this technology. In this study, I integrate the Concern for Information Privacy (CFIP) construct with the Elaboration Likelihood Model (ELM) to examine attitude persuasion and likelihood of adoption of EMRs when concerns about privacy of information are present in consumers. I draw from the literature on attitude formation and change to develop hypotheses that individuals can be persuaded to support the use of EMRs and ultimately adopt EMRs, even in the presence of significant privacy concerns, if arguments about the value of EMRs are framed properly. Using a quasi-experimental methodology, I randomly assign two different types of respondents (high and low involvement) to two different manipulations (strongly framed and neutrally framed arguments) and assess the impact of CFIP on the relationship between these variables, attitude, and likelihood of adoption. I find that an individual's CFIP interacts with argument framing and issue involvement to affect attitudes toward the use of EMRs. In addition, results suggest that attitude towards EMR use and CFIP directly impact the likelihood of adoption of EMR technology. The research reported here makes four main contributions. From a theoretical perspective it extends the ELM to include a key construct affecting persuasion which has not been examined in prior literature, i.e., CFIP. Second, it

focuses on EMRs which are a new and emerging technology that have the potential to radically alter the way health care is managed by consumers and providers. Third, findings from this study hold important pragmatic value for driving public policy decisions related to public perceptions and attitudes towards the use of EMRs, including the crafting of national messages and education. Finally, the moderating effect of CFIP may be useful in other contexts in which personal information is controlled or processed.

3.2 INTRODUCTION

Electronic medical records (EMR) that capture patient information in digital format are important emerging technological innovations that offer the potential to radically transform the health care system. Although the practitioner literature surrounding the adoption of EMRs is growing, no study has examined a key component of the adoption equation – what happens if health systems, and providers adopt EMR systems, but patients refuse to allow their medical information to be digitized? Prior research has underscored the significance of privacy concerns when the Internet is used as a medium for transferring information (Malhotra et al. 2004), or when information is gathered and used in an organizational context (Smith et al. 1996; Stewart et al. 2002). National surveys indicate that the public is particularly sensitive to privacy issues in the context of health related information: a recent report by the California HealthCare Foundation found that 67% of the national respondents felt “somewhat” or “very concerned” about the privacy of their personal medical records (Bishop et al. 2005).

It is apparent that the U.S. is beginning to invest heavily in EMR systems and that there is support for this initiative at the highest levels of the federal government (Bush 2004a). However, there are many examples of information technologies that have failed because of resistance to use from key stakeholders. In this study I pose the question: can individuals be persuaded to change their attitudes and adoption decisions towards electronic medical records, taking into account that there may be privacy concerns associated with use? There is an extensive and robust literature examining the behavioral aspects of technology adoption and usage. Studies in this domain have drawn upon multiple theoretical perspectives such as the Technology Acceptance Model, Theory of Reasoned Action, and Diffusion of Innovation (e.g., Agarwal et al. 1998; Davis 1989; Fishbein et al. 1975; Rogers 1995; Venkatesh et al. 2003). Most of the theoretical models used in extant research, however, assume that the respondent has developed a well-formed attitude toward the target technology, and there is typically no discussion of the fact that the individual could be persuaded to change this attitude. While some work has examined pre and post-adoption behavior (Karahanna et al. 1999), again this research does not tap directly into *how* to persuade a person to change his or her opinion or into the influence process itself (Sussman et al. 2003).

In the psychology literature, the elaboration likelihood model (ELM) provides a theoretical perspective on how attitude can be modified. To examine how privacy concerns facilitate or constrain the modification of attitudes, I integrate the CFIP construct into ELM to examine attitude and intentions regarding the use of EMRs in health systems when concerns about privacy of information are present in patients. I draw from the attitude and attitude persuasion literatures to develop hypotheses that individuals can be persuaded to support the use of EMRs, even in the presence of significant privacy concerns, if an appropriate message about the value and safety of EMR systems is imparted to the recipient.

Using a quasi-experimental[19] methodology (Campbell et al. 1963; Shadish et al. 2002), I randomly assign two different types of respondents (high and low involvement) to two different manipulations (strongly framed and neutrally framed arguments) and assess the impact of CFIP on the relationship between these variables, attitude, and likelihood of adoption. I use structural equations modeling to empirically test the relationships proposed with a sample of 366 people.

This research makes four key contributions. From a theoretical perspective it extends the ELM to include a key construct affecting persuasion and intentions which has not been examined in prior literature, i.e., CFIP. Second, it focuses on EMRs which are a new and emerging technology that have the potentially to radically alter that way that health care is managed by consumers and providers. Third, the findings from this study hold important pragmatic value for driving public policy decisions related to public perceptions and attitudes towards the use of EMRs, including the crafting of national messages and education. Finally, the moderating effect of CFIP may be useful in other contexts in which personal information is controlled or processed.

3.3 LITERATURE REVIEW

The ELM forms a framework for this study and provides a conceptual lens for investigating attitude and persuasion. I integrate an as yet unstudied variable – CFIP – into the ELM and explore its impact. I briefly review the relevant literatures and discuss key findings from each. This provides a foundation for the development of specific hypotheses that guide the empirical analysis.

Elaboration Likelihood Model

[19] This study is termed a quasi-experiment because it lacks full random assignment. The groups of subjects were chosen for specific reasons and then random assignments to treatments were applied.

The ELM (Petty et al. 1981a; Petty et al. 1986a) is one of two, dual-process theories of attitude formation and change arguing that persuasion can act via a central or peripheral route. The second theory, Heuristic-Systematic Model (Chaiken 1980; Chaiken 1987) is similar – and some would argue complementary (Eagly et al. 1993 p. 346) – to the ELM, with one notable exception being that it lacks the empirical validation of the ELM. In both theories, attitudes are viewed as being formed and modified as recipients obtain and process information about attitude objects (Eagly et al. 1993 p. 257). ELM has been empirically tested in scores of studies and has been shown to be a highly predictive model; therefore I have chosen to adapt it here rather than use the Heuristic-Systematic Model.

The ELM can be used to account for differences in the amount of influence accepted by recipients exposed to new information. This information forms new cognitions and can also affect prior beliefs and attitudes (Petty et al. 1999). In simple terms, when a message is presented to various individuals in different contexts, the recipients will vary in how much cognitive energy they devote to the message (Petty et al. 1986a). These variations in cognitive elaboration, *ceteris paribus*, affect the success of the message's influence. The elaborating process involves generating one's own thoughts in response to the information to which one is exposed (Tam et al. 2005). In some situations, message content will be read, cognitively processed, and given consideration by one recipient, while another may ignore the message content all together. This can be due in part to a recipient's knowledge of learning content, structure, and processes (Chaiken et al. 1976; Sussman et al. 2003). According to Petty and Cacioppo (1986a, p. 6), the two factors that must be present in a recipient for elaboration to occur are ability and motivation. Ability has been operationalized as prior expertise, and motivation as involvement and personal relevance.

The ELM suggests that when elaboration is high, the recipient is experiencing a central route of persuasion, but when elaboration is low, a peripheral route is present (Petty et al. 1986a). When elaboration is low, influence typically acts through very simple decision criteria and cues such as celebrity endorsements, charisma, or the attractiveness of the sender. Individuals use these cues either because they do not want to devote the necessary cognitive energy to elaboration or they are unable to expend the effort (Petty et al. 1986a). It has also been noted that non-experts rely less on argument quality and instead focus on what have traditionally been known as peripheral cues[20] such as the credibility of the source (Lord et al. 1995; Petty et al. 1981c).

There is an extensive empirical literature testing variations of the ELM. Table 3.1 summarizes select studied from this literature and highlights the key covariates and interactions that have been tested. Although the list is not exhaustive, references to several reviews and meta-analyses are provided in the table. It is also important to note that several variables have been operationalized as acting through a central or peripheral route depending upon the study context – including issue involvement and argument quality – therefore I have chosen not to categorize the variables based on this criterion.

Insert Table 3.1 about here

Privacy

Allen (1988) describes privacy as an 'elastic' concept meaning that it has no shared meaning amongst individuals. Even privacy scholars acknowledge that the term

[20] Petty and Wegener (1999) argue that it is the degree of elaboration, not the variable, which determines the route of persuasion.

has not taken on a common meaning as it applies to research (Margulis 1977). The term 'privacy' typically is assumed to connote something positive (Warren et al. 1977) – re: ensure the privacy of my information – and the topic is most often researched in the context of how to protect or preserve it (Margulis 2003). With the advent of the Health Insurance Portability and Accountability Act (HIPAA), privacy and security of health information has been elevated to the forefront of medical informatics research (Lazarou et al. 1998). Much evidence suggests that privacy and security of health information is of focal concern for individuals (Bodenheimer et al. 2003; Cantor 2001; Harris-Interactive et al. 2001; Harris-Interactive et al. 2002; Louis_Harris_&_Associates et al. 1999; Masys et al. 2002; Shortliffe 1999; Westin 2003).

Researchers have debated the conceptualization of privacy as a social and/or psychological construct (for a review, see Margulis 2003). In this study, I do not use the term 'privacy' to assume any legal or constitutional concept (Allen 1988; Margulis 2003; McWhirter 1994). I find that these definitions do not adequately represent the operationalization that I desire (Kagehiro 1990). Much of today's privacy research relies on Altman (1975) and Westin's (1967) work. Altman examined privacy in the context of how people regulate access to themselves, while Westin focuses on the types and functions of privacy. More recent work (Culnan 1993; Smith et al. 1996; Stewart et al. 2002) has been conducted examining individuals' concern for information privacy. Drawing from these literatures, my conceptualization of information privacy is that it is a belief that is malleable in response to internal and external stimuli (Altman 1975; Westin 1967).

Only recently have studies emerged that highlight the implications of using electronic medical records to manage patient care and the privacy concerns that will surface as a result of such use (Alpert 1998; Alpert 2003; Naser et al. 1999). As EMRs become more technologically advanced, issues of interoperability between facilities and exchanging data across the Internet will doubtless gain in prominence. Prior research has demonstrated that people's concerns about information privacy are shifting as the Internet diffuses. In 1995, when Harris-Westin began categorizing people into clusters based on their privacy beliefs (Louis_Harris_&_Associates et al. 1995), the national percentage split was as follows:

25% - Privacy Fundamentalists are those who reject consumer-benefit or societal-protection claims for data uses and seek legal-regulatory privacy measures.

55% - Privacy Pragmatists are those who examine the benefits of data collection or use to them or society and evaluate the privacy risks and how organizations propose to control them. Then they decide whether to trust the organization or seek legal oversight.

20% - Privacy Unconcerned are those who are ready to supply their personal information to business and government and reject what is viewed to be too much concern over privacy.

The same survey given in 2001 indicated a considerable shift in what had been very consistent results over the past decade. By 2001, the *Privacy Fundamentalist* group had grown to 34%, *Privacy Pragmatists* to 58%, and *Privacy Unconcerned* dropped to 8% of the population (HarrisInteractive et al. 2002). These results demonstrate that significant challenges may emerge if/when EMR use becomes more ubiquitous.

Concern For Information Privacy

Smith, Milberg and Burke (1996) developed and tested the Concern for Information Privacy (CFIP) construct to measure attitudes and beliefs about individual information privacy related to the use of personal information in a business setting. The instrument proposed by them is composed of four distinct, yet correlated latent factors, labeled *Collection*, *Errors*, *Unauthorized Access*, and *Secondary Use*. Stewart and Segars (2002) expanded upon the Smith study and not only empirically validated the multi-dimensional nature of the CFIP construct, but also found support for the hypothesis that a 2nd-order factor structure is empirically valid, thus confirming the complexity of individual's concern for information privacy. Although I examine CFIP as a higher-order factor, there are reasons to believe that certain dimensions of CFIP can potentially be more salient than others due to the unique nature of a health information system such as the EMR. For example, *collection* and *errors* in health information have received considerable attention in recent years. The oft-referenced Institute of Medicine report, "To Err Is Human: Building a Safer Health System," (Kohn et al. 2000) has been cited more than 3,420 times in the last five years (Google Scholar - To Err Is Human: Building a Safer Health System 2006), and this is not accounting for inclusion in numerous conference and marketing presentations. In addition, collection of medical information appears to be inextricably linked with a national identification and therefore has also received significant press. The issue of the collection of health information has generated considerable controversy. A recent article by Senators Bill Frist and Hillary Clinton reinforced this point when they stated, "[patients] need …information, including access to their own health records…At the same time, we must ensure the privacy of the systems, or they will undermine the trust they are designed to create," (2004).

