ABSTRACT

SHEA, CHRISTOPHER MICHAEL. Understanding Sophistication in the Context of Electronic Medical Record Systems. (Under the direction of Professor G. David Garson.)

The purpose of this study is to further understanding about the state of electronic medical record (EMR) systems in U.S. hospitals. Specifically, the study addresses the following questions: (1) How can sophistication be measured in the context of EMR systems in U.S. hospitals? (2) Is the sophistication level of EMR systems associated with specific information system leadership structures, planning practices, or strategies?

A stage model of EMR sophistication was tested using Guttman scaling techniques and was found not to be a valid characterization of EMR systems. Therefore, using latent class analysis, a three-class model was identified, categorizing EMR system sophistication into basic, intermediate, and advanced systems.

Logistic regression procedures were used to identify whether specific organizational variables correlate to EMR class membership. These variables measured delivery system capacity, hospital capacity, information system leadership structure, and information system planning practices and strategies. Multinomial logistic regression results suggest that the best predictors of EMR sophistication are the size of the delivery system, having a disaster recovery backup facility for information systems, and pursuing a best-of-suite vendor selection strategy.

Understanding Sophistication in the Context of Electronic Medical Record Systems

by
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DEDICATION

This project is dedicated to my wife, Shannon, for her unconditional love and patience; to Mom and Dad for their selfless commitment to the wellbeing of their children and others; and to my children, Evelyn and Cameron, who bring so much laughter and joy to our lives.

BIOGRAPHY

Christopher Michael Shea earned a Bachelor of Business Administration degree in Finance and English from James Madison University, a Master of Arts in English from West Virginia University, and a Master of Public Administration from North Carolina State University. In 2004 he began the Ph.D. program in Public Administration to further his research and teaching interests in the areas of organization studies, management, and information systems. He is currently employed by the University of North Carolina – Chapel Hill and serves as director of the Bachelor of Science in Public Health program in the Department of Health Policy and Management, UNC Gillings School of Global Public Health.

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER ONE: INTRODUCTION

Background

Ensuring high quality health care services and patient safety are longstanding issues in the health care industry. Institute of Medicine publications such as *Crossing the Quality Chasm* (Institute of Medicine, 2001) and *To Err is Human: Building a Safer Health System* (Institute of Medicine, 1999) illustrate the importance of quality and safety in delivering effective health care services and highlight deficiencies of the U.S. health care industry in these areas. *To Err is Human* estimated that as many as 98,000 error-related patient deaths occur in U.S. hospitals each year.

Many have advocated information technology (IT) solutions as tools for improving the quality and safety of health care services (Advisory Board Company, 2001; Halvorson, 2007; Institute of Medicine, 1999; Institute of Medicine, 2001; Office of the National Coordinator for Health Information Technology). Proponents maintain that health information systems can enable health care delivery organizations (e.g., hospitals) to reduce the reliance on paper records and move toward electronic medical records (EMR), which increases the efficiency and quality of care delivery. Sophisticated EMR systems facilitate the sharing of information (e.g., lab orders and results) across departments in the care delivery organizations. Furthermore, proponents maintain that sophisticated electronic systems can reduce care delivery errors by replacing handwritten orders with computer entry, supporting tasks that are subject to human error (e.g., medication administration), and providing decision support to prevent adverse reactions

and increase adherence evidence-based guidelines (L. Burke & Weill, 2009). Although not definitive, the body of evidence to support these claims is growing (e.g., (Chaudhry et al., 2006; Garg et al., 2005; Mahoney, Berard-Collins, Coleman, Amaral, & Cotter, 2007; Menachami, Burkhardt, Shewchuck, Burke, & Brooks, 2006).

Although information systems are increasingly being touted as an important resource for improving quality and safety, adoption of such systems has been not been widespread ((Ahmad, A.T., P. Bentley, T.D., Kuehn, L., Kumar, R.R., Thomas, A., & Mekhjian,H.S., 2002; Jha, A.K., Ferris, T.G., Donelan, K., DesRoches, C., Shields, A., Rosenbaum, S., Blumenthal,D., 2006), and the U.S. lags behind other developed countries in this regard (Schoen, Davis, How, & Schoenbaum, 2006). This lag is not due to a lack of availability of appropriate technologies in the marketplace. Instead, barriers to the adoption and implementation exist due to the structure of the U.S. health care industry, the complexity and uncertainty associated with organizational change, and the lack of clear incentives for health organizations to use health information technologies (Ash, Stavri, & Kuperman, 2003). These barriers have differing effects on care delivery organizations, depending on the type of organization (e.g., physician practice vs. acute-care hospital). Small physician practices are perhaps hindered most because of the total cost associated with implementing sophisticated information systems. A recent study intended to measure electronic health record usage by physicians in ambulatory care settings indicates that only 4% of such physicians have fully functional electronic record systems and 13% have basic systems. Physicians working in large practices, hospitals, or

medical centers were more likely to report using electronic records than physicians working in other types of organizations (DesRoches et al., 2008).

The availability of information systems does not just vary across types of care delivery organizations, however. Within groups of similar organizations (e.g., acute-care hospitals), there is variation in the information system capabilities as well, with some having cutting edge technologies and others having only basic capabilities. It is likely that various factors, such as the competitive environment, available resources, leadership capacity, and strategies of the organization affect the sophistication level of an organization's clinical information system. In order for policy makers and health care delivery organization administrators to begin to bridge this gap in capabilities and to improve the state of health information systems nationwide, more needs to be known about the current state of health information system infrastructures and factors that appear to support the development of the more robust system infrastructures.

Purpose Statement and Research Questions

The purpose of this study is to further understanding about the state of clinical information system infrastructures in U.S. acute-care hospitals. Specifically, the study will focus on electronic medical record (EMR) systems, which are comprised of multiple information system components. While many of the studies conducted on clinical information systems to date have focused on individual components of an EMR system, such as computerized provider order entry (CPOE), this study aims to assess the state of overall EMR systems in U.S. hospitals by determining a useful way

to categorize the sophistication level of these systems and by identifying organizational factors that correlate to having sophisticated EMR systems.

The study addresses the following questions: (1) How can sophistication be measured in the context of EMR systems in U.S. hospitals? (2) Is the sophistication level of EMR systems associated with specific information system leadership structures, planning practices, or strategies? By addressing these questions, the study aims to improve our understanding of how sophisticated electronic medical record system infrastructures are developed in U.S. hospitals.

Defining the Electronic Medical Record (EMR)

Over the past few years, the electronic medical record (EMR) has increasingly been touted as a necessary vehicle for increasing the quality of care for patients. The EMR is aimed at reducing (or ideally eliminating) paper patient records, thereby increasing the efficiency of "handoffs" during the patient care process, decreasing the likelihood of patient care errors, and ultimately facilitating the exchange of health information across care health care providers, between providers and patients, as well as between providers and third-party payers. Although the aims of the EMR are generally accepted, there is not a consensus on what constitutes an EMR system and how best to design one. Therefore, EMR system characteristics are not uniform across all care delivery organizations. That is, EMR systems likely vary between hospitals with respect to the set of applications in the system, the levels of interoperability between applications, and the order in which the applications were

installed.

These differences in EMR systems can lead to confusion and challenges with respect to systematically evaluating information system infrastructures. The definition of EMR provided by the Health Information Management & Systems Society (HIMSS) is helpful in this regard as it provides specific guidelines about the components of an EMR:

> An application environment composed of the clinical data repository, clinical decision support, controlled medical vocabulary, order entry, computerized provider order entry, Pharmacy and clinical documentation applications. This environment supports the patient's electronic medical record across inpatient and outpatient environments, and is used by healthcare practitioners to document, monitor, and manage health care delivery within a care delivery organization (CDO). The data in the EMR is the legal record of what happened to the patient during their encounter at the CDO and is owned by the CDO"
> (Garets, 2006)

While clarifying the necessary components of an EMR system, this definition also illustrates the complexity of such systems. An EMR solution is a system of integrated technologies that standardize data, house data, shape work processes, and link various departments within a health care delivery organization. The level of integration required creates tremendous organizational challenges, including deciding upon a vendor(s) to contract with, developing a plan for implementation, and achieving buy-in from clinicians, among others.

Policy and Management Relevance of the Study

Once a health care delivery organization commits to acquire electronic health

information system components, the decision about which system to purchase is still complex (Walker, 2005)and, therefore, may delay adoption. There are many information system vendors and generally a lack of consensus about the ideal type of EMR system. Health care providers, ranging from large delivery systems to small physician group practices, are faced with the challenge of evaluating available solutions across many criteria, including functionality, ease of use, interoperability with other systems, availability of user support, and cost.

Health care delivery organizations cannot make decisions about specific information system components in isolation because of integration challenges. In other words, an EMR system component must be considered in the context of current IS capabilities, strategies, and needs. This important decision challenge is not captured in much of the literature on information system adoption and implementation, which focuses on individual applications, such as computerized provider order entry and clinical decision support. From a management perspective, this study will explore whether relationships exist between EMR system sophistication and specific decision-making practices regarding information systems, such as steering committee arrangements and vendor selection strategies.

Despite the challenges involved with implementing EMR systems, it appears that increasing numbers of health care delivery organizations will do so in the future, as market forces combined with supportive governmental intervention (Office of the National Coordinator for Health Information Technology) provide the impetus to

develop sophisticated systems. Health care providers are increasingly likely to view information systems as either a competitive advantage or as requirement for reimbursement for services. These two forces will be driven by pressure from payers – employers, public and private insurers, and patients – seeking the delivery of high quality care at the lowest cost.

The trend toward pay-for-performance (P4P) arrangements illustrates the likely increase of pressure on organizations to adopt automated systems. P4P initiatives require health care providers to demonstrate adherence to desired practices, including use of information systems (Mehrotra et al., 2007), and/or to provide data on other quality-related measures in return for financial incentives. For example, the Centers for Medicare and Medicaid Services (CMS) have implemented P4P initiatives over the past couple years, including the Physician Quality Reporting Initiative (PQRI) in 2007. The PQRI was established under the Tax Relief and Health Care Act of 2006 and allowed providers to earn a 1.5% bonus payment of their charges, subject to a cap, if they submit quality data for services (1) provided between July 1 and December 31, 2007 and (2) paid under the Medicare Physician Fee Schedule (Centers for Medicare & Medicaid Services., 2007). Another CMS project, the Hospital Quality Incentive Demonstration (HQID), resulted in nearly $25M in incentive payments between 2003 and 2006 to participating hospitals that reported their quality data for using standardized measures of quality of care. The project claims to have increased quality at 250-plus hospitals by nearly 16% during the three years, saving approximately 2,500 heart attack

patients and leading to the delivery of an estimated 300,000 evidence-based services, such as pneumococcal vaccination (Monegain, 2008).