Summary

The ELM specifies a set of theoretical mechanisms that yield attitude change which subsequently lead to behavioral intentions to engage in specific acts. Central to this theory is the notion of persuasion. In the context of digital health information, it is widely acknowledged that a critical barrier to widespread diffusion is the individual's concern about privacy. Will these privacy concerns hinder the adoption of EMR systems or can people be persuaded to accept the technology if proper messages are conveyed? I explore this research question using ELM as a theoretical framework.

Electronic Medical Record Systems

Prior to discussing the research model and hypotheses, I provide a brief definition for an EMR system. As noted earlier, an electronic medical record is simply information that is in an electronic format that contains medical information about a specific individual. EMR *systems* are the software platforms that physician offices and hospitals use to create, store, update, and maintain EMRs for patients. This distinction is subtle but important due to the fact that these terms are often used interchangeably. I also make the distinction because the research questions are dependent on the respondent understanding the subtle differences. For example, using the definitions provided by others (e.g. Garets 2005), an EMR could simply be a Word® document that is maintained by a patient and stored on his or her home computer. In this case, privacy concerns would not be of central importance. My interest is in the use of EMR *systems* by health providers and how patients react to the fact that their EMR is stored in these systems and can be made available via Internet connections[21].

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[21] From this point forward, I use the term EMR to signify an EMR System, unless explicitly stated.

3.4 RESEARCH MODEL AND HYPOTHESES

The overall research model, as shown in figure 3.1 below, incorporates the CFIP construct and positions it within an ELM framework. There are two outcomes of interest that are highlighted in the model. The first outcome that is an intervening variable in the proposed model, post-manipulation attitude, has been used extensively in ELM research. The ELM lens has been used less often to investigate actual behavior or behavioral intentions, primarily because prior research has consistently demonstrated the empirical link between beliefs, attitude, intentions, and behavior (Ajzen 1991). Prior ELM studies have identified several variables that can influence attitude, including but not limited to argument quality, issue involvement, and the interaction of the two (see Table 3.1 for a more detailed description of antecedents and interactions). I proceed by first defining the mediating and dependent variables and then describe each of the exogenous determinants.

Insert Figure 3.1 about here

Attitude

An attitude has been defined as a 'complex mental state involving beliefs and feelings and values and dispositions to act in certain ways,' (Attitude 2006) and 'positive or negative views of an "attitude object": a person, behavior, or event,' (Bernstein et al. 2000). Fishbein and Ajzen (1975) suggest that attitudes influence behavior via their influence on intentions. In addition, they conclude that attitude towards *using* a system is more predictive of behavior than attitude towards the technology artifact itself (Fishbein et al. 1975). Extending this argument using an information-adoption-based view, it has been suggested that people will not only form intentions toward adopting a technology, but they will also form opinions toward adopting advocated ideas and behaviors (Sussman et al. 2003).

Prior work has suggested that attitudes are formed and modified as people gain information about attitude objects (Eagly et al. 1993 p. 257). When an attempt is made to change an attitude, persuasion is said to have occurred. Persuasion has been defined as a change in a private attitude or belief resulting from the receipt of a message (Kenrick et al. 2005, p. 145). It has been shown that an individual's behavioral response to a stimulus can serve as an indicator of evaluation if the response results from a reaction to the attitude object (Eagly et al. 1993). Problems can surface when attempting to isolate whether the response directly results from the attitude object or if it is caused by other determinants. For this reason, assessing attitude and/or attitude change can be problematic unless indexes of behavior – indicating some degree of agreement in favorableness or unfavorableness toward the attitude object – aggregated over multiple acts or repeated observations, are used (Fishbein et al. 1974; Fishbein et al. 1975). The semantic differential scale (Karwoski et al. 1938; Osgood et al. 1957), demonstrated to be effective in assessing attitude and attitude change (e.g. Eagly et al. 1993; Gallagher 1974; Taylor et al. 1995), is used in this study.

Determinants of Attitude

Argument Framing. Argument quality refers to a subject's perception that a message's arguments are strong and cogent as opposed to weak and specious (Petty et al. 1986b). Prior ELM literature has shown that argument quality is a strong determinant of attitude and persuasion. While Petty et al. (1981b) argue that persuasion is influenced by several factors including argument quality, Fishbein and Ajzen (1981) state that message content is the most significant predictor of attitude, rather than source credibility, attractiveness, or other cues. With strong argument quality, the message contains facts that are justified and compelling (Petty et al. 1981b). Persuasive messages divert the attention of the subject, leading to a reallocation of cognitive resources and eliciting responses (such as an attitude change) or a behavior (Tam et al. 2005). If messages lead to predominantly positive thoughts, the message is said to be relatively successful in eliciting changes in attitude and behavior (O'Keefe 1990, p. 103). If messages lead to predominantly negative thoughts, the messages will not elicit strong changes in attitude or behavior. It also has been demonstrated that the influence of unfavorable thoughts can be weakened with positive, strong argument quality (Kim et al. 2003). In summary, there is strong evidence suggesting that argument quality will affect attitude.

My research draws from the insights of the 'argument-quality/attitude' relationship and extends it. While the quality of the argument is important, it is actually the framing of the messages (either in a positive or negative way) as a whole that are important to persuasion. For example, under a positively framed manipulation, I test messages which are classified as 'strong' but more importantly, they are framed in a way that present positive aspects of EMR adoption. Because this project is a quasi-experiment, if positively framed manipulations elicit more positive attitudes than neutrally (or negatively) framed arguments, this will demonstrate that attitudes can be changed in a favorable way. If argument framing (AF) is not important, even positively framed manipulations will not elicit more favorable post-manipulation attitudes, *ceteris paribus*. I test this assertion in the following hypothesis:

H1: After controlling for pre-manipulation attitude, post-manipulation attitude will be more favorable towards EMR use in individuals presented with positively framed manipulations versus neutrally framed manipulations.

Issue Involvement. Issue involvement (II) has been defined as the extent to which recipients perceive that a message topic is personally important or relevant (Johnson et al. 1989; Petty et al. 1979; Petty et al. 1986a; Petty et al. 1990). There has been some debate, however, surrounding whether the construct is uni- or multi-dimensional (Johnson et al. 1989). In their meta-analysis, Johnson and Eagly argue that there are three distinct types of involvement: 1) value-relevant involvement, 2) outcome-relevant involvement, and 3) impression-relevant involvement. Value-relevant involvement, also known as ego-involvement (Ostrom et al. 1968), is the manner in which the individual defines himself (Johnson et al. 1989). Outcome-relevant involvement exists when involvement has the ability to attain desirable outcomes and impression-relevant involvement is the impression that involvement makes on others (Johnson et al. 1989).

My conceptualization of issue involvement is most closely aligned with value-relevant involvement (Johnson et al. 1989). I argue that those who have experience and/or knowledge of medical records in the health care setting will have salient beliefs about electronic medical records and they will, in turn, believe that the message topic is personally relevant. Because these individuals are embedded (Boninger et al. 1995; Pomerantz et al. 1995) in an environment affected by EMRs, I believe they will elaborate in detail about the use of EMR systems. In this study I treat II as an individual's psychological state that exists at a particular point in time rather than one that can be manipulated. This is consistent with prior work that has demonstrated that membership in religious groups, political organizations, or labor unions is an appropriate proxy for involvement (Cacioppo et al. 1982; Sherif et al. 1961).

Research findings regarding the impact of II on attitudes and persuasion are equivocal. For example, it is known that strong attitudes, which are more stable and able to fend off persuasive arguments, are more resistant to change than weak attitudes (Bassili 1996; Petty et al. 1995). In addition, social judgment theory argues that highly involved persons exhibit more negative evaluations of a communication because high involvement is associated with an extended 'latitude of rejection,' (Sherif et al. 1965), i.e. increasing II increases resistance to persuasion.

As discussed above, II is a complex construct in regard to its relationship with attitude. Yet, most scholars agree that highly involved people appear to exert the cognitive effort required to evaluate the issue relevant arguments presented, and their attitudes are a function of this information-processing activity (central route). Because of this high involvement and assumed elaboration, it is plausible that involvement will be positively related to attitude. This leads to the next hypothesis.

H2: After controlling for pre-manipulation attitude, post-manipulation attitude will be more favorable towards EMR use in high involvement (HI) individuals than in low involvement (LI) individuals.

Argument Framing x Issue Involvement: Although AF and II are known to be key drivers of attitude, my primary interest is not in these main effects, but rather in the interaction effect. As shown in Figure 3.1, I theorize that AF and II interact in their effect on attitude change. Individually, the AF-Attitude and II-Attitude links have been explored in detail in prior studies (see Table 3.2). ELM argues that people are more motivated to devote the cognitive effort required to evaluate the true merits of an issue or product when involvement is high rather than low. However, it has also been shown that increased issue involvement enhances persuasion with strongly framed arguments but inhibits persuasion with weakly framed arguments (Petty et al. 1984a; Petty et al. 1981b; Petty et al. 1983b). Yet some studies find support for this hypothesis only in relation to argument frames that contain strong persuasive messages and not weak messages (Axsom et al. 1987; Burnkrant et al. 1984; Johnson et al. 1989). As issues become increasingly more important, the receiver is more likely to exert the cognitive effort to thoughtfully consider the message (Petty et al. 1986a; Petty et al. 1981c). Receivers that are highly involved with the argument issue are likely to engage in extensive elaboration, while those that are not involved will be less likely to be engaged in elaboration and more likely to be influenced by peripheral cues (Petty et al. 1981c; Stamm et al. 1994). Thus it should be true that positively framed arguments will have an enhancing effect on the II-AC relationship.

Following from these findings, I posit that argument framing will positively moderate the relationship between issue involvement and attitude change. I therefore test the hypothesis:

H3: After controlling for pre-manipulation attitude, argument framing positively moderates the effect of issue involvement on post-manipulation attitude.

Insert Table 3.2 about here

Concern for Information Privacy: As noted earlier, there is substantial and growing evidence that privacy and security of health information is of utmost importance to individuals. It has been suggested in prior research that concern for information privacy is related to personality traits such as sensitivity to trust, paranoia, and social criticism (Smith et al. 1996). Others argue that previous personal experiences may influence one's concerns about information privacy (Culnan 1993; Stone et al. 1990). For example, it has been shown that individuals who have been victims of personal information misuses have stronger concerns regarding information privacy. Rather than the antecedents of CFIP, however, my focus is on the effect that varying levels of CFIP have on peoples' attitudes towards the use of EMRs.

Studies related to privacy concerns have predominantly focused on domains such as corporate uses of personal information (Graeff et al. 2002; Milne et al. 1999; Smith et al. 1996), electronic commerce and Internet buying behavior (Dommeyer et al. 2003; Long et al. 1999; Milberg et al. 2000; Porter 2000; Smith et al. 1996), and the economics of privacy (Petty 2000; Rust et al. 2002a). Aside from descriptive opinion-poll surveys, no work has empirically investigated the privacy concerns associated with using electronic medical records. The characteristics of digital information in general and EMRs in particular are such that there is an expected increase in the likelihood of privacy violations and misuse of information. For instance, digital information can be easily replicated at very low marginal cost compared to data stored on other traditional media. To the extent that people have stronger concerns about information privacy, their attitudes should be more negative about the use of EMRs (Chellappa et al. 2005). There I test:

H4: After controlling for pre-manipulation attitude, CFIP will be negatively associated with post-manipulation attitude.

In addition to the direct effect described above, prior literature notes that concern for privacy may be more complex and, in particular, it may moderate the hypothesized relationships (Van Slyke et al. 2006). In general, individuals who harbor strong concerns about a particular issue require particularly compelling arguments to modify their belief structure (Gurak 1997). The stronger the concern, the more persuasive a message needs to be in order to overcome the associated apprehension. Not only must the message contain strong evidence, it should also highlight the positive consequences that might accrue from ignoring the individuals' concern. In other words, the message argument must be framed positively. Sheehan and Hoy (1999) found that as privacy concerns increased, people were more likely to provide incomplete information to online queries and opt-out of mailing lists or websites that required registration. Moreover, as concern for privacy decreases, individuals increasingly provide information with little elaboration on the consequences such as being profiled or identified (Berendt et al. 2005). As described earlier, Louis Harris & Associates and Westin (1995) found three distinct categories emerge related to people's levels of concern about privacy of information. Consider, for example, the group that is most concerned about privacy; the so-called privacy fundamentalists. If this group supports "social welfare-based" appeals to digitize data – especially when the use of EHRs is grounded in facts – then the other, less concerned groups should be even more supportive. Based on this logic we test:

H5a: After controlling for pre-manipulation attitude, individuals with a stronger concern for information privacy will have a more favorable attitude towards EHR use under conditions of positive argument framing than under conditions of neutral argument framing.

As in the case of argument framing, we also expect an interaction effect for CFIP with issue involvement. When privacy concerns are high, only those individuals who have an understanding of the use and value of EHRs will be open to persuasion. For others, because the issue is not personally relevant or consequential, less cognitive processing and elaboration will occur, and therefore, their attitudes towards EHR use are likely to change less. We therefore test:

> H5b: After controlling for pre-manipulation attitude, individuals with a stronger concern for information privacy will have a more favorable attitude towards EHR use when they have greater issue involvement.

Predicting Likelihood of Adoption

The timing of this study is such that, at this point, EMR use by patients is not at a stage in diffusion where it is feasible to assess actual adoption behaviors. In the vast majority of the cases, respondents cannot actually adopt the technology: they can only form attitudes and beliefs about the concept of using the technology. Because EMRs are used by clinicians at hospitals and doctor's offices, but in almost no cases are they stored in interoperable systems or made available via the Internet to patients, beliefs about use must be assessed through perceptual measures rather than actual use. However, it is important to ascertain whether people will choose to opt-in to an EMR system if they are given the choice in the future. Therefore, I incorporate the variable – likelihood of adoption – into the model as a means of estimating actual future behavior.

There is currently a spirited debate among those in the medical profession, civil liberty groups, informaticians, and the general public surrounding the topic of opt-in versus opt-out of electronic medical record systems (Cundy et al. 2006; Watson et al. 2006; Wilkinson 2006). This debate considers whether the general public should have the right to decide if their health information can be digitized and made available for various purposes in a de-identified way, or if it should be available to *only* the health provider who *created* the record, thus making it unavailable to others who can treat the patient (Wilkinson 2006). I view, and operationalize, the likelihood of adoption (LOA) construct as an opt-in behavioral intention (Ajzen 1991; Davis et al. 1992). Behavioral intentions capture the motivational factors that influence the behavior of an individual (Ajzen 1991, p. 181). The criteria for carrying out the behavior are that the individual has the means, ability, and volition to do so. Prior work in the ELM domain has incorporated behavioral intentions (see for example, Petty et al. 1983b) but only from the perspective of the strength of the intention relative the route of persuasion. My research positions LOA as a perceptual measure that is an outcome of the attitudes and beliefs of an individual relative to EMR use, and manifests itself in the decision to either opt-in or opt-out of an EMR system.

Attitude. Sufficient evidence exists demonstrating a positive relationship between attitudes and intentions (Ajzen 1985; Ajzen 1991; Ajzen et al. 1986; Fishbein et al. 1974; Fishbein et al. 1975), including an extensive literature examining this link in the context of IT adoption (Agarwal et al. 1998; Davis 1989; Davis et al. 1992; Taylor et al. 1995; Venkatesh et al. 2003). Most of the research related to IT adoption intentions, however, is set in a context in which adoption is not considered fully volitional, such as a new system implementation in a firm. In the context of this study, likelihood of adoption, operationalized as opt-in behavior – by definition – is volitional. Here the motivation for the individual to adopt the technology is largely intrinsic rather than extrinsic and arguably, all other aspects of the system being equal, stronger than when adoption is mandated. Regardless of whether the motivation is intrinsic or extrinsic, however, the relationship between attitudes and intentions derives from the basic human need to achieve cognitive consistency (Festinger 1957) such that attitudes and behaviors are aligned with each other. Therefore I test,

> H6: Post-manipulation attitude towards the use of EMRs will be positively related to the likelihood of adoption (opt-in behavior).

With few exceptions (Malhotra et al. 2004; Van Slyke et al. 2006), there is limited prior research that has tested privacy concerns as an antecedent to intentions. Van Slyke and colleagues (2006) explore the relationship between CFIP and willingness-to-transact but find that the relationship is fully mediated by risk-perception and non-significant as a direct effect. However, there is some evidence in literature (Smith et al. 1996) suggesting that CFIP has a direct effect on intentions. To the extent that an individual's privacy concerns are high, his or her tendency to opt-in to an EMR will be low. Therefore I test:

> H7: CFIP will be negatively related to the likelihood of adoption (opt-in behavior)

3.5 METHODOLOGY

Study Design

I tested the research hypotheses using an experimental methodology as shown in Figure 3.2. I compared two purposively selected groups (involvement: high or low) and two argument frames (positive or neutral), and individuals were assessed on a third variable – CFIP. Below I describe the subjects used in this study and well as the procedure that was followed.

Insert Figure 3.2 about here

Subjects. My goal was to compare the responses of subjects considered to be high issue involvement with those of low issue involvement. To assure enough respondents for an acceptable sample size for high-involvement individuals, I worked with the organizers of an HIT stakeholder conference and collected the email addresses of 129 of their members. I randomly assigned these subjects to either positively or neutrally framed manipulations and sent them the associated Web-based survey. After two email reminders, I received 67 completed surveys (52% response rate).

The 'general' group of subjects was a quasi-random sample of people who opted-in to an online survey sample list provided by Zoomerang™. The Zoomerang service sends email solicitations to a database of email addresses and in exchange for membership points which can be redeemed for merchandise, an individual can opt-in to complete a survey. Since Zoomerang collects demographic information, I requested a random sample based on national census statistics. Again, individuals were randomly assigned to either a positive or neutral argument frame manipulation and the surveys were sent. Zoomerang estimates a 25-45% response rate based on the general group that was surveyed. After two email reminders, 299 completed low-involvement surveys were collected. Since demographic information was collected, I could ascertain if any individual belonged in the high-involvement group. I reclassified 35 of them as high-involvement based on demographics, job description, or prior electronic medical record knowledge (see Operationalization of Variables section for details). The final sample was 366 subjects (102 high-involvement, 264 low-involvement).

Procedure. At the beginning of the Web-based survey, the subjects were asked to consent to participation in the study via a checkbox query. If the subject consented, s/he was then asked several questions about his or her familiarity with electronic personal health records and electronic medical records in general. To ensure that respondents understood my use of the term EMR, I provided a detailed description of medical record technology and also included pictures and screen captures of several types ranging from paper-based forms to fully interoperable, Internet-based EMR systems. I made it clear in the survey that the questions were related to EMR systems that stored medical records on an Internet-based platform that could be accessed by multiple clinicians, other health entities, and possibly by the patient or caregiver.

I proceeded by querying the subject about his or her concern for information privacy and assessing his or her pre-manipulation attitude. In the next step, I randomly assigned the subject to either a strong argument frame or a neutral argument frame. The strong AF group received a manipulation in the form of six strong messages endorsing the use of EMRs and highlighting some of the facts surrounding medical errors and the connection between HIT and reduced errors (see Appendix A3; Argument Framing). The messages were pre-tested to confirm which generated the strongest and weakest responses. The second AF group received a manipulation where the four messages were weak, consisting of user endorsements, anecdotal evidence, and opinions. After reading the messages, the subject was asked to confirm that s/he read the messages by checking 'yes.' If 'yes' was not selected, the subject was asked to go back and read the messages. Everyone in this study selected 'yes.' I then asked the subject two questions about the messages – one about the trustworthiness of the subject and the other about the reliability of the information presented in the messages (see Appendix A3; Manipulation Check). I used this information to confirm that the manipulation was effective. I proceeded to ask several more questions about electronic medical records and finally asked the subject to respond to the same attitude items – this was the post-manipulation attitude. Demographic data were collected at the end of the survey.

Operationalization of Variables

Likelihood of Adoption. In the specific case examined in this study, the choice to opt-in to an EMR is simply an affirmative or negative response. To introduce some variance into this outcome variable, I queried the subject as to when s/he would opt-in. The subject was also given the option of choosing that s/he would never opt-in to the system. The scale ranged from 1 (I will never use them) to 6 (I am already a user).

Attitude. Semantic differential scales anchored by polar adjectives have been used in several studies to assess attitude (e.g. Eagly et al. 1993; Gallagher 1974). Some argue that covert techniques are better able to tap into true attitudes when people have reason to be dishonest (Fazio et al. 1995), however, it has been demonstrated that self-reports of attitude are preferred when there is no reason for respondents to hide their true feelings (Fazio et al. 1997). As I was unable to identify any compelling reasons why someone would not be honest in this survey, I use the approach that directly measures attitude.

The underlying premise behind using semantic scales is that they can define a given stimulus (attitude towards using EMRs) through significates (descriptive adjectives) without actually asking the respondent directly about the stimulus. This method can also be used to verify the validity and reliability of direct questions involving the stimuli. Studies of attitude and persuasion often focus on three components of attitude change which emerge when using a semantic differential scale – those being Evaluation-, Potency-, and Activity-based measures (Di Vesta 1966; Friedman et al. 1969; Osgood et al. 1969; Osgood et al. 1957). In this study, I assume attitude to be a single latent construct constructed of Evaluation, Potency, and Activity (EPA). Others in the IS research literature have simplified this further by using four items to assess attitude (Bhattacherjee et al. 2006; Taylor et al. 1995). I assess attitude towards the use of EMRs using a 7-point semantic differential scale (Karwoski et al. 1938; Osgood et al. 1957). I pre-tested thirteen pairs of polar adjectives and used those that elicited the strongest factor loadings. Seven of these demonstrated discriminant and convergent validity in the pre-test for three factors (see Appendix A3; Semantic Differential – Polar Adjectives Used). I conducted a pre-manipulation attitude evaluation using these multidimensional assessments of attitude, and aggregated the results into a composite measure to simplify the analysis. After the subject completed the attitude evaluation, s/he was given the manipulation consisting of either a positively or a neutral frame and then a post-manipulation attitude examination was conducted. In addition to the semantic differential scale, four post-manipulation questions were asked which directly queried the respondent about whether or not his or her attitude had changed as a result of the manipulation (see Appendix A3; Post-Manipulation Assessment). I used this data to explore the agreement between the calculated attitude change and the self-report.

Argument Framing. Thirteen arguments were pre-tested to assess the relative strength of the EMR message (see Appendix A3; Argument Framing). There were six messages that elicited strong positive responses. These typically involved a statistical link between electronic medical record usage, error reduction, and decreases in deaths attributed to medical errors. All messages are true and the literature from which the message is taken is cited. The messages are all delivered by a recognizable source that is assumed to be credible and is subsequently checked in the survey for trustworthiness and reliability. I classified this group of messages as positively framed and coded them as a 1. The messages that did not elicit strong responses are entirely fabricated, typically anecdotal, lacking any statistical validations and a source, if given, is anonymous. Again, these messages were tested to see if respondents indeed viewed them as weak sources of information. These were classified as neutrally framed and coded as 0.

Involvement. In most studies of attitude change and dual process modes of persuasion, involvement is artificially manipulated via a description given to the respondents. For example, it is common to suggest to high involvement participants that a decision they are about to make will have a direct impact on them in the near future while telling low involvement participants that the decision they will make will not affect them or will affect them at a much later date (e.g. Apsler et al. 1968; Petty et al. 1983b; Sherif et al. 1961). This method has been used quite extensively but one needs to be diligent about confirming that the manipulation actually took effect and the respondent takes on the prescribed involvement (for a discussion, see Petty et al. 1983b). In this study, a different and arguably more objective method of assessing involvement is used. I assess high and low involvement using several factors including: 1) does the respondent currently use an EMR in a health setting, 2) does the respondent work in the health care industry, 3) and does the respondent have good or excellent knowledge of

EMRs. If any of the questions are answered affirmatively, the respondent is assumed to be high involvement and is coded as a 1. Therefore, II is a psychological state that exists in the respondent by virtue of there current position and knowledge and I do not make this a random assignment.