If health information systems do improve the quality and long-term efficiency of care, as proponents believe, many health care providers in a P4P environment will view the increased quality benefit of such systems as outweighing the costs of implementation. Furthermore, the reporting requirements of P4P initiatives require health care providers to have the capability to capture and aggregate clinical data in a standardized format. Adequate health information systems are needed to facilitate such reporting efforts; therefore, reporting requirements could provide the impetus for health care delivery organizations to implement information systems.

As the movement toward implementing clinical information systems, particularly electronic medical record systems, gains momentum in health care delivery organizations, the stakeholders (e.g., health care delivery organizations, private insurance companies, government agencies, and advocacy groups) will want to ensure that benefits are maximized in terms of increased service efficiency and quality. Ultimately, this means that *sophisticated* systems need to be developed to automate appropriate work processes and create linkages across departments and organizations to facilitate information exchange and communication. Therefore, those interested in increasing adoption of health information systems would benefit from more information about what constitutes sophisticated electronic medical record systems and the factors (e.g., leadership structures and resources) associated with the development of such systems.

Additional information regarding these issues will better enable health information system proponents to develop incentives for adoption and facilitators for implementation to help ensure that desired benefits are realized.

Contribution to Research on Health Information Systems

Several studies have focused on individual information technology (IT) applications in a health care organization with the purpose of developing knowledge about the adoption and implementation processes. This focus on single IT applications, however, does not account for how other applications affect the adoption and implementation of a given application (Rogers, 2003) or provide a way for assessing clusters of information system capabilities within a given organization. To offset this concern there is a need to learn more about health information system infrastructures.

The HIMSS Analytics EMR Adoption Model (HIMSS Analytics, 2006) provides guidance for thinking about electronic medical systems as complex sets of information technology applications. The model posits that development of these complex systems involves distinct phases or stages. That is, an EMR system must have foundational systems in place before it can advance to the next stage of development. However, given that organizations themselves tend not follow a standardized, linear path in development, it is quite possible that the information system infrastructures of organizations do not develop in a lock-step stages fashion either. The path a hospital follows to develop its information system infrastructure could be shaped by its environment, resources, organizational structure, and strategy. It is also possible that information system

infrastructures do follow a progression of sophistication, but that the progression is not identical to the stage model tested in this study. Both of these possibilities are reasons to determine whether the hypothesized stage model holds true in practice. Without a valid measure of information system sophistication, it is difficult to conduct useful research on barriers and facilitators to system adoption and implementation.

If the stage model explanation of EMR development is not descriptively accurate for all hospitals, identifying categories or classes of hospital information system infrastructures could facilitate a better understanding of how to measure system sophistication. Finding organizational variables associated with the categories could provide insight into how the environment, structure, resources, and strategies of a hospital affect its IS development. Such information would be useful for researchers interested in measuring EMR sophistication and modeling the development of EMR systems. Given past research has begun to explore environmental, structural, and resource variables, perhaps the greatest contribution of the present study will be the focus on IS leadership practices and strategies associated with the various categories of IS sophistication.

CHAPTER TWO: CONCEPTUAL FRAMEWORK

Two theoretical perspectives that commonly influence studies on health information systems are diffusion theory and contingency theory. Both of these perspectives have guided the conceptual framework for this study as well. Diffusion theory proves useful, particularly for conceptualizing innovation, stages of adoption, and innovation "clusters" (i.e., instead of individual innovations). Contingency theory proves useful for thinking about alternative ways that information system infrastructures might develop, in addition to a linear, stages fashion. Contingency theory also guides thinking about factors that might influence the development of these infrastructures.

Diffusion Theory

The foundation of diffusion theory is Everett Rogers' *Diffusion of Innovations*, which defines "diffusion" as "the process in which an innovation is communicated through certain channels over time among members of a social system" (Rogers, 2003). One of the major contributions of this work is defining key concepts. For example, Rogers defines "innovation" as "an idea, practice, or object that is perceived as new by an individual or other unit of adoption." This definition makes the clear distinction that an innovation need not be "objectively" new (i.e., new to the world), but instead new to the potential adopter in that the adopter is not currently using the innovation: "Someone may have known about an innovation for some time but not yet developed a favorable or unfavorable attitude toward it, nor have adopted or rejected it" (Rogers, 2003). This definition of innovation is commonly applied in research that takes a user's perspective to

analyze the implementation of an innovation, such as the current study, rather than a source perspective, which focuses on the original development of an idea by an inventor or organization and the steps taken to market the new idea or product (Kohane, Greenspun, Fackler, Cimino, & Szolovits, 1996).

Two of the most noted aspects of diffusion theory are the S-shaped adoption curve and the subsequent adopter categories developed based on this distribution. The S-shaped curve reflects the tendency of several years passing with only a small number of organizations adopting an innovation, then relatively fewer years with the majority of organizations adopting the innovation, and finally several years for the remainder of organizations to adopt. This trend, when graphed, looks similar to the letter *S*. The approximately normal distribution of this adoption distribution led to the development of adopter categories – innovators, early adopters, early majority, late majority, and laggards – that have a statistical basis (Rogers, 2003) and that have become commonly used in innovation discourse.

In addition to adopter categories, Rogers's work identified the importance of defining the boundaries of innovations, a task that can be challenging with respect to technological innovations. He identifies the flaw of some innovation research that oversimplifies the adoption process by assuming each innovation to be independent from others, rather than acknowledging that an adopter's previous experience with innovations will influence perceptions of future innovations. Therefore, he encourages consideration of *technology clusters*, which have "one or more distinguishable elements of technology

that are perceived as being closely interrelated"(Rogers, 2003).

Several studies have used Rogers's cluster approach to guide analysis of information systems applications in health care organizations (Bhattacherjee A, Hikmet N, Menachemi N, & et al., 2007; D. E. Burke & Menachami, 2004; D. E. Burke, Wang, Wan, & Diana, 2002; Menachemi, Ford, Chukmaitov, & Brooks, 2006; Wang, Wan, Burke, Bazzoli, & Lin, 2005). Each of these studies has categorized information systems into three clusters: clinical, administrative, and strategic. The current study attempts to build on this previous work by drilling down within the clinical cluster to identify lower-level clusters (i.e., sub-clusters). Specifically, the study identifies clusters of applications within the electronic medical record (EMR) system, which is a part of the larger clinical cluster.

Contingency Theory

Contingency theory is a popular perspective through which to analyze management and organizational development issues. Three ideas that have been posited as foundational to contingency theory are as follows:

- "Organizations are open systems that need careful management to satisfy and balance internal needs and to adapt to environmental circumstances"
- "There is no one best way of organizing. The appropriate form depends on the kind of task or environment with which one is dealing"
- "Management must be concerned, above all else, with achieving alignments and 'good fits'" (Morgan, 1997).

With respect to hospitals, internal needs relate to staffing, workflow, and business development, for example. Environmental circumstances include such factors as laws and regulations, accreditation/certification standards, reimbursement from third-party payers, and competition from other health care providers. From a contingency theory perspective, information systems may serve to fill internal needs and/or to address environmental opportunities or threats, with decisions about information system adoption being made in the context of organizational resources and strategies in order to achieve a "good fit."

Achieving "good fits" throughout complex organizations is a difficult process to both understand and achieve. Health care delivery systems are hierarchies, that is, complex systems composed of subsystems (e.g., organizations), which in turn are composed of subsystems (e.g., departments), and so on. Viewing care delivery systems under this hierarchical arrangement is useful for understanding how information systems could develop. Because individuals within a given subsystem tend to interact amongst themselves more frequently than with individuals in other subsystems (including their own superiors), equilibrium tends to be achieved within a given subsystem at the lowest level, prior to being achieved across subsystems and at higher levels (Simon, 1962). In terms of clinical information systems, therefore, development might be expected to be compartmentalized, for example, achieved at the departmental level, prior to being achieved at the hospital level or delivery-system level.

Stage Models of Innovation Adoption and Implementation

Phenomena in organizations are often conceptualized, at least initially, with stage models. Organizational innovation is no different in this regard. One classic adoption/implementation stage model consists of two dimensions: (1) *initiation,* which involves the steps leading up to the decision about whether to adopt the innovation and (2) *implementation,* which involves the activities needed to put the innovation to use after it has been adopted. Initiation and implementation consist of distinct stages (Rogers, 2003), which are complex enough alone to warrant in-depth study. This stage model illustrates the complementary nature of diffusion and contingency theories.

Initiation involves two stages: *agenda-setting* and *matching*. In agenda-setting, an organization identifies a problem that creates a need for an innovation. The problem may be identified via gap analysis, which identifies a performance problem (Rogers, 2003). For example, a hospital might identify an undesirable gap between a standard for the acceptable number of drug-allergy reactions among its patients during a given period of time and the actual number of drug-allergy interactions that occurred within the hospital during the period.

In the matching stage, the organization attempts to find an innovation that appropriately addresses the previously identified problem. If an innovation is determined to be a poor fit for the problem, then the innovation is not adopted. Once a good "match" is found, then the organization moves from the initiation stage to the implementation stage (Rogers, 2003). Health information technology systems, for example, are

increasingly being identified by hospitals and other stakeholders as solutions to problems related to quality of care, such as drug-allergy interactions.

Implementation consists of three stages: *redefining/restructuring*, *clarifying*, and *routinizing*. During redefining/restructuring, the innovation is adapted to the organizational context and organizational structures are re-aligned to facilitate and adapt to the innovation (Rogers, 2003). For example, user interfaces of an information system might be modified to adapt to the user preferences of a particular organization. On the other hand, the organization will need to adapt as well, for example, by creating a new committee to oversee the innovation implementation, hiring new technical support staff, modifying its employee training program, and altering work processes and work flows.

Clarifying refers to the social process of defining the relationship between the organization and the innovation more specifically. Individuals within the organization seek answers about what the purpose of the innovation is, how it works, and how it will affect them. The innovation may be framed in multiple ways as the fit between the innovation and the organization becomes clearer (Rogers, 2003). For example, a computerized provider order entry system might be framed from an efficiency perspective, a quality of care perspective, or a compliance perspective.

Routinizing occurs when the innovation has become integrated into the activities of the organization. The innovation is no longer viewed as new or as separate from the organization or its work processes. The implementation process is complete. Routinization is closely related to sustainability, which refers to whether the innovation

continues to be used after initial adoption and implementation efforts are complete (Rogers, 2003).

Other proposed stage models offer variations on Rogers's model. For example, Cooper and Zmud's model (Cooper & Zmud, 1990) consists of six stages – initiation, adoption, adaptation, acceptance, routinization, and infusion. While routinization focuses on changes to organizational governance systems, infusion refers to the extent of "adjustments in (operational and managerial) work systems as well as technological configurations to which they relate." An innovation is infused if it reaches an advanced level of use in an organization, meaning that it is deeply embedded "within an organization's operational and/or managerial work systems." In other words, infusion occurs as the "interconnectedness of organizational work flows" increases (Zmud & Apple, 1992). This "interconnectedness" is directly relevant to understanding how clinical information system implementation affects hospitals. For example, EMR systems become increasingly sophisticated and useful as the applications comprising the systems become increasingly integrated, work processes become increasingly interconnected, and information exchange becomes faster and more common. Because the concepts of integration and interconnectedness are not readily observable, measuring the level of sophistication of an information system poses many challenges.