Concern For Information Privacy. I measure CFIP using a modified scale developed by Smith, Milberg and Burke (1996), which was later tested and empirically validated by Stewart and Segars (2002). I made minor changes to their instrument to reflect privacy concerns relative to health data instead of corporate data by replacing the word *corporations* with *health care entities* – defined as "any and all parties involved in the health care process, such as doctors, hospitals, clinics, health insurance providers, payers, pharmacies, etc." The CFIP instrument has not been used to test people's perceptions about how information is used and shared within and across the healthcare system. However, using the term 'health care entities' in place of the term 'companies' adds a new dimension to CFIP that I argue brings a heightened level of personal salience due to the known concerns about access to medical data rather than financial or demographic data (Boritz et al. 2005).

As described below, in the structural model, I use CFIP as a continuous Likert scale aggregate measure of all four of its components. However, in an effort to simplify the analysis and interpretation in the post hoc analysis, I follow in the tradition of Louis Harris & Associates and Westin (1995) and divide the sample into varying levels of CFIP. This also serves the purpose of controlling for extreme difference in sample sizes. I categorize the highest 25 percent as privacy fundamentalists and the lowest 20 percent as privacy unconcerned based on their aggregate scores on CFIP. Using this dichotomized sub-group approach, I further investigate the moderating effect of CFIP (Stone-Romero et al. 1994).

3.6 ANALYSIS AND RESULTS

Hypothesis Testing: Analysis Approach

I tested the hypothesized relationships among the constructs using structural equation modeling (SEM) and the software program EQS6.1/Windows (Bentler 1985; Bentler et al. 1993). Only recently have researchers discovered ways to use SEM in models when data is categorical and there are interaction effects. In my model, both situations are present which restricts me to using only composite measures in the model (Loehlin 1998; McDonald 1996), rather than latent constructs. However, when calculated correctly, composite measures have been shown to be reliable and in fact, are preferred when sample size is small (Bagozzi et al. 1994; McDonald 1996).

Two recent reviews of the SEM literature suggest four strategies for handling categorical data in SEM (Kupek 2005; Kupek 2006): 1) a method employing asymptotic distribution-free (ADF) estimators (Browne 1984; Yuan et al. 1998), 2) robust maximum likelihood estimation (Browne et al. 1988; Chou et al. 1991), 3) using multi-serial, multi-choric correlations between pairs of variables with non-normal joint distribution as inputs for SEM (Joreskog et al. 1994; Muthen 1984; Muthen 1993), and 4) estimating probit or logit model scores for observed categorical variables as the first level, then proceeding with SEM based on these scores as the second level (Muthen 1993). The conclusion that Kupek (2005) draws based on tests of all four models, is that there are advantages and disadvantages to each – such as large sample size requirements with the ADF estimation and poor performance of choices 3 and 4 if the initial model does not fit well – but all methods perform nearly the same in his simulation. He suggests that the method chosen should be more a function of the study and data rather than the relative performance differences (Kupek 2005).

In this study, I use a *robust* maximum likelihood estimation method (Bentler 1985; Browne et al. 1988; Chou et al. 1991) because it has been shown to be effective in modeling interactions (Bollen 1989). One advantage of using SEM over other analytical methods is that SEM will model all regression equations simultaneously, allowing for the calculation of direct and indirect (interaction) relationships.

Demographics, Descriptives, and Measurement Model Fit

Demographic and descriptive variables are presented in Table 3.3. The total sample size is 366. The sample has nearly double the number of females as it does males. This result is not by design but instead is an unintended artifact of the study. I tested for significant differences in descriptive variables between males and females and found that age, education, income, computer experience, and computer skill were all reported higher in males than in females ($p<0.05$ in all cases). Self-assessed health and presence of a chronic illness were not significantly different between males and females. Because I found several demographic variables to be different between men and women, I controlled for gender in the analysis.

As mentioned earlier, a measurement model was fit to the data. The estimation of the structural model yielded the following goodness of fit indices: comparative fit index (CFI) = .91, CFI > 0.90 is recommended (Jiang et al. 1999); adjusted goodness of fit (AGFI) = 0.91, AGFI > 0.80 is recommended (Gefen et al. 2000); root mean square residual (RMSR) = 0.06, RMSR < 0.10 is recommended (Chang et al. 2005). Because the measurement model displays an acceptable fit, no modifications were made to the model parameters.

Finally, all variables were checked for multicollinearity and in all cases the test statistics were within acceptable ranges such that the tolerance was greater than 0.2 (Menard 1995) and the VIF was less than 10 (Myers 1990).

Assessing Attitude. Upon analyzing the final data, I found that only the 'evaluation' adjectives loaded correctly in both the pre- and post-manipulation. Since I used pre-manipulation attitude as a control variable to post-manipulation attitude[22], it was necessary to use only those pairs of adjectives that loaded consistently in both the pre- and post- conditions. Thus, I used the 'evaluation' measure of attitude, consistent with others (Bhattacherjee et al. 2006; Taylor et al. 1995). The polar adjectives used were Bad-Good, Foolish-Wise, and Unimportant-Important (Cronbach alpha=0.85). I also confirmed that the semantic scale was effective in assessing attitude change by asking specific questions about changes in attitude as a result of the manipulation (see Appendix A3; Post-Manipulation Assessment). I found a significant correlation between the calculated attitude change (semantic scale) and the self-reported attitude change in all cases except willingness to pay more for access (see Table 3.4).

Insert Table 3.4 about here

Manipulation Check

To assess the effectiveness of the text-based manipulations, I asked two questions of the subject immediately following the manipulation. First, subjects were

[22] Because I include pre-manipulation attitude as a control, I am creating a baseline attitude level for each respondent such that the magnitude of post-manipulation attitude is tempered by pre-existing attitude. Empirically, this equates to attitude change.

asked if they felt the sources of information were trustworthy. Next they were asked if they felt the sources were reliable (see Appendix A3; Manipulation Check). Using a one-way ANOVA with trustworthiness and reliability as dependent variables and argument frame as a fixed factor, I found strong statistical evidence that respondents perceived more trust and reliability when AF was positive, confirming that the respondents read and understood the messages (Trust: $M_{positve}$=5.33, $M_{neutral}$=4.51, p<0.001; Reliable: $M_{positive}$ =5.42, $M_{neutral}$ =4.40, p<0.001).

Results

As hypothesized, several paths in the structural model are significant. I first examine the standardized path coefficients, which are used to evaluate the hypotheses. However, while the path coefficients and associated p-values are useful for understanding the directional relationships between variables, because several variables are binary, further exploration is warranted to fully interpret the relationships. Therefore, I conduct post-hoc analyses to examine interactions in greater detail.

In the first hypothesis, I propose the relationship between argument framing and post-manipulation attitude. The path coefficient is positive and significant (β_1=.09, p<.05) suggesting that positively framed arguments yielded higher post-manipulation attitudes (Note: positive AF was coded 1 and neutral AF was coded 0). Therefore, H1 is supported. In the second hypothesis, I posit that high issue involvement individuals will have a greater post-manipulation attitude. This hypothesis is supported, suggesting that greater involvement does influence attitude (β_2=.06, p<.05). The variance in post-manipulation attitude explained by AF, II, and pre-manipulation attitude is 47.2 percent (F(3,314)=96.7, p<.001).

With hypothesis 3, I propose that AF will positively moderate the relationship between II and post-manipulation attitude. I create the AFxII interaction term by dummy coding the variables to create a 2x2 design, which assesses the effect of II when AF is zero and the effect of AF when II is zero (Kenny 2004). The resultant standardized coefficient measures how the effect of II varies as AF varies. In my analysis, the AFxII coefficient was -0.22 ($p<.05$), indicating that the effect of II on attitude change decreases as AF goes from 0 to 1. This finding is significant, but opposite of that proposed in H3, therefore it is not supported.

A key objective of this study is to evaluate the impact that privacy concerns have on attitude and likelihood of adoption. In the next hypothesis, H4, I test the direct effect of CFIP on post-manipulation attitude. I do not find support for the hypothesis that CFIP has a negative relationship with attitude ($\beta_4=.05$, $p=.36$). The negative relationship between CFIP and LOA, however, is present and is quite powerful ($\beta_7=-.17$, $p<.01$). This suggests that individuals with a high degree of privacy concerns related to the use of EMRs will be less likely to actually opt-in to using the technology and that their behaviors are not closely modeled by their attitudes. Therefore, H4 is not supported, but H7 is supported.

CFIP was also hypothesized to moderate the relationship between attitude, AF, and II. Following the procedure outlined by Kenny (2004), I operationalized this as the product of AF (Positive/Neutral AF) and CFIP, and II (Low/High II) and CFIP for the structural analysis and used the continuous aggregated variable CFIP as the moderator. The AFxCFIP interaction was positive and significant ($\beta_{5a}=.42$, $p<.05$), demonstrating that CFIP does in fact positively moderate the relationship with attitude, thus confirming hypothesis 5a. However, the IIxCFIP interaction was not significant (β_{5b}=-.05, p=.81). The variance in post-manipulation attitude explained by AF, II, AFxII, AFxCFIP, and pre-manipulation attitude is 54.7 percent (F(6,311)=64.7, p<.001)

The last finding I report is the relationship between post-manipulation attitude and likelihood of adoption of EMRs. Results show a positive relationship between post-manipulation attitude and LOA (β_6=.42, p<.001). This confirms H6, thus demonstrating a positive association between attitude and LOA, even under purely volitional conditions (see Table 3.5 for a summary of results).

Insert Table 3.5 about here

Finally, this model explains a substantial amount of variance in the dependent measures, particularly post-manipulation attitude (i.e. Post-Manipulation Attitude adjusted R^2=.55; Likelihood of Adoption adjusted R^2=.19). This fact, coupled with the significant paths highlighted above, provide strong empirical evidence that CFIP is an important component of EMR attitudes and use.

Post Hoc Analysis

As noted earlier, the interactions require further investigation. SEM provides support for the hypothesized relationships, but more elaboration is necessary to be able to interpret the path coefficients appropriately. In this section, I elaborate some of the detailed findings.

Argument Frame x Issue Involvement. I hypothesized that the framing of arguments would influence the relationship between issue involvement and attitude and found support for this assertion; however, the direction was in the opposite as hypothesized. To investigate this further and to provide more detail beyond the structural model, I categorized the sample into subgroups based on their position in the AQxII matrix. Using ANOVA, I investigated the differences between positively and neutrally framed arguments and the effect that each had under both low and high II. To test this, I used planned post-hoc multiple comparisons. Overall, the ANOVA was found to be statistically significant ($F(3,317)=4.77$, $p<.01$). A more detailed analysis revealed that positive AF elicited much greater attitude change than neutral AF (see Figure 3.3). In particular, notice the significant difference between AC when AF is neutral (.23 to .45, $p<.001$), versus when AF is positive (from .36 to .46, $p<.001$). From this, I can conclude that persuasion can occur in people when positively framed arguments about the value of EMRs are presented under both low and high II. In addition, because the interaction term was negative ($\beta_3=-.22$, $p<.05$), it can be concluded that as issue involvement increases, the effect of argument framing diminishes, e.g. for clinicians and other HIT stakeholders, the magnitude of attitude change is less dependent on the framing of the arguments. One explanation for this somewhat surprising finding is that the involved subjects have reason to believe in the value of the use of EMRs and therefore respond favorably to all messages, irrespective of whether they are strongly framed.

Insert Figure 3.3 about here

Argument Frame x CFIP. As demonstrated above, the interaction of AF and CFIP was significant and positive. A more detailed investigation of endpoints reveals some intriguing findings. To test the endpoints, I created a group variable based on AF (positive/neutral) and CFIP (privacy fundamentalists [high]/privacy unconcerned [low]) and coded each subject accordingly. Next I conducted independent-samples t-tests between groups. To simplify the presentation of results and their interpretation, I use attitude change as the variable of interest in this post hoc analysis. Because I controlled for pre-manipulation attitude in the structural model, I essentially was measuring attitude change even in the prior analysis. Yet, conceptually and theoretically it does not make sense that attitude change influences intentions, but rather that post-manipulation attitude is the determinant. Since I am not including LOA in this post hoc analysis, I use attitude change, which is the difference between pre- and post-manipulation attitude. The goal of examining the two-way interactions was to tease out the contributions of the variables of interest when interacting with CFIP. The data represented in figure 3.4 shows the small difference in attitude change under *low* CFIP ($AC_{neutral}$=.29 versus $AC_{positive}$=.22, p=.65) and a large disparity under *high* CFIP ($AC_{neutral}$=.27 versus $AC_{positive}$=.59, $p<.05$). What this result shows is that when concerns about privacy are strong, only strong argument frames will elicit persuasion. When CFIP is low, the strength of the argument frame is less important for persuasion to take place.