Measuring the Sophistication of Information Systems

A promising framework for increasing knowledge about the development of

information systems identifies three dimensions of "sophistication": (1) technological sophistication, (2) functional sophistication, and (3) integration. Technological sophistication refers to the hardware devices, such as bar coding equipment and wireless networks. Functional sophistication refers to the extent to which work processes or activities, such as medication administration, are automated. Integration refers to "the degree to which the computer-based applications are integrated both internally via a common database and externally via electronic communication links" (Paré & Sicotte, 2001/10). This framework reflects the concept of "interconnectedness," discussed above. In doing so, it accounts for the fact that achieving information system sophistication requires more than simply the hardware; it also requires interfaces between system components, acceptance by system users, and sufficient IS personnel to support system development, maintenance, and use.

This framework has proved useful for assessing the overall level of sophistication of hospital information systems and comparing information systems across groups of hospitals in Canada (Paré & Sicotte, 2001/10). Specifically, the authors found that most hospitals in Quebec and Ontario exhibited relatively low levels of technological sophistication, as well as low systems integration. A more recent study using this framework found that technological sophistication among a relatively small sample (n = 74) of U.S. hospitals occurred primarily in the administrative area involving patient management (e.g., admissions and discharge), not in areas involved with direct patient care. The level of clinical IS integration was low (Jaana, Ward, Pare, & and Sicotte,

2006).

The HIMSS Analytics EMR Adoption Model (HIMSS Analytics, 2006) has some similarities to this sophistication framework. Although it does not explicitly detail three dimensions of sophistication, it does incorporate the dimensions, implicitly, in the stages of EMR system sophistication. The HIMSS Analytics model assumes that the implementation of EMR system components occurs in a progression of stages, with EMR system applications, associated work processes, and levels of integration "clustering" according to distinct stages. In essence, the HIMSS Analytics model measures sophistication by the presence of specific information system components and applications that are integrated to enable automation of work processes and exchange of information. Each stage consists of a technology cluster, and the clusters build upon each other in a predictable way, with each new cluster representing an increase in overall system sophistication.

The underlying assumption of the HIMSS Analytics model is that EMR system components are implemented in a similar fashion across organizations. This assumption runs counter to the previously discussed stage models that focused on contingency-based characteristics of the adoption and implementation decision-making process, as well as the complexities involved with the interconnectedness of the innovation and work processes. Rogers's initiation and implementation model, for example, posits that organizations make decisions about information system adoption based on finding a "good fit" for the organization, relative to internal needs and environmental

circumstances. While the hardware, software, and work processes reflected in the HIMSS Analytics Model are important considerations in the design of an EMR system, it is possible that hospitals do not commonly follow such distinct stages in EMR implementation. Determining whether hospitals actually follow these stages is necessary in order to assess the practicality of using such a stage model for assessing EMR sophistication.

A recent study focusing on electronic record usage by physicians in ambulatory care settings offers another method for categorizing electronic record system sophistication. The authors of the study used a modified Delphi process to identify key functions of an outpatient electronic health record. These functions can be categorized as "recording patients' clinical and demographic data, viewing and managing results of laboratory tests and imaging, managing order entry (including electronic prescriptions), and supporting clinical decisions (including warnings about drug interactions or contraindications)." Each function consists of components that are classified as a requirement for either (1) a fully operational electronic record system or (2) both a basic and fully functional system. For example, under the order-entry function, having the capability to handle prescription orders is a requirement for both basic and fully operational systems, whereas handling orders for lab tests and for radiology tests (among other capabilities) are classified as requirements only for fully operational systems (DesRoches et al., 2008). In other words, this approach focuses on levels of capabilities within the four functions of the electronic record system.

Finally, another measure related to information system sophistication in hospitals, IT munificence (D. E. Burke & Menachemi, 2004), was developed using a stakeholder perspective to account for the need for hospitals to communicate to external parties, as suggested by the "integration" dimension of sophistication discussed above. Recognizing that information system capability encompasses more than the presence of IT applications, IT munificence, is measured by not only counts of information system applications in the clinical, administrative, and strategic clusters, but also measures of linkages with external stakeholders: (1) clinicians accessing information from outside the hospital, (2) the general public, and (3) organizations such as vendors and third-party payers. While the study found the construct to fit the data well, the authors recognize that other measures of hospital information system capabilities could be developed to account for the sophistication of such systems, specifically with respect to the integration of information technology applications.

Environmental Factors and Organizational Characteristics Affecting IS Implementation

Because of the challenges with measuring the sophistication of information systems, there has been little published in the literature about factors that facilitate the development of such systems. There is no commonly accepted model for explaining how sophisticated clinical information technology systems are implemented, and many of the published articles on the topic are not grounded within any theoretical framework. Furthermore, the literature on the adoption and implementation of health information

technology is relatively new and varied in terms of methodological approach (e.g., expert opinion pieces, informal case studies, cross sectional studies). There are few studies that analyze large datasets of health care organizations with the purpose of generating conclusions that are generalizable. The studies using large datasets tend to explore factors related to the presence or absence of particular information system components or capabilities, but tend not to measure the overall sophistication levels of the systems and then identify correlates to the most sophisticated systems. Therefore, the relationship between several organizational characteristics and the adoption of health information technologies have been explored in the literature, but the results tend to be difficult for practitioners to act upon. For example, public vs. private ownership status (Cutler, 2005), rural vs. urban location (Ohsfeldt et al., 2005), health system membership (D. E. Burke et al., 2002; Jaana et al., 2006; Wang et al., 2005), hospital size (D. E. Burke et al., 2002), and competition (D. E. Burke et al., 2002; Wang et al., 2005) have been proposed as keys to understanding adoption patterns of computerized provider order entry (CPOE), one component of an EMR, in hospitals. Generally speaking, hospital size, health system affiliation, urban location, and a competitive environment have been hypothesized as correlates to information system adoption; however, results have been somewhat mixed.

Further clarification is needed regarding which characteristics are most influential in the adoption decision-making process, particularly related to sophisticated clinical information systems, not simply particular components of such a system (Jaana et al., 2006). Furthermore, it is possible that the higher-level characteristics, such as the

competitive environment and hospital size, are important to consider and control for statistically, but that they do not have a strong, direct influence on information system sophistication. The more influential factors could be the information system practices and strategies at the organizational level.

Organizational Capacity and Information System Sophistication

Organizational capacity has been proposed as a construct for categorizing proposed antecedents to clinical information system sophistication and, therefore, could serve as a useful guide for better understanding barriers and facilitators for adoption and implementation. Under this framework, organizational capacity encompasses four domains: structural capacity (i.e., organizational size), financial capacity, leadership capacity, and knowledge sharing capacity (Jaana et al., 2006). This framework has facilitated study of the relative importance of some organizational characteristics with respect to implementing sophisticated information systems, using the three dimensions of sophistication (Paré & Sicotte, 2001/10)outlined above.

Jaana et al. (2006) found that the structural capacity domain, operationalized as hospital size (number of FTE employees and number of beds) did not predict clinical IT sophistication. This finding is perhaps surprising, as larger hospitals have been hypothesized as being more likely to adopt information systems since the potential benefits in terms of efficiency and patient outcomes are greater relative to smaller hospitals. The authors posit that the number of FTE employees might be higher in hospitals with lower IT sophistication because more employees are needed to handle the

work processes manually. Furthermore, they speculate that more beds might reflect more differentiated services, “which do not necessarily translate into more clinical IT sophistication” (Jaana et al., 2006). However, it is also possible that these indicators were found not to be significant because they affect the adoption decision process (initiation) and the implementation process differently (Rogers, 2003). For example, organizational size might affect the decision to adopt positively, but the implementation process negatively or insignificantly.

Jaana et al. (2006) also found that the financial resources domain did not predict clinical IT sophistication. This finding, too, is contrary to common belief. It is important to note that financial resources were operationalized as public-sector payer mix and slack resources, which are intended to capture the lower profit margin associated with public payers and the amount of resources that are available after maintaining basic operations, respectively (Jaana et al., 2006). However, it is possible that structural capacity and financial resources are influential in the development of sophisticated clinical information systems, but the capacity and resources that matter most are concentrated in the area of information technology. This proposition is supported by the finding that technical knowledge resources (i.e., technical staff) within a hospital, categorized in the knowledge sharing domain in the Jaana et al. (2006) study, influenced sophistication positively across the three dimensions. Nevertheless, it is not a foregone conclusion that larger information system staffs and budgets are correlated to greater information system sophistication.

Jaana et al. (2006) found that the leadership capacity domain was an important predictor of clinical IT sophistication. Specifically, the managerial tenure of the IT director had a negative effect across the three dimensions of sophistication. The IT-related tenure of the IT director had a positive effect on sophistication. These findings imply the importance of IT knowledge among leadership in facilitating information system sophistication. However, it is possible that management tenure might not be the best indicator of the effect of managerial expertise on information system sophistication. Instead, the amount of responsibility an IT director has within the hospital might be a better indicator of his or her capabilities as a manager and his or her ability convey to non-IT-related stakeholders the implications of sophisticated information systems for efficiency and quality. Furthermore, the presence of traditional management approaches applied in the IT realm, such as strategic planning, could further demonstrate the leadership capacity of the IT director, even if the IT director does not have a long tenure in managerial roles.

In Jaana et al. (2006), the knowledge sharing domain influenced sophistication as well. This domain is conceptualized to capture opportunities for communicating new ideas to foster innovation. Jaana et al. (2006) found technical knowledge resources (i.e., technical staff) to be positively associated with the three dimensions of sophistication. Furthermore, Jaana et al. (2006) found hospital membership in a system, reflecting common ownership, had no effect on clinical IT sophistication.

IS Leadership Structures, Planning Practices, and Strategies

The organizational capacity concept encompasses many important organizational resources related to information system sophistication. However, a limitation of the framework regarding predicting information system sophistication is that it does not include particular practices and strategies employed by organizations. In other words, an organization with adequate capacity, as defined by financial and leadership resources for example, has to use these resources wisely in order to achieve sophisticated IS systems. Making this distinction in the data analysis is one contribution of the present study, as it includes measures of both leadership resources and the accompanying practices and strategies used by the leadership.

Steering Committees and Strategic Plans

As the stages model proposed by Rogers (2003) indicates, adoption and implementation involve traditional management approaches to problem solving. For example, the agenda-setting (problem identification) and matching (selection of solutions for identified problems) could involve such management tools as SWOT analysis and/or gap analysis, which are common components of strategic planning initiatives designed to assist with setting organizational priorities. These activities are time consuming and require active participation among those involved. Therefore, the leadership must have in place formalized practices to facilitate IS planning, such as instituting a steering committee to develop a formal IS plan.

Key Strategic Initiatives: Information Exchange and Disaster Planning

Two strategic issues that are commonly considered in light of information systems development in hospitals are information exchange initiatives (HIMSS, 2008) and disaster preparedness, particularly since the Katrina disaster (Boom, Dragsbaek, & Nelson, 2007). Examining whether participation in formal information exchange initiatives and disaster planning activities are associated with having sophisticated clinical information systems could help clarify whether such strategies are facilitators for information systems development.

Vendor Selection Strategies

Information system acquisition strategies are another key component that should be explored to determine possible effects on IS infrastructure development. In many sectors, developing an enterprise-wide information system using a single IT vendor is the clear choice. In healthcare, however, the choice is not clear, due to the complexity of care delivery and the varying needs across departments within organizations and across organizations within delivery systems (Hagland, 2005). Some organizations have even elected to develop their own systems, particularly in the early years of health information systems; however, this strategy is relatively rare at the present time.

Most health care delivery organizations attempt to develop vendor selection strategies that are believed to be most compatible to their particular circumstances. Three such strategies include (1) a single-vendor approach, (2) best-of-breed, and (3) best-of-suite (a.k.a., cluster). The single-vendor approach provides the most simplicity. Under

this approach interoperability across system components is assumed to be a non-issue because each component is developed by the same vendor. However, all of the components developed by a single vendor are not typically considered the best available. The best-of-breed strategy refers to selecting applications deemed to provide the best functionality for a particular need. These are often offered by small vendors focused on developing the best product for a specific need or type of service (Rao, 2006). However, these small vendors do not tend to offer the best products in a range of components. Therefore, the best-of-breed approach requires developing interfaces between system components that are not inherently compatible (i.e., interoperable). The best-of-suite strategy is a sort of middle ground between the single-vendor and best-of-breed strategies. It refers to the approach of selecting applications that are integrated around a strong vendor product for the cluster (Hagland, 2005). These products may not be as strong as the best-of-breed options. However, the best-of-suite approach facilitates system integration across the enterprise without requiring the costly development of interfaces (Rao, 2006).

No articles were found in the peer reviewed literature focusing on the relationship between vendor selection strategy and level of sophistication of information system infrastructures. Identifying whether a particular vendor selection strategy is associated with sophisticated systems would prove useful for decision makers.

Implementation Success Factors: Achieving Physician Buy-in

After adopting information system components, health care organizations face

perhaps an even greater challenge in determining how best to implement the EMR in order to realize a maximum benefit. It is well documented that information technology projects, across all types of organizations, are often delivered behind schedule, over budget, or without originally specified functionality (Garson, 2006).

The implementation process is complex. The transition to an EMR system entails more than simply digitizing records that were previously documented on paper. Given the interrelatedness of roles and responsibilities, work flows and decision making, and technology infrastructure, a change to any one of them necessitates change in the others (Stead, 2007). To complicate matters, physicians and nurses, who tend to believe there is no slack time in their day, often resist spending time learning a new way of doing their jobs (Walker, 2005).

Some physicians also tend not to be supportive of new information systems because of concerns about possible negative affects on the quality of care. For example, some have argued that information systems often are inflexible, not able to account for the non-linear and contingent aspects of care delivery, leading to errors in the entry and retrieval of information as well as the communication and coordination of care (Ash, Gorman, Seshadri, & Hersh, 2004). Another criticism is that while the standardization in data entry entry required by many systems may facilitate reimbursement, the aggregation of outcomes data, and adherence to guidelines, it also can hinder the ability of physicians to probe for important information from patients, think critically about each case, and customize care for their patients (Hartzband &

Groopman, 2008). These concerns generally do not reflect a belief that electronic records are inherently flawed. Instead, the criticisms emphasize the need to balance efficiency and quality concerns, to involve physicians directly in system design, as well as to collect more evidence regarding how (or whether) electronic records improve care quality.

The health information technology literature includes a variety of barriers to successful implementation, such as resistance to changing work processes (Kuperman & Gibson, 2003), as well as "success factors" for overcoming barriers, such as identifying physician champions (Ash et al., 2003; Poon et al., 2004) and preparing the organization for the financial costs associated with system implementation, such as initial reductions in productivity (Miller & Sim, 2004). However, lists of success factors are often of limited usefulness to practitioners (Garson, 2006), as they do not account for common themes underlying individual success factors and fail to offer guidance on how to prioritize the success factors.

The Technology Acceptance Model (TAM) is commonly cited in the information system literature as a useful guide for understanding individual's voluntary use of technologies. This model, a variation of the Theory of Reasoned Action (TRA), proposes two key constructs as influencing an individual's (1) attitude toward and (2) intentions to use a particular technology. The first construct, *perceived usefulness*, "is defined as the prospective user's subjective probability that using a specific application system will increase his or her job performance within an

organizational context." The second, *perceived ease of use*, "refers to the degree to which the prospective user expects the target system to be free of effort" (F. D. Davis, Bagozzi, & Warshaw, 1989).

A recent review of the TAM literature applied to health care settings finds that while TAM does generally serve as a strong predictive model of technology use, it assumes that technology use is entirely voluntary. In other words, TAM does not account for the influence of external variables and barriers, such as resource scarcity and a lack of evidence that a technology will improve productivity and quality of care. The authors of the review propose that such barriers to technology acceptance directly influence the perceived usefulness, perceived ease of use, attitude, and behavioral intention that a physician has toward using a technology (Yarbrough & Smith, 2007). Incorporating such barriers into future models seems necessary for understanding facilitators of the adoption and implementation of health information systems.

This study aims to contribute not by testing a new version of the TAM model, but instead by identifying factors, at the organizational and care delivery system level, that correlate to increased levels of information system sophistication. A working assumption is that particular organizational characteristics and strategies likely facilitate physician acceptance of technologies, which is necessary for implementation. The correlates identified in this study perhaps could contribute to the identification of external variables and barriers for inclusion in modified TAM models.

CHAPTER 3: RESEARCH METHODS

The focus of this study on information system *sophistication* is informed by the following definition: "the diversity of technological devices and software applications used to support patient management and patient care [and] clinical support … as well as the extent to which computer-based applications are integrated [via] electronic and automatic transfer of information" (Paré & Sicotte, 2001/10). First, a stage model was tested to determine whether electronic medical record (EMR) systems in hospitals are characterized by distinct stages, with each stage representing a new level of system sophistication.

A stage model, consistent with the definition of EMR systems provided in chapter 1, has been described in a previous study produced by HIMSS Analytics (HIMSS Analytics, 2006). Although the stages for the model were described in the study, the operational measures used for the model are proprietary and, therefore, not publicly available (M. Davis, 2006). The current study identified appropriate measures to test the validity of a conceptual stage model similar to the one described by HIMSS Analytics (2006). The measures identified in this study, however, likely are not identical to those used in the HIMSS Analytics (2006) study.

It also is important to note that the HIMSS Analytics study (2006) aimed to identify correlations between EMR system sophistication and patient outcomes. The stage model developed for the study served as a tool for accomplishing that aim. The study did not hypothesize that the stage model accurately characterized all hospital

EMR infrastructures (HIMSS Analytics, 2006). Nevertheless, the model was developed based on over ten years of research, blending both descriptive and normative approaches about EMR implementation (M. Davis, 2007).

One contribution of the current study is determining whether a stage model, similar to the one conceptualized in the HIMSS Analytics study, accurately characterizes information system infrastructures in U.S. hospitals. If the stage model is found not to be a valid representation, then the model might have useful normative qualities, but it would not serve as a descriptive model. The purpose of this study is *not* to assess the appropriateness of the stage model as a normative model.

Of course, if the stage model tested in this study is found to not accurately characterize EMR system sophistication, one could argue that the measures used in the analysis are not optimal. Furthermore, it is possible that a different stage model could be descriptively valid. Therefore, this study aimed to determine only whether the specific stage model tested is valid based on the indicators available, not whether all potential stage models for EMR sophistication are valid.

The approach used in the remainder of the study depended on whether the stage model was found to be valid. If the stage model was deemed valid, the study would test for associations between advanced EMR sophistication and factors proposed as facilitators of IT implementation, as informed by the health information technology and diffusion of innovations literatures. If the stage model was found not to be a valid representation of how hospitals develop EMR systems, the study would

use an alternative method, Latent Class Analysis, for assessing sophistication of clinical information system infrastructures.

Latent class analysis identifies groupings of infrastructures that can be interpreted to discern patterns. These patterns could reflect stage-like levels of sophistication; however, they could also reflect another method of organization, such as emphases on particular types of services (e.g., drug administration) or particular users (e.g., nurses). Further analysis would be used to identify organizational factors associated with the clusters.

Data Source and Study Design

The present study is cross-sectional, using the HIMSS Analytics dataset (updated 1/2/07), which is derived from the Dorenfest IHDS+ Database. For data manipulation and analysis, the data were converted from Microsoft Access format to SAS and SPSS files using the StatTransfer program. HIMSS Analytics data include indicators of organizational resources and capabilities, such as revenues, operating costs, services provided, organizational arrangements, and information system capabilities. They do not capture employee attitudes or perceptions about these resources and capabilities.

The 2006 edition of the dataset contains survey data from 32,911 health care organizations of various types, of which 3,271 are acute care hospitals with 50 or more beds. These acute care hospitals are the unit of analysis for this study. Each hospital is classified as being affiliated with either an integrated delivery system

(IDS) or independent hospital system. This system-level measure represents the parent organization for the hospital.

HIMSS Analytics / Dorenfest data have been collected for several years and have been used primarily as a benchmarking tool for health care organizations. However, the data have been useful for research purposes as well. One study used 1999 Dorenfest data to explore organizational and market factors influencing adoption of administrative, strategic, and clinical information systems in hospitals (D. E. Burke et al., 2002). Another study used the same data to develop a theoretical construct, "IT munificence," to be used to measure information system capability within a hospital (D. E. Burke & Menachemi, 2004).

The HIMSS Analytics / Dorenfest survey instruments changes from year to year to accommodate the information needs of its health care organization client base. Therefore, the 2006 data used in this study includes important indicators that were not collected in previous years. Because of this limitation of the data, the study design will be cross-sectional, not longitudinal. Although the diffusion process of innovations in organizations occurs over time, cross-sectional data previously have been used successfully in diffusion studies of health information systems {{;23 Burke,D.E. 2004; 32 Cutler,D.M. 2005; 156 Jaana, M. 2006; }}. Cross-sectional data in those studies were sufficient because the aims did not require data about timeliness of adoption (e.g., early adopter vs. laggard) or how an innovation (or organization) changed over time. The same holds true for the current study.