Insert Figure 3.4 about here

Issue Involvement x CFIP. Specifically related to II, it is critically important to understand the interaction with CFIP because for EMRs to be widely diffused, individuals with varying degrees of II need to be persuaded. To test the endpoints, I followed the procedure described above and created a group variable based on II (high/low) and CFIP (privacy fundamentalists/privacy unconcerned) and coded each subject accordingly. As demonstrated earlier, the interaction term IIxCFIP was not significant. Upon examination of the individual endpoint, I did not find a significant relationship under either *low* (AC_{lowII}=.21 versus AC_{highII}=.30, p=.58) or *high* CFIP (AC_{lowII}=.49 versus AC_{highII}=.52, p=.88; see Figure 3.5).

Insert Figure 3.5 about here

Limitations

Prior to reflecting on the implications of these findings, I discuss the limitations of the research. Although I attempted to educate the subject about electronic medical record systems, it is possible that some respondents did not understand the technology – in particular, those I classified as low issue involvement. Because EMRs are not part of the lexicon of most people, there is the chance that some people formed their own mental construal of the artifact which was not accurate and therefore, biased their responses. Recent work has suggested that people's responses to privacy-based survey questions do not align with actual exhibited behaviors – particularly if there is an award associated with the behavior (Berendt et al. 2005). In this work I am not examining actual behaviors but I caution the reader and future researchers to allow for the possibility that stated preferences may be more conservative that actual actions.

Issue involvement is a complex construct and as discussed earlier, findings have been mixed when it is used in ELM studies. The operationalization of II has removed some of the concerns with the construct such as the assurance that the manipulation has taken effect, but I have also introduced new issues. For example, my classification based on job and/or knowledge of EMRs may not truly represent the involvement that an individual feels relative to the impact that EMR use may have. I do believe, however, that the theoretical justification for using the classification is powerful and the results indicate that there are distinct differences across the groups. I therefore feel confident that the operationalization is justified.

For the high involvement individuals, I used a convenience sample. I was not able to randomly sample from a large pool of potential respondents and therefore was left with a high proportion of females and a demographic mix that may not be representative of the society as a whole. Also, my sample included only those subjects who had access to the Internet for completion of the survey. Since this study was conducted as a quasi-experiment in which I compared groups of individuals, I do not believe the tech-bias causes undue concern. I do control for gender and make assertions only about the relative differences between groups rather than generalizability of the findings. Caution should be taken that these results may not be applicable to a population of individuals who do not use computers or the Internet.

3.7 DISCUSSION

> "[Privacy of health information] is not something that we can long ignore. The Senate and House do need to revisit privacy soon," *statement from William Pewen, senior health policy adviser to Senator Olympia Snowe (R-Maine), April 11, 2006* (Ferris 2006).

While replete with anecdotal and opinion poll data related to privacy and medical information, my literature review revealed a very limited amount of extant *academic* research discussing information privacy. Because of this paucity of theory, it is not surprising that some of the findings are not supported and in the case of post hoc analysis, the results are in directions contrary to prediction. In addition, there have been some inconsistent findings surrounding the effects of some of the key variables used in ELM studies (e.g., Bassili 1996; Johnson et al. 1989; Petty et al. 1984b; Petty et al. 1995; Sherif et al. 1965). These shortcomings not withstanding, this research revealed several interesting findings and the core hypotheses were supported. What follows is a discussion of findings and plausible explanations for contradictory results.

Key Findings

Consistent with prior research, I find that people's attitudes can be modified in a favorable way. The results also add to a growing body of literature in support of the concept that CFIP is an important construct in belief structures of individuals as they relate to the institutional use of personal information. Equally important, this result provides evidence that privacy concerns are important issues to consider as related to beliefs about the use of EMRs. A striking finding of this study is the complex relationship between privacy concerns, AF, and II. These interactions and how they impact attitudes merit further investigation. To the extent that people believe their medical information is vulnerable when input into an EMR, it is imperative that assurances about security and value are communicated to the individual, since people with high privacy concerns are more difficult to persuade.

Results also show that in addition to having more favorable pre-manipulation attitudes toward the use of EMRs, high issue involvement individuals demonstrated a statistically significant increase in attitude change but only under conditions of neutral AF. This is an intriguing finding. One explanation for this is that it is easier to persuade high II individuals of the value of EMRs than it is to persuade low II individuals. In a sense, one could argue that high II individuals *want* to believe in the value of EMR use, while low II individuals need to be persuaded by very strong argument framing. This may be due to a lack of understanding, or misunderstanding, of the uses of EMRs by low II respondents. It may also be the case that the uninformed are unnecessarily concerned about functions and features of EMRs, which may or may not exist. For example, evidence from this study also revealed respondents had great concern about their employer finding out about personal medical information if their data were located in an electronic, Internet accessible database.

Relative to privacy concerns, I find that most respondents, even those with higher than normal concerns for privacy, reacted favorably to positively framed arguments. This provides some evidence that privacy concerns, while a salient barrier, may not be enough to halt the acceptance of electronic records, which is an intriguing finding with significant practical implications. While I did not specifically hypothesize a significant difference between positive and neutral argument frames and the impact they would have when factoring in the effect of CFIP, I did find that across the board, positive AF elicited greater changes. Even when CFIP was very high, there was evidence that positive AF messages would change attitudes. This is encouraging since it demonstrates that with proper messaging, attitudes toward EMR use can improve.

An intriguing result from the post hoc analysis was the finding that attitude change was greater in people with high CFIP, but only under conditions of positive AF. There are two possible explanations for this finding. First, people who have strong privacy concerns may be basing their beliefs on unfounded assumptions. For example, they may not understand the true merits of the EMR system, but when they read the positively framed messages, they are easily persuaded. The same may be true of low

CFIP individuals but the result may not manifest itself in attitude change because it was already factored into their pre-manipulation response. Supporting this claim, in a follow up analysis, I discovered that people with low CFIP had a more favorable view of EMR use than high CFIP individuals ($M_{lowCFIP}$=5.20, $M_{highCFIP}$=5.00, p<0.10). A second explanation is that the interaction of CFIP with AF is more complex and there is, in fact, a three-way interaction such that the result shown in figure 3.4 is an artifact of issue involvement interacting with the AF and CFIP. While the IIxCFIP two-way interaction was not significant, I did find the three-way interaction to be positive and significant ($\beta_{3\text{-}way}$=.090, p<.01). The interpretation of this finding is highly complex and warrants further investigation. One explanation for the non-significant finding in H5b (IIxCFIP) is simply that a confounding effect exists. As suggested, it may be true that under conditions of high CFIP only high II are persuadable (because they believe in the technology), but at the same time these same individuals perceive more control over events, in which case CFIP should play a lesser role.

Moving beyond the empirical findings, I was intrigued that very little work incorporating intentions into the ELM framework has been done (see Bhattacherjee et al. 2006 for a recent exception). In one of the few studies, Petty and colleagues (1983b) found that attitudes were better predictors of intentions under high rather than low involvement. They suggest that this provides support for ELM in that attitudes which result from central route will be more predictive of behavior than those formed via a peripheral route. I did not find a significant difference in predictive power of attitudes to behavioral intentions between high and low involvement, but this is not surprising. Petty and Wegener in a later study (1999), argued that the variable itself does not determine the route of persuasion but instead it is the degree of elaboration. Since I cannot determine with certainty the route of persuasion employed, it is not possible to make any statements about which level of involvement should elicit stronger relationships between attitudes and intentions.

Consistent with prior research, I find a significant relationship between attitudes towards the use of EMRs and intentions to opt-in at some point in the future. However, the variance explained in this relationship was much lower than the variance explained by the predictors of attitude (.19 vs. .55, respectively). One plausible explanation is that ELM almost exclusively focuses on attitudes (Petty et al. 1986a); therefore its explanatory power as a theoretical lens when intentions are included is less profound. Another intriguing point recently argued by Bhattacherjee and Samford (2006) is that, depending upon the route of persuasion, attitudes may not be the only mediating factor to influence an individual's intentions. They posit that other behavioral factors, such as perceived usefulness, will mediate the relationship between some commonly used ELM antecedents and intentions.

As hypothesized, the relationship between concern for information privacy and opt-in behavior is strongly negative, indicating that peoples' concerns can impact their decision to adopt. Interesting, CFIP did not affect attitudes in a direct way, but did moderate the AF x II interaction term, suggesting that there is a highly complex interaction; one that is suggestive of a trade-off between protecting one's privacy and the desire for improving one's health.

3.8 CONCLUSION

With enabling technologies such as the Internet, wireless communication, powerful processors, and extended battery life for laptop and tablet PCs becoming mature, society has reached a point where fewer technical barriers to innovation adoption exist. With technical barriers being overcome with regular frequency, it is important for similar strides to be made in understanding why people struggle to accept the change that new innovations bring. Because they involve human behavior, in many ways, social and societal issues are more difficult to resolve than those which involve research in the physical sciences. The potential value afforded by the use of information technology in healthcare is far too compelling to ignore simply because there are challenges – such as concerns about privacy infringement – to getting a system implemented and embedded into work processes.

Information systems' researchers have made substantial progress in examining behavioral aspects associated with technology adoption, yet very little of this work has been integrated into the practice of healthcare. In addition, while privacy of information is becoming more topical, the privacy of medical information has not been studied in a rigorous way. There are very strong, visceral feelings about this type of highly personal data and it behooves researchers to examine the barriers to IT adoption in the presence of such concerns.

It is very likely concern for privacy of all types of personal information will become increasingly important in the near future as more and more information is digitized. Therefore, information privacy should be examined in multiple contexts and domains. The national media exposes breaches in private digital information on a regular basis and it is becoming apparent that diverging views are emerging in the population. The construct CFIP has been used in a limited fashion in IS research and as yet, has not been widely tested in other disciplines. I find CFIP to be very useful in this research but acknowledge that more work needs to be done to tease out the individual contributions of its four related factors. In particular, I find that this research could be extended and strengthened by examining the impact of collection, secondary use, errors, and unauthorized access as individual discrete latent components that, by themselves, have unique impacts on attitude change. Prior work suggests that errors in medical data can hold grave consequences and I believe interesting insights will emerge from exploration at a more fine grained level.

Although I use a privacy-focused lens, I acknowledge that other variables may impact attitudes toward EMR use. For example, there is a rich body of literature that explores demographic and social issues affecting attitudes towards new technologies. My choice of privacy was motivated by three primary reasons. First, opinion-poll data would lead one to believe that privacy concerns will negatively affect attitudes towards EMRs to such a degree as to render any national efforts unachievable. I sought to demonstrate that through proper messaging and education, attitudes could be changed, even in the presence of great privacy concern. Second, there has been tremendous media attention given to privacy of data; not only medical data but also other types of data such as financial. Typically this attention has been highlighted in negative connotations such as breaches of security, fraud, or theft of information. This study is a first attempt at investigating whether these concerns are unfounded or if people weigh the costs and benefits of potentially compromising some degree of privacy for the possibility of getting better health results. This so called, 'calculus of behavior,' (Culnan 1993; Laufer et al. 1977) is a cognitive process that people undergo as a means of assessing future ramifications from choices made today (e.g., if one chooses to opt-out of an EMR, could this result in negative consequences in the future?). The final reason I explored privacy is that I believe that privacy concerns are the single greatest threat to successful rollouts of EMRs. Considerable work remains with respect to the investigation of the variances in beliefs related to privacy concerns and in particular, whether public opinion will impact the use of information technology that has been developed to store and maintain personal information.

Implications

The compelling call for research investigating the antecedents of attitude and persuasion has never been fully addressed. After more than 20 years, researchers are still using most of the original antecedents proposed by Petty and Cacioppo (1981a). This study investigates the impact of privacy concerns on one's beliefs about the use of technology. With the increased ubiquity and availability of the Internet, and the fact that people are relying on the web to transfer and store much more personal data, researchers need to begin including privacy into models of technology adoption and attitude towards technology. The ramifications of loss of privacy are significant. Researchers have identified consequences ranging from stress (Johnson 1974; Stone-Romero et al. 2003) and negative feedback about competence (Margulis 2003) to very severe long-term consequences such as dehumanization and failure to integrate into ordinary life (Goffman 1961; Ingham 1978) to life or death (e.g., a Jewish male posing as a Christian in Nazi Germany, Stevens 2001). As Margulis (2003) says, "When privacy is invaded or violated, it is lost."

From a practical standpoint, this research investigates a topic that requires significant exploration if the goal of electronic medical records for most consumers in the US is to be met by 2014. These results show that messages can be crafted to elicit changes in attitudes about the use of electronic medical records, even under high concerns about privacy. In fact, I found that under most conditions, I was able to persuade people and improve their attitudes towards use; a finding that should be of value to policy makers. For example, I provided a very limited amount of education about EMRs and even so, was able to persuade people by presenting them with strong text-based messages. This suggests that a national educational program designed to demonstrate the benefits of EMR use has the potential to improve the uptake of the EMR technology significantly.

On the basis of published research, it is also abundantly clear that there is limited knowledge related to the role that *patients* play in the health information technology arena – especially as it relates to patient involvement in the delivery, monitoring, and dissemination of information related to their health care. This study seeks to fill some of these gaps in current knowledge. Thus, it can serve as a foundation not only for making decision related to EMR design, adoption, and implementation, but also as a basis for future research.

3.9 FIGURES

Figure 3.1. Conceptual Model Highlighting Proposed Relationships

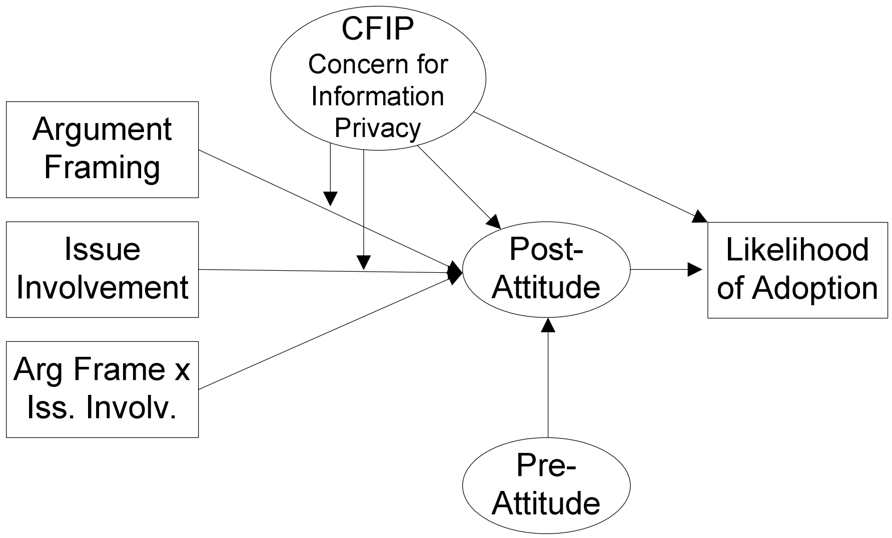


Figure 3.2. Flowchart Describing Attitude Persuasion Experiment

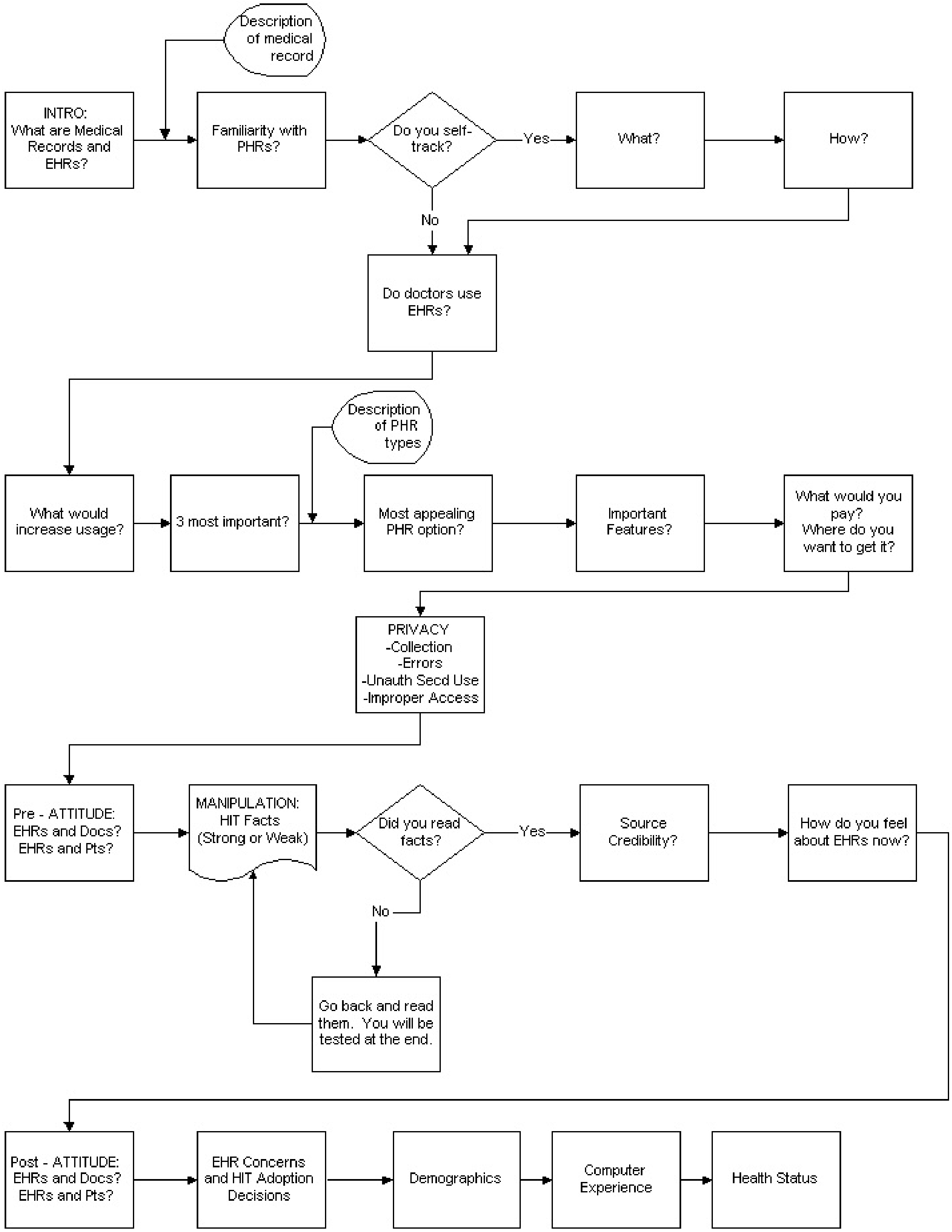
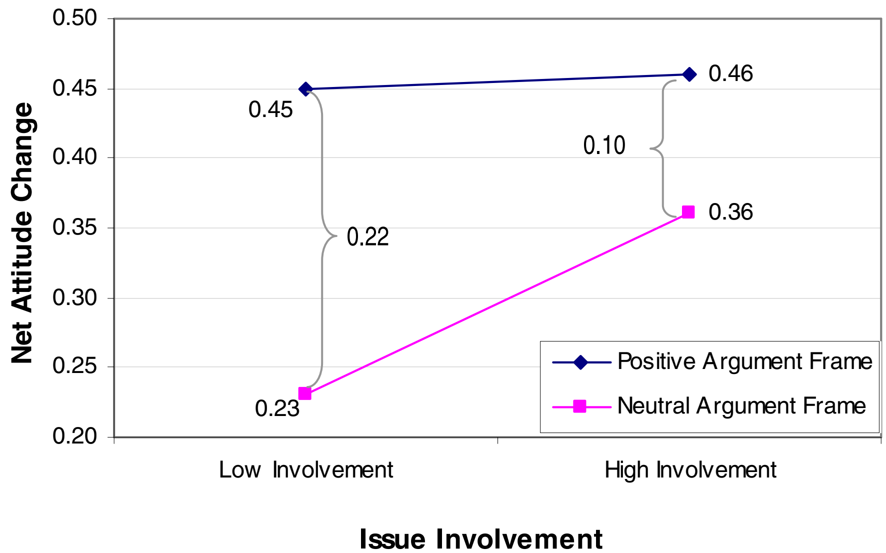


Figure 3.3. Interaction Effect of Issue Involvement and Argument Frame on Attitude Change



Note: Attitude change represents the difference between pre- and post-manipulation attitudes about the use of EMRs. The attitudes were measured on three seven-point semantic differential scales anchored at 1 and 7 (Bad-Good, Foolish-Wise, Unimportant-Important).

Figure 3.4. Effect of CFIP on the Relationship between Argument Frame and Attitude Change

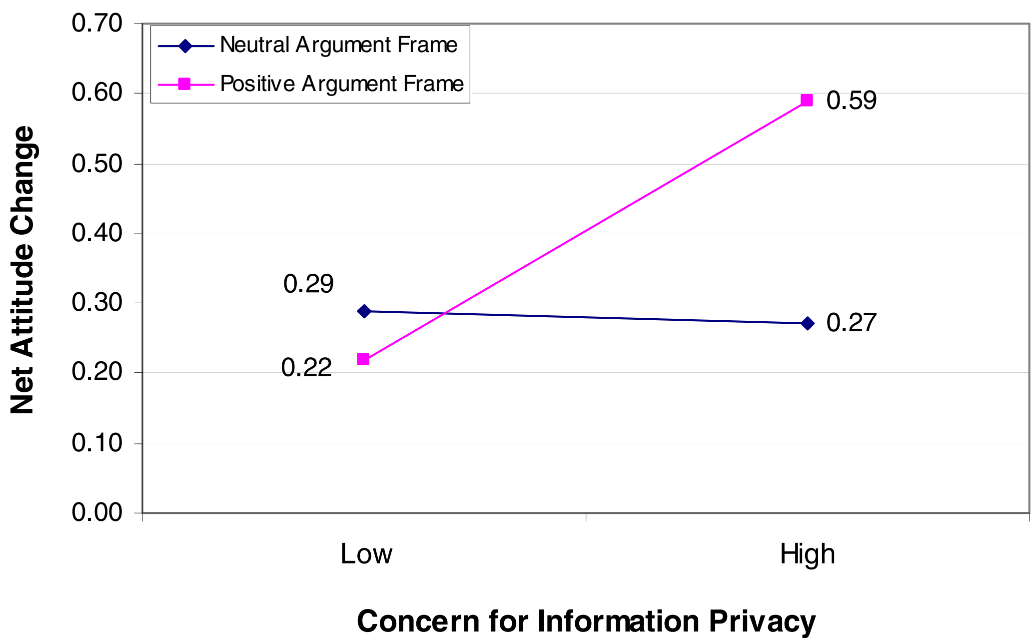
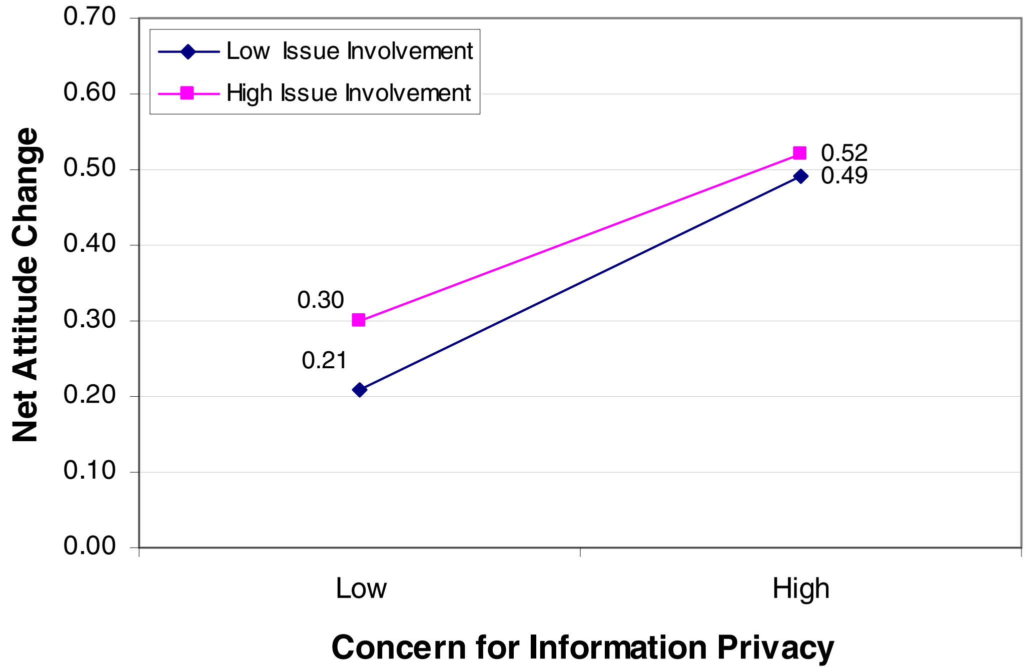