As stated in chapter 1, the aim of this paper was to assess methods for measuring electronic medical record system sophistication. Along these lines, this study tests the validity of a particular stage model for describing the sophistication of EMR systems. Using a “snapshot” of EMR systems across multiple U.S. hospitals allows for the use of scalogram analytic methods to determine whether the stage model is valid. In a scale, for example, stage three of a model, cannot be achieved until stages one and two have been achieved. In terms of this study, cross-sectional data was sufficient for determining whether electronic medical record systems in hospitals fit this stage pattern.

Another aspect of assessing how to measure EMR sophistication is to identify alternative patterns to the stage model. Cross-sectional data allows for the identification of groups of hospitals with particular classes of EMR system capabilities and for the interpretation of the classes of capabilities.

Cross-sectional data also are sufficient for identifying correlates to the patterns of EMR system infrastructures, whether the patterns are stages or otherwise. These correlates provide information about hospital characteristics that are associated with different patterns of EMR capabilities. A limitation with cross-sectional data, of course, is that it is not possible to determine whether the characteristics cause the hospital to have certain EMR capabilities. Furthermore, it is not possible to determine whether a hospital characteristic becomes more influential over time. For example, the data does not allow for the determination of whether having had an information system steering committee in place for five years has a greater impact than having such a committee in place for 1 year.

Nevertheless, very few studies have used large data sets to identify correlates of EMR system sophistication. The results of this study could inform future studies utilizing longitudinal data to analyze the correlates over time.

Measures Used in the Study

The analysis presented uses variables measuring the presence or absence of specific electronic medical record (EMR) system capabilities, as guided by the HIMSS Analytics EMR Adoption Model (HIMSS Analytics, 2006). Indicators for some components of the EMR Adoption Model were not found in the dataset; therefore, this analysis tests a leaner stage model than the EMR Adoption Model. In other words, this study does not specifically test the EMR Adoption Model (HIMSS Analytics, 2006). Table 1 illustrates the stages and respective indicators used in this study.

Table 1: Stage Model Indicators Used in the Study

Stage 1	Laboratory Information System, Pharmacy Management System, Radiology Information System
Stage 2	Controlled Medical Vocabulary (CMV), Clinical Data Repository (CDR)
Stage 3	Order Entry, Nursing Documentation, Picture Archiving Communication Systems (PACS)
Stage 4	Computerized Provider Order Entry (CPOE), Clinical Decision Support System (CDSS)
Stage 5	Electronic Medication Administration (EMAR), Barcode or Radio Frequency Identification (RFID)
Stage 6	Physician Documentation

Stage 1 requires the presence of information systems in the three major ancillary departments: laboratory, pharmacy, and radiology. In terms of hospital services,

ancillary services are “therapeutic or diagnostic services provided by specific hospital departments (other than nursing service) including but not limited to imaging, laboratories, … and Pharmacy” (Griffin, 2006). It is hypothesized that these ancillary department systems provide the foundation for the EMR system.

Stage 2 requires a clinical data repository (CDR), a “clinical database optimized for storage and retrieval for individual patients and used to support patient care and daily operations.” A controlled medical vocabulary (CMV) – “a finite, enumerated set of terms intended to convey information unambiguously” – also is needed (Shortliffe & Cimino, 2006). These components are important for the integration of information systems across departments and functions, as well as for facilitating a shared understanding of terminology the standardization of data captured in the EMR system.

Stage 3 requires general order entry, computerized nursing documentation, and a picture archiving and communication system (PACS). General order entry systems can be accessed by a variety of users, including those in ancillary departments, to enter patient information. Nursing documentation refers to capturing nursing notes about observations made during patient interactions, as well as decisions made and outcomes for a given patient. A PACS “is an electronic and ideally filmless information system for acquiring, sorting, transporting, storing, and electronically displaying medical images” (Becker & Arenson, 1994). In this study, PACS was measured by whether the hospital reports having the functionality to distribute images throughout the hospital with the PACS system.

Stage 4 requires computerized practitioner order entry (CPOE) and clinical decision support (CDSS). CPOE differs from general order entry, required in Stage 3, as, while CPOE systems are intended for clinical practitioners with prescribing authority. Clinical decision support involves error checking and alerts, for example, with respect to medication prescribing and clinical protocols.

Stage 5 requires electronic medication record (eMAR) and either barcoding or RFID capabilities. These technologies are intended to reduce medication errors, for example to ensure that the patient is receiving the actual medication that was prescribed.

Stage 6 requires physician documentation software to capture such items as notes made during physician-patient interactions, decisions made, and patient outcomes. Computerized physician documentation facilitates access to these records by multiple physicians as needed.

Determining whether a stage is complete is not straightforward because hospitals report one of seven status categories for all of the IS components, with the exception of PACS. PACS is reported as either "Current" (i.e., operational) or "Planned" (i.e., to be implemented in the future); therefore, those reporting "Current" were coded as having PACS capability. However, the other IS components are reported as one of the following statuses:

- "Live and operational"
- "Installation in process"
- "Contracted / not yet installed"
- "To be replaced"
- "Not yet contracted"

- “Not Automated”
- “Not Reported”

Because there is some debate about what constitutes a complete “implementation,” three analyses were run using different criteria for assessing whether a given hospital satisfies the requirement for having a particular IS component. By using three sets of criteria, it is possible to determine how sensitive the analyses are to assumptions made about what constitutes implementation of a given IS component.

One set of criteria used a strict definition of implemented, with only the “Live and operational” and “To be Replaced” statuses satisfying the requirement of having the given component, as both statuses indicate that the component is currently being used, even if it might be planned for replacement. The second set of criteria added “Installation in process” to the previous two status categories as satisfying the requirement for implementation. The rationale for including this criterion is that the component could have some functionality presently being used, even if the component is not considered fully operational. The final set of criteria added “Contracted / not yet installed” to the previously mentioned criteria. This set of criteria is the most liberal definition of implementation, as the organization has only contracted for the component but has not yet begun the implementation process.

For each stage criterion, dichotomous variables were created to represent whether or not the information system components necessary for each stage are present in the hospital. The dummy variables were created for each set of criteria discussed above.

Some hospitals report a status for two versions of the same IS component. For example, a hospital might have one CPOE system coded as "To be Replaced" and another CPOE system, likely provided by a different vendor, as "Contracted/Note Yet Installed." In this situation, the more advanced status was coded for the hospital. In other words, the "To be Replaced" status would be coded and the "Contracted/Not Yet Installed" status would be ignored because the hospital does have a working CPOE system, even though it has plans to replace that system with another.

Two of the indicators in the dataset are potentially problematic due to how they are coded in the dataset. First, the HIMSS Analytics EMR Adoption Model posits three levels of Computerized Decision Support Systems (CDSS) to differentiate between rudimentary error checking and guidance regarding clinical practice guidelines (HIMSS Analytics, 2006); however, the data used in this study includes only one measure of CDSS. Therefore, the measure was interpreted as level 2 CDSS, as defined in the HIMSS Analytics EMR Adoption Model, because it appears to most closely match the definition of CDSS provided to survey respondents (HIMSS Analytics, 2007). Thus, CDSS was included only in stage 4 of the model.

The Picture Archiving and Communications System (PACS) measure is problematic because the dataset coded non-responses for this variable as a "no" (i.e., 0) for whether the capability is present in the hospital. In other words, rather than having response categories of "yes," "no," and "no response," there are only two categories: "yes" and "no." Because of this coding issue, the number of hospitals without PACS

capability might be overestimated. This problem could be mitigated, however, by the fact that the non-response rate for all the other indicators is fairly low, ranging from 1.93% (order entry) to 5.56% (CMV). Therefore, actual non-response for the PACS variable may have fallen in this range as well, which could mean the "no" responses were not inflated substantially.

Another limitation of the measures used in this study is that they do not explicitly account for the integration of components. While the EMR Adoption Model (HIMSS Analytics, 2006) correctly includes integration as a component of its stages, this study is unable to do so. One example of this limitation is the CDSS, mentioned above, with different levels of CDSS capability requiring different levels of integration. Another example, is the eMAR component, which was included as a Stage 5 indicator in this study, but perhaps could have been included in Stage 3 with nursing documentation. Including eMAR at Stage 5 implies a level of integration not possible at Stage 3, specifically that the eMAR is integrated with the CPOE system to facilitate medication safety from the point of prescription to administration. The eMAR measure available in the dataset does not appear to distinguish between these capabilities.

A final important consideration regarding the measures used in the study is the split between "complete" and "not complete" responses. Generally, it is recommended that variables with greater than 90-10 splits should be considered univariate outliers and removed from the model because those observations in the smaller category will be more influential in the analysis than those in the larger category (Rummel, 1970). Using the

moderate criteria, frequencies for response categories of three of the thirteen stage model indicators have greater than 90-10 splits: laboratory information system, Pharmacy system, and order entry. Two others – radiology information system and CMV – are very close to this threshold. The radiology information system exceeds the split under the lenient criteria. (See appendices for frequencies under the strict and lenient sets of criteria.) According to the stage model, the first three of the indicators are theorized as being foundational systems for the electronic medical record system (HIMSS Analytics, 2006). Given the theoretical importance of the variables with large splits, these variables were used in this study.

Table 2: Frequencies of Stage Model Indicators, Full Sample, Moderate Criteria

LabIS	Frequency	Percent	Cumulative Frequency	Cumulative Percent
.	81	2.48	81	2.48
1	78	2.38	159	4.86
2	3112	95.14	3271	100.00

RadIS	Frequency	Percent	Cumulative Frequency	Cumulative Percent
.	107	3.27	107	3.27
1	224	6.85	331	10.12
2	2940	89.88	3271	100.00

Pharm	Frequency	Percent	Cumulative Frequency	Cumulative Percent
.	68	2.08	68	2.08
1	37	1.13	105	3.21
2	3166	96.79	3271	100.00

Table 2 (continued)

OrderEntry	Frequency	Percent	Cumulative Frequency	Cumulative Percent
.	63	1.93	63	1.93
1	193	5.90	256	7.83
2	3015	92.17	3271	100.00

CMV	Frequency	Percent	Cumulative Frequency	Cumulative Percent
.	183	5.59	183	5.59
1	2683	82.02	2866	87.62
2	405	12.38	3271	100.00

CDR	Frequency	Percent	Cumulative Frequency	Cumulative Percent
.	71	2.17	71	2.17
1	779	23.82	850	25.99
2	2421	74.01	3271	100.00

CPOE	Frequency	Percent	Cumulative Frequency	Cumulative Percent
.	68	2.08	68	2.08
1	2360	72.15	2428	74.23
2	843	25.77	3271	100.00

CDSS	Frequency	Percent	Cumulative Frequency	Cumulative Percent
.	67	2.05	67	2.05
1	1173	35.86	1240	37.91
2	2031	62.09	3271	100.00

eMAR	Frequency	Percent	Cumulative Frequency	Cumulative Percent
.	65	1.99	65	1.99
1	1859	56.83	1924	58.82
2	1347	41.18	3271	100.00

NursDoc	Frequency	Percent	Cumulative Frequency	Cumulative Percent
.	114	3.49	114	3.49
1	1574	48.12	1688	51.61
2	1583	48.39	3271	100.00

Table 2 (continued)

PACS	Frequency	Percent	Cumulative Frequency	Cumulative Percent
1	1691	51.70	1691	51.70
2	1580	48.30	3271	100.00

BarcodeRFID	Frequency	Percent	Cumulative Frequency	Cumulative Percent
.	152	4.65	152	4.65
1	2414	73.80	2566	78.45
2	705	21.55	3271	100.00

Testing the Stage Model

The EMR Adoption Model reportedly has been validated in a previous study (HIMSS Analytics, 2006)with a relatively small and homogenous subset of the HIMSS Analytics data. However, a request for access to the measures for the model was denied, as HIMSS Analytics considers the model proprietary (M. Davis, 2006). Therefore, while this study uses measures from the HIMSS Analytics dataset to test the validity of the conceptual model, the measures are not likely identical to those used in the previously referenced study. In other words, this study does not test the validity of the HIMSS Analytics EMR Adoption Model. Instead, it attempts to test the validity of a stage model guided by the conceptual framework of the HIMSS Analytics EMR Adoption Model using measures identified by the researcher of this study.