Figure 3.5. Effect of CFIP on the Relationship between Issue Involvement and Attitude Change



3.10 TABLES

Table 3.1. Key Covariates and Interactions Affecting Attitude Change

Variable[23]	Findings	Reference
Issue Involvement (also known as Self-Referencing or Personal Relevance)	Elaboration on information is greater when people can relate the information to themselves and to their own experience. When motivation is low, self-referencing has no effect on elaboration or persuasion.	(Burnkrant et al. 1989; Burnkrant et al. 1995; Petty et al. 1980) (Meyers-Levy 1991) For Meta-Analysis, see (Johnson et al. 1989)
Multi-Dimensional Issue Involvement	The effect of involvement on attitude is dependent on the type of involvement. Manipulations that require extensive issue- or product-relevant thought in order to be effective have a greater impact under high rather than low involvement conditions. Manipulations that allow one to evaluate an issue or product without engaging in extensive issue- or product-relevant thinking will have a greater impact under low rather than high involvement.	(Johnson et al. 1989)
Argument Quality	Argument quality positively influences perceived usefulness of information.	(Bhattacherjee et al. 2006; Sussman et al. 2003)
Issue Involvement x Argument Quality	High Involvement – Quality of arguments has a greater impact on persuasion. Argument quality has an impact only under high involvement conditions. Low Involvement – Quality of arguments has a lesser impact on persuasion. Increased issue involvement enhances persuasion only when messages are strong. Increased issue involvement increases 'latitude of rejection,' i.e. increases resistance to persuasion Involvement and expertise moderated the main effects of argument quality and source credibility on perceived information usefulness. Involvement significantly interacts with argument quality to affect perceptions of message utility.	(Mak et al. 1997; Petty et al. 1979; Petty et al. 1981d) (Petty et al. 1984b) (Petty et al. 1979; Petty et al. 1981d) (Johnson et al. 1989) (Sherif et al. 1965) (Bhattacherjee et al. 2006; Deighton et al. 1989) (Sussman et al. 2003)

[23] I have not included cue-type in this table due to the considerable debate surrounding the validity of categorizing a variable as acting through a central or peripheral route rather than recognizing the multiple roles for variables (Petty & Wegener 1999).

Variable	Findings	Reference
Source Credibility (Source Expertise or Source Attractiveness)	Source expertise typically associated with peripheral route to persuasion but also can act through a central route Source credibility positively influences perceived usefulness of information.	(Heesacker et al. 1983; Moore et al. 1986; Puckett et al. 1983) (Homer et al. 1991) (Bhattacherjee et al. 2006; Sussman et al. 2003)
Elaboration x Source Credibility (Source Expertise or Source Attractiveness)	Low motivation and/or ability - Source expertise acts as simple acceptance or rejection cue. High motivation and/or ability – Source expertise is relatively unimportant since it makes little sense to waste time thinking about a message from someone who does not know very much.	For a review, see (DeBono et al. 1988)
Issue Involvement x Source Credibility (Source Expertise or Source Attractiveness)	Involvement – Source attractiveness has impact only under low involvement conditions. Expertise or attractiveness of a message source has a greater impact on persuasion under conditions of low rather than high involvement.	(Petty et al. 1984b) (Chaiken 1980; Petty et al. 1981c; Rhine et al. 1970)
Factual Messages	Factual messages are more believable and more persuasive, particularly for high involvement people	(Ford et al. 1990; Puto et al. 1984; Wells 1989)
Number of Messages (Arguments)	Low involvement - People agreed with message more when more arguments were presented. High involvement - More arguments led to more persuasion when the arguments were compelling, but to less persuasion when the arguments were specious.	(Petty et al. 1984a)
Prior Knowledge	Greater prior knowledge allows for greater elaboration of issue-relevant information. When prior knowledge is low, the search effort will increase when issue involvement is high.	(Alba et al. 1987) (Krishnamurthy et al. 1999; Lee et al. 1999)
Message Repetition	Moderate repetition will lead to a favorable brand attitude as long as the arguments are strong and tedium is not induced.	(Anand et al. 1990; Batra et al. 1986; Cox et al. 1988; Lane 2000; Rethans et al. 1986)
Media Type	Print ads have limited opportunity to influence uninvolved	(Greenwald et al. 1984)
Distractions	The presence of distraction impairs most people from processing a communication.	(Petty et al. 1976)

Table 3.2. Variables Crossed with Argument Quality and Issue Involvement

Variable	Findings	Reference
Variables crossed with Argument Quality	Issue Involvement (or Participation)	(Chaiken 1980; Deighton et al. 1989; Petty et al. 1984b; Petty et al. 1981c; Rhine et al. 1970)
	Expertise	(Sussman et al. 2003)
	Mood	(Bless et al. 1990; Worth et al. 1987)
	Recipient posture	(Petty et al. 1983a)
	Deprivation of control	(Pittman 1993)
	Expectation of discussion with another	(Chaiken 1980; Leippe et al. 1987)
	Number of message sources	(Harkins et al. 1987; Moore et al. 1987)
	Message repetition	(Cox et al. 1988)
	Ambivalence about the message topic	(Maio et al. 1996)
	Speed of speech	(Smith et al. 1991)
	Physiological arousal	(Sanbonmatsu et al. 1988)
	Time pressure	(Ratneshwar et al. 1991)
	Knowledge about the issue	(Wood et al. 1995)
Variables crossed with Issue Involvement	Prior Knowledge	(Krishnamurthy et al. 1999; Lee et al. 1999)
	Number of messages	(Petty et al. 1984a)
	Source attractiveness	(Petty et al. 1984b)
	Source expertise	(Chaiken 1980)
	Media type	(Greenwald et al. 1984)

Table 3.3. Sample Characteristics

Variable	Mean	Standard Deviation	Missing
Age	46.1	12.8	2
PC experience (Years)	13.0	7.5	4
Self-rated PC skills (1=None to 5=V. Extensive)	3.7	0.85	2

Variable	Category	N	Missing
Gender	Male	128	1
	Female	237	
Chronic Illness	No	225	0
	Yes	141	
Race	American Indian or Alaskan Native	3	1
	Hispanic	6	
	Black, not of Hispanic origin	26	
	White, not of Hispanic origin	295	
	Asian or Pacific Islander	17	
	Mixed racial background	10	
	Other	8	
Education	Some high school or less	6	1
	Completed high school or GED	34	
	Some college	103	
	Associates degree	34	
	Undergrad/bachelors degree	97	
	Masters degree	55	
	Beyond masters	36	
Industry employed	Healthcare and/or social services	80	4
	Not employed/retired	43	
	Homemaker	35	
	Student	30	
	Education	29	
	Retail trade	22	
	Professional, scientific, mngmt services	19	
	Finance, insurance, real estate	19	
	Other	85	
Annual income	Less than $20,000	21	5
	$20,000 - $29,999	24	
	$30,000 - $49,999	59	
	$50,000 - $74,999	68	
	$75,000 - $99,999	42	
	$100,000 - $124,999	33	
	$125,000 - $174,999	22	
	$175,000 or more	20	
	Decline to answer	72	

Table 3.4. Descriptive Results and Correlation Matrix

Variable	Mean	Std. Dev.	1	2	3	4
(1) Attitude Change	0.43	0.89				
(2) BIG_ROLE	5.36	1.31	0.15**			
(3) MORE_IMPORT	5.48	1.33	0.11*	0.70***		
(4) MORE_TIME	5.36	1.32	0.16**	0.75***	0.74***	
(5) PAY_MORE	3.94	1.63	0.06	0.36***	0.32***	0.39***

Note: n=366, * p<.05, ** p<.01, *** p<.001. Items 2-5 are measured using a seven-point Likert scale anchored at 1=Strongly Disagree; 7=Strongly Disagree.

Table 3.5. Hypothesis Testing Results

<table>
<tr><th>Hypo-thesis</th><th>Description</th><th>Result</th><th>Path Coef.</th><th colspan="2">Adj R^2</th></tr>
<tr><td>H1</td><td>Positively framed arguments will generate more favorable attitudes toward EMR use</td><td>Supported</td><td>β_1=.09 p<.05</td><td rowspan="3">0.47</td><td rowspan="6">0.55</td></tr>
<tr><td>H2</td><td>High II individuals will have more favorable attitudes toward EMR use</td><td>Supported</td><td>β_2=.06 p<.05</td></tr>
<tr><td>H3</td><td>Argument frame positively moderates the relationship between II and attitude</td><td>Significant but negative</td><td>β_3=-.22 p<.05</td></tr>
<tr><td>H4</td><td>CFIP is negatively associated with attitudes toward EMR use</td><td>Not Supported</td><td>β_4=.05 p=.36</td><td rowspan="5"></td></tr>
<tr><td>H5a</td><td>Privacy fundamentalist will experience greater persuasion under conditions of positive argument framing</td><td>Supported</td><td>β_{5a}=.42 p<.05</td></tr>
<tr><td>H5b</td><td>High II privacy fundamentalists will experience greater persuasion than low II fundamentalist</td><td>Not Supported</td><td>β_{5b}=-.05 p=.81</td></tr>
<tr><td>H6</td><td>Attitude is positively associated with likelihood of adoption</td><td>Supported</td><td>β_6=.42 p<.001</td><td rowspan="2">0.19</td></tr>
<tr><td>H7</td><td>CFIP is negatively associated with likelihood of adoption</td><td>Supported</td><td>β_7=-.21 p<.01</td></tr>
</table>

APPENDICES

APPENDIX A1: ESSAY 1, HIT ACRONYMS USED

Acronym	HIT Application	Description as used in survey
CLIS	Clinical Information System	An enterprise-wide registration and shared clinical data repository that allows multiple parties to view real-time clinical results and patient listings.
CPACS	Cardiology PACS	Systems that facilitate image viewing at diagnostic, reporting, consultation, and remote computer workstations, as well as archiving of pictures on magnetic or optical media using short- or long-term storage devices. CPACS are specifically focused on the application of PACS to cardiology.
CDR	Clinical Data Repository	A centralized database that allows organizations to collect, store, access and report on clinical, administrative, and financial information collected from various applications within or across the healthcare organization that provides healthcare organizations an open environment for accessing/viewing, managing, and reporting enterprise information.
CDSS	Clinical Decision Support	An application that uses pre-established rules and guidelines, that can be created and edited by the healthcare organization, and integrates clinical data from several sources to generate alerts and treatment suggestions. Enter six levels of CDSS here as examples. Example: All patients who have potassium below 2.5mg% should not have a cardiac glycoside. The physician would enter into the system the prescription for a cardiac glycoside and the system would pop up an alert to the fact that the patient should not be given this medicine due to the low level of potassium in their blood.
CPOE	Computerized Practitioner Order Entry	An order entry application specifically designed to assist clinical practitioners in creating and managing medical orders for patient services or medications. This application has special electronic signature, workflow, and rules engine functions that reduce or eliminate medical errors associated with practitioner ordering processes.
EMAR	Electronic Medication Administration Record	An electronic record keeping system that documents every drug taken by a patient during a hospital stay. This application supports the five rights of medication administration (right patient, right medication, right dose, right time, and the right route of administration) by utilizing bar coding functionality with pharmacy medication dispensing and nursing medication administration services. This functionality is implemented to reduce medication errors. This functionality requires tightly coupled data flows between the CPOE, pharmacy, automated dispensing machines, robotic devices, and nursing medication administration applications. Medical errors are reduced, drug inventory costs are reduced, and billing is more accurate.

EIS	Executive Information System	A specific application that provides sophisticated software tools to integrate, process, and present key operational performance data to executives in an easy-to-learn and highly user-friendly format (e.g. graphics). An executive information system integrates and presents existing data but typically does not create data. An executive information system may provide cost, budget, facility utilization, staffing ratios, or revenue and profit figures. It may also provide physician profiles, practice patterns, admission and dollar volume contribution rankings, etc. It is more than just standard or customized reports generated by HIS.
LIS	Laboratory Information System	An application used to streamline the process management of the laboratory for basic clinical services such as hematology and chemistry. This application may provide general functional support for microbiology reporting, but does not generally support blood bank functions. Provides an automatic interface to laboratory analytical instruments to transfer verified results to nurse stations, chart carts, and remote physician offices. The module allows the user to receive orders from any designated location, process the order and report results, and maintain technical, statistical, and account information. It eliminates tedious paperwork, calculations, and written documentation while allowing for easy retrieval of data and statistics.
PMS	Pharmacy Management System	An application that provides complete support for the Pharmacy department from an operational, clinical and management perspective, helping to optimize patient safety, streamline workflow and reduce operational costs. It also allows the pharmacist to enter and fill physician orders and, as a byproduct, performs all of the related functions of patient charging, General Ledger updating, re-supply scheduling and inventory reduction/statistics maintenance. During order entry, the module automatically checks for Drug-Drug and Food-Drug Interactions and monitors for allergy contraindications. Maintenance of an on-line patient medication profile allows easy access by the pharmacist and may be viewed by nursing stations, ancillary departments and physicians.
RPACS	Radiology PACS	CT (computed tomography), sometimes called CAT scan, uses special x-ray equipment to obtain image data from different angles around the body, and then uses computer processing of the information to show a cross-section of body tissues and organs.
EMR	EMR	A measure used by Bower (2005) to classify a provider as having implemented an EMR. This is the year when a provider has implemented a clinical decision support system, a computerized patient record system, and a clinical data repository. If a provider purchased a CDSS in 1984, a CPR in 1986 and a CDR in 2000, the EMR-year would be 2000 (i.e. when all applications were implemented).

APPENDIX B1: ESSAY 1, HANDLING OF MISSING DATA

Missing Data

Examination of the data revealed that some respondents indicated that their facility adopted a specific HIT but the year in which it was adopted was unknown. This occurred in 13.6% of the surveys. This created a problem when developing the diffusion curves. In a recent paper, (Bower 2005), the author eliminated the cases when the year was unknown, however, this will artificially deflate the diffusion. Instead, I used a weighted average assuming that every year had an equal ratio of respondents to non-respondents and added that to each count. It would not be accurate to simply add a constant to every year because that would shift the graph up, when it actually needs to 'stretch' up.

An alternative approach to the weighted average method is to eliminate all cases with missing data. In this case, instances where the diffusion rate is high would not be negatively affected to a great degree, however, in low diffusion technologies, the impact is tremendous (LIS changed from 95.0% to 93.5% and EMR changed from 34.4% to 24.1%). Intuitively it would not be correct to drop this subset – the point is that the health system has adopted, it is just a question of how to account for the absence of the year of adoption and the weighted average is more robust.

To verify that this weighted average method was fundamentally sound, I examined an HIT known as an Electronic Claims Information System (ECIS). The ECIS has almost completely diffused through the health system in the US because payers (insurance companies) require claims to be submitted electronically. The diffusion was rapid and is widely believed to be at a saturation point. In this sample, 96.9% (3860 out of 3983) of the hospitals had adopted the ECIS by 2005. Yet, there were 1,177 respondents who said their hospital had an ECIS but did not list the year of adoption. If one were to use this value, the actual diffusion would be significantly depressed ((3860-1177)/3983= 67.4%).

APPENDIX A2: ESSAY 2, LIST OF HIT ACRONYMS

Acronym	Full Name	Description
AIT	Administrative IT	An information technology system that provides information in the form of analytics and reports to middle level managers with the goal of reducing costs and/or increasing yield.
CIS	Cardiology Information System	An application that specifically automates functions in the cardiology department. The application must provide some of the following: order processing, permanent patient history index maintenance, image and EKG tracing storage, transcribing and distributing results, clinical documentation, prep instruction cards maintenance, appointment scheduling, and management reporting.
CIT	Communication IT	Information technology that is primarily used for conveying messages between individuals, both internal and external to the firm.
CompIT	Complementary IT	Information technology that is viewed as complementary to the focal technology. AIT, CIT, PMIT, and TrIT are each complementary IT's.
CPACS	Cardiology Picture Archiving and Communication System	Uses special x-ray equipment to obtain image data from different angles around the heart, and then uses computer processing of the information to show a cross-section the heart.
EMR	Electronic Medical Record System	An application environment that is composed of the clinical data repository, clinical decision support, controlled medical vocabulary, order entry, computerized physician order entry, and clinical documentation applications. This environment supports the patient s electronic medical record across the continuum of care (e.g. across inpatient and outpatient environments), and is used by healthcare professionals to document, monitor, and manage health care delivery.
HIT	Health Information Technology	Information technology used to improve the quality, efficiency, and safety of health care[24]
PMIT	Patient Management IT	A systems used for, or are directly related to, treating patients and/or managing their care.
RPACS	Radiological Picture Archiving and Communication System	Uses special x-ray equipment to obtain image data from different angles around the body, and then uses computer processing of the information to show a cross-section of body tissues and organs.
TrIT	Transactional IT	Information technology that is primarily used to improve productivity through automation.

[24] Office of the National Health Information Technology Coordinator (ONCHIT; 2004): Mission. Retrieved November 17, 2004, from http://www.hhs.gov/healthit/mission.html#

APPENDIX B2: ESSAY 2, DESCRIPTION OF CARDIO QUALITY INDICATORS

Heart Attack

Every year, about one million people suffer a heart attack (acute myocardial infarction or AMI). AMI is among the leading causes of hospital admission for Medicare beneficiaries, age 65 and older. Scientific evidence indicates that the following measures represent the best practices for the treatment of AMI. The goal is to achieve 100% on all measures.

Aspirin at arrival - Acute myocardial infarction (AMI) patients without aspirin contraindications who received aspirin within 24 hours before or after hospital arrival.

Aspirin at discharge - AMI patients without aspirin contraindications who were prescribed aspirin at hospital discharge.

Beta Blocker at arrival - AMI patients without beta - blocker contraindications who received a beta-blocker within 24 hours after hospital arrival.

Beta Blocker at discharge - AMI patients without beta-blocker contraindications who were prescribed a beta-blocker at hospital discharge.

Smoking cessation advice/counseling - AMI patients with a history of smoking cigarettes, who are given smoking cessation advice or counseling during a hospital stay.

Heart Failure

Heart failure is the most common hospital admission diagnosis in patients age 65 or older, accounting for more than 700,000 hospitalizations among Medicare beneficiaries every year. It is associated with severe functional impairments and high rates of mortality and morbidity.

Substantial scientific evidence indicates that the following measures represent the best practices for the treatment of heart failure. The goal is to achieve 100% on all measures.

Discharge instructions - Heart failure patients discharged home with written instructions or educational material given to patient or care giver at discharge or during the hospital stay addressing all of the following: activity level, diet, discharge medications, follow-up appointment, weight monitoring, and what to do if symptoms worsen.

Smoking cessation advice/counseling - Heart failure patients with a history of smoking cigarettes, who are given smoking cessation advice or counseling during a hospital stay.

APPENDIX C2: ESSAY 2, FACTOR ANALYSIS OF CARDIO QUALITY

Rotated Component Matrix			Component	
Abbreviation	Description	Label	1	2
ASPA_HSP	Heart Attack Patients Given Aspirin at Arrival	$Qual_1$	0.729	
ASPD_HSP	Heart Attack Patients Given Aspirin at Discharge		0.772	
BTAA_HSP	Heart Attack Patients Given Beta Blocker at Arrival		0.795	
BTAD_HSP	Heart Attack Patients Given Beta Blocker at Discharge		0.781	
SMK_HSP	Heart Failure Patients Given Smoking Cessation Advice/Counseling	$Qual_2$		0.864
DSCH_HSP	Heart Failure Patients Given Discharge Instructions			0.782
SMOK_HSP	Heart Attack Patients Given Smoking Cessation Advice/Counseling			0.712
Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization.				

APPENDIX A3: ESSAY 3, SURVEY INSTRUMENTS & MANIPULATIONS

Argument Framing

Positively Framed Manipulation

1. Rates of serious errors fell by 55% in one study by using computerized medical system (Partners HealthCare System, Brigham and Women's Hospital – Bates, Leape, et al., 1998).
2. Implementing a computerized record system in an urban or suburban hospital could save 60,000 lives, prevent 500,000 serious medication errors, and save $9.7 billion each year (Leapfrog Group, 2004).
3. Between 44,000 and 98,000 Americans die in hospitals each year as a result of medical errors (Institute of Medicine – Kohn, Corrigan, & Donaldson, 1999).
4. "By computerizing health records, we can avoid dangerous medical mistakes, reduce costs, and improve care," (President George W. Bush, State of the Union Address, January 20, 2004).
5. Existing technology can transform health care...if all Americans' electronic health records were connected in secure computer networks…providers would have complete records for their patients, so they would no longer have to re-order tests (Newt Gingrich & Patrick Kennedy, NY Times, May 3, 2004).
6. By 2002, only 17% of US primary care physicians used an EMR system compared with 58% in the United Kingdom and 90% in Sweden (American Medical News – Chin, 2002).

Negatively Framed Manipulation

1. "I have been using a software program for 2 years for managing my health records and it has really helped me," (electronic medical record user).
2. "Electronic medical records are the wave of the future," (anonymous user).
3. Most students say they would like to use electronic medical records to maintain their health information (yahoo weblog, 2003)
4. The US Government is serious about promoting the use of electronic medical records.

Manipulation Check

1. Taken as a whole, how trustworthy are the sources of the information posed above, relative to the message's content?
2. Taken as a whole, how reliable are the sources of the information posed above, relative to the message's content?

Likelihood of Adoption (Opt-In)

I would like to begin using electronic medical records...

1 I will never use them
2 Not sure I will ever use them
3 Sometime in the future
4 In the very near future
5 As soon as possible
6 I am already a user

Semantic Differential – Polar Adjectives Used
(E) Bad-Good
(E) Foolish-Wise
(E) Unimportant-Important
(P) Weak-Powerful
(P) Cowardly-Brave
(P) Youthful-Mature
(A) Complex-Simple

E=Evaluative, P=Potency, A=Action

Post-Manipulation Assessment
With what you now know about electronic medical records:

- I would be willing to play a bigger role in managing my medical records [BIG_ROLE].
- I think it is more important to have access to electronic medical records [MORE_IMP].
- I would be willing to devote more of my time to maintaining my health records [MORE_TIM].
- I would be willing to pay more to be able to personally manage my medical records [PAY_MOR].

Concern for Information Privacy Instrument
Here are some statements about *personal information.* From the standpoint of personal privacy, please indicate the extent to which you, *as an individual,* **agree or disagree** with each statement by circling the appropriate number (1-strongly disagree; 7-strongly agree).

Collection
C1. It usually bothers me when health care entities ask me for personal information.
C2. When health care entities ask me for personal information, I sometimes think twice before providing it.
C3. It bothers me to give personal information to so many health care entities.
C4. I'm concerned that health care entities are collecting too much personal information about me.

Errors
E1. All the personal information in computer database should be double-checked for accuracy—no matter how much this costs.
E2. Health care entities should take more steps to make sure that the personal information in their files is accurate.
E3. Health care entities should have better procedures to correct errors in personal information.
E4. Health care entities should devote more time and effort to verifying the accuracy of the personal information in their databases.

Unauthorized Access (Improper Access)

UA1. Health care entities should devote more time and effort to preventing unauthorized access to personal information.

UA2. Computer databases that contain personal information should be protected from unauthorized access no matter how much it costs

UA3. Health care entities should take more steps to make sure that unauthorized people cannot access personal information in their computers

Secondary Use

SU1. Health care entities should not use personal information for any purpose unless it has been authorized by the individuals who provided the information.

SU2. When people give personal information to a company for some reason, the company should never use the information for any other reason.

SU3. Health care entities should never sell the personal information in their computer databases to other health care entities.

SU4. Health care entities should never share personal information with other health care entities unless it has been authorized by the patient who provided the information.

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