The hypothesized stage model assumes that no EMR system can be in place without information systems in the laboratory, pharmacy, and radiology departments; hence, all of these systems are required in order for a hospital to achieve stage 1 of EMR sophistication. The sophistication progresses as additional applications become

available. The stages are cumulative; for example, stage 2 must be completed prior to stage 3. Testing the validity of this model allows for the determination of whether the stages tend to be accurately defined and sequential.

The extent to which the data fit the stage model was assessed using Guttman scaling methods (i.e., scalogram analysis) on the entire sample of acute care hospitals with 50 or more beds. Guttman defines a *scale* as follows: "For a given population of objects, the multivariate frequency distribution of a universe of attributes will be called a scale if it is possible to derive from the distribution a quantitative variable with which to characterize the objects such that each attribute is a simple function of that quantitative variable. Such a quantitative variable is called a scale variable" (L. Guttman, 1944). Under the criteria of a perfect scale, an affirmative response to a given item (or stage in this study) should correspond with affirmative responses to all previous items (i.e., items in which the frequencies of affirmative answers are higher). Scalogram methods determine how well an observed pattern of multivariate responses fit the perfect scale pattern of multivariate responses. It is generally accepted that the perfect model will not hold true for all cases in a study. Scalogram analysis intends to determine the degree to which the perfect scale is violated. If the amount of deviation is within acceptable limits, the scale can prove useful (McIver & Carmines, 1981).

In many situations, such analysis is conducted without a priori assumptions about the ordering of the items, that is, the scale is derived from the observed responses (L. Guttman, 1944). Of course, for this study, the scalogram analysis was conducted to

determine whether the ordering of the items fit the hypothesized version of the stage model for electronic medical record system sophistication.

Scalogram analysis required creation of dichotomous variables to represent a hospital's status for each stage. Hospitals completing all criteria for a given stage were coded as 1 for that stage variable. Cases without all of the criteria completed for a given stage were coded as 0 for that stage variable. The criteria indicators with greater than 90-10 splits were not removed from the scalogram analysis as outliers. The effect of such substantial splits on measuring the scalability of the data is discussed below in the section on coefficient of scalability (CS).

Since the purpose of the scalogram analysis is to determine how well the observed pattern of item responses fit the expected pattern, it was necessary to determine how many scale errors occurred for each case, that is, how many changes in values to the stage variables were needed for the responses of a given hospital to fit the expected stage pattern. There is some debate about how to count the number of errors for a given case. Two common methods are minimization of error (L. Guttman, 1947) and deviation from perfect reproducibility (Edwards, 1948; Goodenough, 1944). The deviation from perfect reproducibility (a.k.a. Goodenough-Edwards) method leads to a greater number of errors found in the scalogram analysis (i.e., it is a more conservative test) than the minimization of error approach and has been proposed as being more consistent with scalogram theory (McIver & Carmines, 1981). Therefore, the Goodenough-Edwards approach was used in this study.

The Goodenough-Edwards method involves calculating the total number of stage variables answered affirmatively for each case. The number of errors is then determined by identifying how many changes in responses would need to occur so that the total points achieved would match the pattern of the perfect Guttman scale (McIver & Carmines, 1981). Table 3 illustrates this process.

Table 3: Sample Calculation of Scale Errors

	Stage 1	**Stage 2**	**Stage 3**	**Stage 4**	**Stage5**	**Stage 6**
Sample Hospital	1	0	1	1	1	0
Perfect Scale for a hospital satisfying requirements for 4 stages	1	1	1	1	0	0
Scale Errors		X			X	

In this example, the hospital satisfies four stages; however, in order to achieve a fit to the perfect scale, two changes would have to be made: stage 2 would change from 0 to 1 and stage 5 from 1 to 0. Using the Goodenough-Edwards technique with six stage variables, the minimum number of Guttman errors for any hospital is 0 (a perfect fit with the Guttman scale) and the maximum is 4.

Three measures were used to assess the goodness of fit to the Guttman scale: Coefficient of Reproducibility (CR), Minimum Marginal Reproducibility (MMR), and Coefficient of Scalability (CS). Coefficient of reproducibility (CR) is “a measure of the

relative degree with which the obtained multivariate distribution corresponds to the expected multivariate distribution of a perfect scale" (L. Guttman, 1950). It therefore reflects the relationship between the total number of scale errors and the total number of responses. The commonly used threshold for the CR value is 0.9, meaning that a scale is useful if it yields 10% or less error (McIver & Carmines, 1981). This threshold is based on the underlying theory and logic presented in Guttman's works on the topic, for example, "if the reproducibility of the entire universe [of content] is very high, say over 90%, then that may be sufficient for many practical purposes" (L. Guttman, 1947).

The minimum marginal reproducibility (MMR) measure is useful in coordination with the CR measure. MMR helps determine whether extreme marginal distributions (i.e., response items for which one response category dominates) are inflating the value of CR (Edwards, 1957). According to McIver and Carmines, MMR "reflects the reproducibility of a series of items based only upon knowledge of the item marginal distributions." Calculating MMR requires the identification of the modal category for each item (i.e., the response category with the highest number of responses for each questionnaire item). The value of MMR reflects "the fact that an item's reproducibility can be no less than the proportion of responses in its modal category" (McIver & Carmines, 1981).

$$CR = (TR - SE) / TR$$
$$MMR = (TR - ME) / TR$$

TR = total number of responses
(i.e., the number of respondents times the number of items)

SE = scale errors
(using Goodenough-Edwards approach for error counting)
ME = marginal errors
(i.e., the sum of all nonmodal frequencies)
(McIver & Carmines, 1981)

According to McIver and Carmines, "the difference between [CR and MMR] is a function of the improvement in prediction provided by the scale over the marginal frequencies of individual items." The calculated difference between the coefficients (i.e., CR minus MMR) ranges from 0 (i.e., the scale does not improve prediction) to 0.5, given that MMR theoretically cannot equal less than 0.5 (McIver & Carmines, 1981).

The coefficient of scalability (CS) is an alternate measure of a scale's predictive effectiveness. Menzel developed the measure to account for perceived weaknesses in the coefficient of reproducibility measure. Specifically, CS is intended to differentiate between predictive ability due to scalability and predictability due to other factors, namely extremeness of items (i.e., items that have very high frequencies of one response category) and extremeness of individuals (i.e., individuals who respond overwhelmingly in one response category for all items) (Menzel, 1953).

Unlike CR, which cannot be less than 0.5 when all items are dichotomous and rarely reaches that low point even when scalability is not present, CS varies from 0 (if the scale does not provide any predictive improvement compared to marginal frequencies) to 1 (a perfect scale fit). This is important because it better enables assessments of degrees of scalability, rather than simply relying on a rule of thumb cutoff, such as 0.9 for CR (Menzel, 1953). The following formula was used to calculate CS:

$$CS = 1 - (SE/ME) = (ME - SE)/ ME$$

SE = scale errors
ME = marginal errors
(McIver & Carmines, 1981)

The CR, MMR, and CS values for the scalogram analysis of the data used in this study are discussed in the "Results" chapter.

Latent Class Analysis

Using SAS 9.1, two randomly selected subsamples of acute care hospitals with 50 or more beds were selected from the HIMSS Analytics 2006 data, each consisting of approximately 50% of the cases (n = 1,636 and n = 1,635). Latent class analysis (LCA) was then performed on the thirteen dichotomous variables representing the criteria included in the stage model.

LCA has been called a "categorical analog to factor analysis," as "factor analysis attributes the covariance structure of a sample with multiple variables to unobserved factors [while] latent class analysis posits unobserved classes to explain association in a multi-dimensional contingency table" (Thompson, 2006). Although factor analysis is intended for use with continuous variables, some studies have used the approach with categorical data, which can yield misleading parameter estimates and goodness-of-fit indices (Vermunt & Magidson, 2005). One study concludes that factors can be extracted, using standard rules of thumb, from dichotomous variables whose values have been randomly generated (i.e., that are not attached to real cases or meaningful measures), and these factors tend to explain a substantial amount of the variance (Shapiro, Lasarev, &

McCauley, 2002).

LCA also can be used to identify typologies (Mccutcheon, 1987), in a manner similar to cluster analysis, by identifying latent classes (i.e., groupings) of cases from a sample or population based on responses to multiple categorical items. Each subject is assumed to belong to one and only one category, and the category membership is assumed to affect subject responses to multiple items of interest to the researcher (Vermunt, 2008). LCA estimates two probabilities: the prevalence of each category (i.e., latent class) and the probability, given the particular latent class membership, that a subject will provide a particular response to an observed variable (Thompson, 2006).

The purpose of using latent class analysis in this study was to identify categories of EMR system infrastructures in a cluster analytic fashion. Like other latent construct approaches, LCA results must be interpreted to identify the best fitting model. Prior to conducting the analysis, it was unknown how many categories of EMR infrastructures would emerge and whether the categories would reflect levels of sophistication of infrastructures or some other pattern, such as infrastructures focused on particular services or users.

Models identifying two through five classes were assessed to determine the best fit. Likelihood ratio chi-square (G^2), Akaike's Information Criterion (AIC), and Bayesian Information Criterion (BIC) were used in the assessment, with smaller G^2, AIC, and BIC values indicating a better fit. However, interpretability of the classes and the probability of an organization belonging to a particular class were also considered, as classes with

near-zero likelihood of membership are not useful for analytic purposes. In addition, LCA was run on both samples, using the same four seed values for starting values, to identify the optimal model (Lanza, Collins, Lemmon, & Schafer, 2007). Finally, LCA results for the selected model were compared to the results of two-step cluster analysis.

Predictors of IS Infrastructure Class Membership

After identifying the best fitting model, the categories were interpreted, and then relationships between the categories and particular organizational factors were explored. Latent Class Analysis allows for the calculation of odds ratios for the organizational factors through logistic regression, with class membership serving as the dependent variable. The logistic regression was run first with each covariate individually to identify bivariate parameter estimates and significance levels. This analysis enables identification of whether a particular response on a covariate is associated with an increased likelihood of belonging to one of the latent classes (Lanza et al., 2007). Multinomial logistic regression was then run with all of the organizational factors simultaneously to assess the relative importance of each factor and to identify interaction effects.

For both the bivariate and multinomial logistic regression, P-values are reported to assess whether a given organizational factor has a significant relationship with latent class membership. Cases with missing data on the organizational factor response are omitted from the bivariate analysis for that covariate. The level of analysis and value of the covariate should not affect the item response probabilities (i.e., Rho estimates) for the classes. If the Rho parameters change substantially after introducing the covariate into

the model, then the data might not be representative of the population (Lanza et al., 2007).

The covariates selected for analysis in this study were guided by contingency theory and diffusion theory perspectives, as well as by the literature on information system adoption and sophistication, particularly the concept of organizational capacity (Jaana et al., 2006). Some of the measures analyzed are at the individual acute-care-hospital level, while others are at the higher level of the delivery system (i.e., integrated delivery system or independent health system), which of course encompasses multiple organizations and, sometimes, multiple acute-care hospitals. An underlying assumption of the study is that the most influential factors on information system sophistication are not general organizational characteristics, such as health system membership, annual revenues, or hospital size, but instead an organization's IS leadership structures, practices, and strategies, which are dedicated specifically to developing the information systems infrastructure in the hospital. Therefore, while a few general organizational capacity measures were included in the analysis, they were included as controls, with the focus being on IS strategy measures at both the delivery-system and hospital levels of analysis. Figure 1 illustrates the conceptual model guiding the selection of factors influencing EMR sophistication.

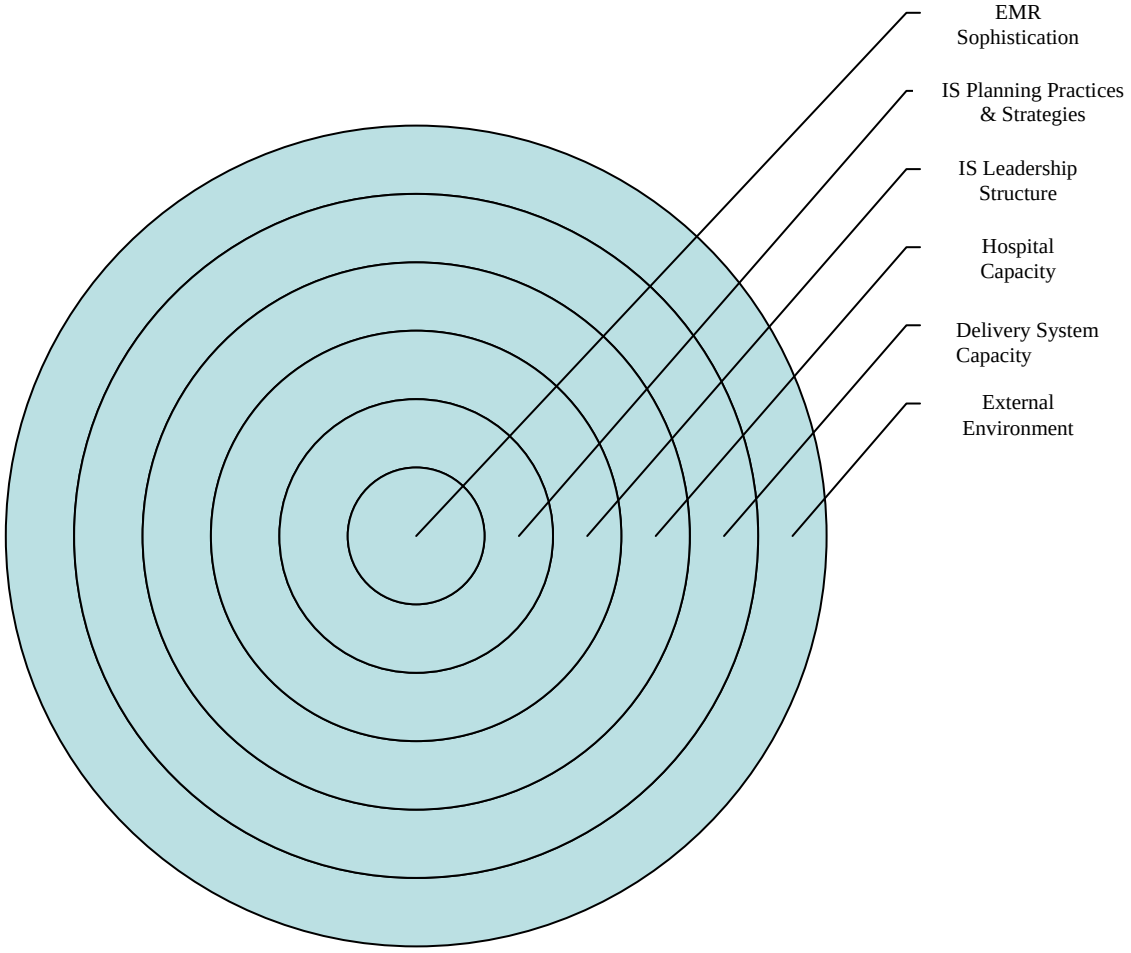


Figure 1: Conceptual Model of Factors Influencing EMR Sophistication

While this model acknowledges many sources of influence on EMR sophistication, the focus of this study is on those hypothesized as having the most direct influence: (1) IS Leadership Structure and (2) IS Practices and Strategies. The rationale for this focus, of course, is the belief that a better understanding of the differences among information system sophistication across hospitals is most likely to be gained by focusing

on these IS-specific factors. Furthermore, the IS leadership structures, practices, and strategies could be the most important for hospital administrators because they are theoretically easier to manipulate than the size of the hospital and the competitiveness of the environment, for example.

CHAPTER 4: RESULTS

Scalogram Analysis

As outlined above, three different sets of criteria were used to determine how sensitive the results of the scalogram analysis are to assumptions about whether a given IS component is present in a given hospital. The first set of criteria, hereafter referred to as "strict," included two statuses: "Live and Operational" and "To be Replaced." The second set of criteria, labeled "moderate," included "Installation in Process" as well. The final set, called "lenient," included these three statuses and "Contracted/Not Yet Installed." The coefficient of reproducibility (CR), coefficient of scalability (CS), and minimum marginal reproducibility (MMR) were calculated for each set of criteria to assess how well the hypothesized stages fit the study data.

Coefficient of Reproducibility (CR) and Minimum Marginal Reproducibility (MMR)

Using the Goodenough-Edwards technique for counting scale errors, the number of errors increased as the criteria for implementation became more lenient. The strict criteria resulted in 3,174 scale errors, the moderate resulted in 3,480, and the lenient resulted in 4,398. This means that, using the strict criteria, 3,174 item responses had to be changed in order for each respondent's set of responses to match the hypothesized scale of EMR stages. With 19,626 total number of response choices made (i.e., six scale items times 3,271 respondents), the CR was calculated as 0.84 for the strict criteria, 0.82 for the moderate criteria, and 0.78 for the lenient criteria. These values fall below the

rule of thumb for acceptable reproducibility (0.9), indicating that the hypothesized scale is problematic across all three sets of criteria used for determining whether a hospital has a given IS component.

CR = (TR – SE) / TR

TR = total number of responses = 19,626

(i.e., the number of respondents times the number of items)

SE = scale errors = 3,174 (strict); 3,480 (moderate); 4,398 (lenient)

(using Goodenough-Edwards approach for error counting)

CR = 0.84 (strict), 0,82 (moderate), 0.78 (lenient)

As noted above, it is customary to interpret the value of CR in combination with MMR to determine whether extreme marginal values may be inflating the value of CR. Since CR value is lower than the standard 0.9 threshold, the MMR is perhaps less important since no value of MMR would offset the low CR value. In fact, the values of MMR (0.84, 0.84, 0.77) are similar to that of the CR values (0.84, 0.82, 0.78), which reinforces the finding that the data do not fit the hypothesized scale well. Specifically, the difference between the two values indicates the improvement of the scale's reproducibility over the marginal frequencies, as the reproducibility of an item cannot be less than the frequency of the modal response category for the item. A good scale yields a substantial difference between CR and MMR, with a maximum possible difference being 0.5. In this study, the difference is near zero for all three sets of criteria, indicating that the scale does not substantially improve predictive ability (i.e., reproducibility) over the marginal frequencies (McIver & Carmines, 1981).

MMR = (TR – ME) / TR

TR = total number of responses = 19,626
(i.e., the number of respondents times the number of items)
ME = marginal errors = 3,127 (strict); 3,447 (moderate); 4,510 (lenient)
(i.e., the sum of all nonmodal frequencies)
MMR = 0.84 (strict), 0.84 (moderate), 0.77 (lenient)

Coefficient of Scalability (CS)

The coefficient of scalability reinforces the findings of the CR and MMR. The CS values for the three criteria (-0.02, -0.01, 0.02) fall well short of the commonly accepted 0.60 threshold. This threshold "has no explicit theoretical justification" (McIver & Carmines, 1981); however, given that the CS has a range of 0 (no scale fit) to 1 (perfect scale fit), 0.6 represents a moderate level of fit, unaffected by extremeness of items or individuals. In this study, the CS values for all three sets of criteria fall at the "no-scale-fit" end of the spectrum. In fact two of the CS values are negative, indicating more scale errors than marginal errors.

CS = (ME - SE)/ ME

SE = scale errors
ME = marginal errors

CS = -0.02 (strict), -0.01 (moderate), 0.02 (lenient)

Overall Assessment of the Hypothesized Stage Model

The low CS and CR values, and the fact that MMR has a similar value to CR, provide clear indication that the stage model, as hypothesized and measured, does not fit

the observed data well. Looking at frequencies of response categories for individual items, it appears that much of the error in the stage model may be due to the controlled medical vocabulary (CMV) item. CMV, important for ensuring that terms are standardized for entry into computerized provider order entry (CPOE) systems, was hypothesized as a stage two component. However, more than 80% of the hospitals in the sample reported not having CMV capability, even under the lenient set of criteria. Therefore, these hospitals have not achieved stage two of the model, but many likely have achieved advanced stages, leading to a large number of scale errors.

Clinical decision support systems (CDSS) is another problematic item. More than 60% of the hospitals in the sample, using all three sets of criteria, reported affirmatively to the presence of CDSS. Proposed as a stage 4 component, it has a higher frequency of affirmative responses than one stage-2 component (CMV) and two stage-3 components (nursing documentation and PACS). Therefore, CDSS also could be the cause of many scale errors.

Finally, because the eMAR measure could be debated as a Stage 3 or Stage 5 indicator, sensitivity analysis was run on the dataset using the lenient criteria to determine if moving eMAR from Stage 5 to Stage 3 improved the fit of the model. The analysis yielded very similar CR, MMR, and CS values (0.76, 0.77, -0.04, respectively) after making this change, indicating that the placement of eMAR in the model was not the likely cause of the poor fit.

Because the hypothesized stage model does not fit the data well according to the

CR, MMR, and CS statistics, an alternative approach to describing electronic medical record system sophistication was explored.

Latent Class Analysis

Multiple latent class models were run on both split samples using three different seeds for starting points and the three sets of criteria for the information system components (i.e., lenient, moderate, and strict). The results were generally consistent across starting points and across the sets of criteria. Based on (1) the likelihood ratio chi-square (G^2), AIC, and BIC values, (2) stability of Rho parameter estimates, (3) the size of the distributed probabilities of class membership, and (4) and the interpretability and usefulness of the classes, the three-class model was deemed to provide the best fit. While the four-class model generally yielded preferable G^2, AIC, and BIC values, the Rho and Gamma parameter estimates for the this model were not as consistent as the three-class model, making the interpretation of the class characteristics and likelihood of hospitals belonging to a given class potentially unreliable. The three-class model is parsimonious and interpretable and therefore was deemed most useful. Also, the three-class model was compared to results of a three-cluster model using two-step cluster analysis. The LCA and cluster models yielded similar results with respect to how responses to particular items grouped across classes and clusters.

Table 4: Fit of 3-Class Model, Lenient Criteria, Sample 1

```
Log-likelihood:     -8374.33
G-squared:           1125.32
AIC:                 1207.32
```

Table 4 (continued)

```
BIC:                  1428.72
Degrees of freedom:     8150

Test for MCAR
      Log-likelihood:     -7811.67
      G-squared:            724.79
      Degrees of freedom:    55702
```

Table 5: Parameter Estimates of 3-Class Model, Lenient Criteria, Sample 1

```
Gamma estimates (class membership probabilities):
Class:                    1          2          3
                       0.3795     0.4767     0.1438

Rho estimates (item response probabilities):
  Response category  1:
Class:                1          2          3
  LabIS   :       0.0000     0.0000     0.0623
  RadIS   :       0.0103     0.0174     0.2052
  Pharm   :       0.0000     0.0056     0.0163
  CMV     :       0.7383     0.9362     0.9680
  CDR     :       0.0156     0.1686     0.8540
  NursDoc :       0.0260     0.5495     0.9156
  eMAR    :       0.0943     0.5797     0.7249
  OrderEntry:     0.0000     0.0201     0.2566
  CDSS    :       0.1806     0.2827     0.9120
  CPOE    :       0.1803     0.6798     0.9766
  PhysDoc :       0.3094     0.8378     0.9446
  PACS    :       0.4180     0.5271     0.8052
  BarcodeRFID:    0.6717     0.8800     0.7556

  Response category  2:
Class:               1          2          3
  LabIS   :       1.0000     1.0000     0.9377
  RadIS   :       0.9897     0.9826     0.7948
  Pharm   :       1.0000     0.9944     0.9837
  CMV     :       0.2617     0.0638     0.0320
  CDR     :       0.9844     0.8314     0.1460
  NursDoc :       0.9740     0.4505     0.0844
  eMAR    :       0.9057     0.4203     0.2751
  OrderEntry:     1.0000     0.9799     0.7434
  CDSS    :       0.8194     0.7173     0.0880
  CPOE    :       0.8197     0.3202     0.0234
  PhysDoc :       0.6906     0.1622     0.0554
  PACS    :       0.5820     0.4729     0.1948
  BarcodeRFID:    0.3283     0.1200     0.2444
```

For interpretation, it is necessary to analyze the Rho estimates, which are the probabilities of the given item-response conditional on the given latent-class membership (Lanza et al., 2007). Response category 2 corresponds to affirmative answers about the presence of the information system component in the hospital. The Gamma estimates reflect the percentage of hospitals expected to belong to the particular class. Therefore, the Rho estimates provide information about the characteristics of the information infrastructure represented by its particular class, while Gamma estimates provide information about the proportion of hospitals that are likely to belong to each class.

To facilitate interpretation of the class characteristics (i.e., Rho estimates), it is perhaps easiest to begin with Class 3, since it has the fewest items (information system components) with a high likelihood of affirmative responses. Hospitals in this class tend to respond affirmatively to having a laboratory system (0.94), pharmacy system (0.79), radiology system (0.98), and order entry (0.74) in place. Interestingly, three of these are the ancillary systems hypothesized as comprising stage 1 of the stage model. These ancillary systems can be considered the foundation of an EMR system since they capture vital information about test results, drug prescriptions, and diagnostic imaging. In addition to these systems in ancillary departments, class 3 infrastructures tend to include order entry, which allows for digitized orders to be entered from multiple sites. Order entry is a complementary feature to the ancillary systems because it may be accessed by ancillary departments and nursing stations, as opposed to computerized provider order entry (CPOE), which is a tool for those with prescribing authority (e.g., physicians and

nurse practitioners). These Class 3 infrastructures tend not to have any other components, with all other items having less than a 0.3 probability of being in place. Therefore, these EMR systems are labeled "basic infrastructures." Based on the Gamma parameter estimates, approximately 14% of the hospitals can be expected to fall into this class.

Class 2 infrastructures have an even higher likelihood of answering affirmatively to the presence of the ancillary systems and order entry than Class 3, with 100% or near 100% probability of the presence of each of these capabilities. In addition, Class 2 EMR infrastructures tend to have clinical data repository (CDR) and clinical decision support system (CDSS) capabilities, with 83% and 72% probability, respectively. The presence of these two components illustrates a movement beyond ancillary services into clinical data aggregation and decision support capabilities. The CDR supports the clinical CDSS capability, as the data repository feeds needed patient information to the decision support system. While this is a notable difference from the "basic systems" infrastructure (i.e., Class 3), Class 2 still tends not to include components that most directly involve the roles and responsibilities of nurses and physicians, such as electronic medication administration and computerized provider order entry. Along these lines, it is possible that the CDSS capability present in Class 2 hospitals is "lower level" support, such as error checking for drug-drug interactions, which typically takes place in the pharmacy, rather than guidance on treatment protocols (M. Davis, 2007). Since the data do not differentiate between CDSS capabilities, it is not possible to make this distinction with

any certainty. While Class 2 infrastructures are more likely than Class 3 to have nursing and physician-oriented components, such as EMAR and CPOE, the probabilities are still below 50%. Therefore, Class 2 will be referred to as "intermediate infrastructures." According to the Gamma parameter estimates, approximately half (48%) of the hospitals fall into this class.

Class 1 infrastructures have all six of the components that Class 2 hospitals tend to have, with even a greater likelihood for CDR (98% vs. 83%) and CDSS (82% vs. 72%). In addition, Class 1 hospitals have high probabilities of nursing and physician oriented components not likely to be found in Class 2. The nursing-oriented systems have near 100% likelihood: nursing documentation (0.97) and EMAR (0.91). The physician-oriented systems also have high probabilities: CPOE (0.82) and physician documentation (0.69). These capabilities specifically involve nurses and physicians interacting directly with patients at the bedside. The nursing documentation, physician documentation, CPOE, and eMAR systems replace handwritten notes and orders with computerized entry by the clinicians and/or automate tasks, such as verification or tracking, that otherwise would be done manually.

Class 1 infrastructures also are more likely than the other two classes to have picture archiving and communication systems (PACS) capabilities; however, only slightly more than half (0.58) of the hospitals in this class tend to have this capability. The PACS capability facilitates the diagnostic process when linked to CPOE by providing filmless images, further reducing reliance on paper records. The EMR

systems found in Class 1 require a high level of integration and will, therefore be labeled as “advanced infrastructures.” According to Gamma parameter estimates, approximately 38% of hospitals can be expected to fall into this class.

Two of the thirteen system components, controlled medical vocabulary (CMV) and barcoding/RFID, tended not to be present in any of the three classes of infrastructures. CMV is particularly surprising, given that it was hypothesized as a stage-two component in the hypothesized stage model. Apparently, hospitals are proceeding with the development of EMR systems without the benefits of standardized terminology CMVs offer. Perhaps, this is due to a belief that CMVs are most critical for interoperability across systems in different organizations, and hospitals are more focused primarily on developing systems to suit their own needs. The lack of barcoding/RFID techologies is perhaps not as surprising since some hospitals are still likely considering which approach (barcoding vs. RFID) is most appropriate for given needs. Nevertheless, in the future more hospitals will likely adopt one of these technologies to integrate with CPOE and eMAR to ensure medication safety (M. Davis, 2007).

In summary, the three ancillary systems, hypothesized as stage 1 in the stage model, in addition to order entry, appear to be foundational systems found in nearly all hospitals in the sample. EMR systems that tend to have just these four components can be considered basic infrastructures. In addition to being more likely than the basic infrastructures to have the ancillary systems and order entry, intermediate infrastructures tend to have clinical data repository and clinical decision support systems, representing a

movement beyond ancillary systems. Finally, advanced infrastructures have high probabilities of having the six components of the intermediate infrastructure, plus the nursing and physician-oriented systems: nursing documentation, electronic medication administration record, computerized provider order entry, and physician documentation. These advanced systems most directly affect the roles and responsibilities of nurses and physicians providing patient care at the bedside.

Bivariate Analysis of Organizational Factors and Class Membership

LCA allows for analysis of covariates to determine whether particular variables are significant predictors of class membership. The analysis is conducted using logistic regression with latent class membership as the dependent variable. Prior to conducting the analysis, a decision had to be made about which set of IS criteria should be used (i.e., lenient, moderate, or strict). For this purpose, the mean posterior probabilities of class membership were analyzed to assess the reliability of the class membership measure across the three sets of IS criteria.

The posterior probabilities for a given hospital indicate the probability of the hospital being classified in each of the three EMR categories (i.e., advanced, intermediate, and basic) given the hospital's responses on the thirteen EMR component indicators. The mean posterior probabilities reflect the statistical average of the posterior probabilities for all hospitals classified in a given EMR category, as determined by the highest posterior probability for the hospital. For example, hospitals with a higher

posterior probability of being classified in the "advanced" category than in the other categories were grouped together as the advanced EMR class. For the hospitals in this advanced EMR class, the mean posterior probabilities were then calculated for each of the EMR classes (i.e., basic, intermediate, and advanced). Ideally, the mean posterior probability for the hospitals in a given class would approach 1 for the class in which the hospitals were assigned and near zero for the other two classes. This pattern reflects a reliable classification system because it is clear which class a given hospital belongs to.

While all three criteria datasets led to fairly similar mean posterior probabilities of class membership, the lenient criteria dataset had the highest mean posterior probabilities across the three assigned classes. For the lenient criteria dataset, the means ranged from 0.85 to 0.89 for the assigned class, which is slightly lower than the 0.9 proposed cutoff for determining whether class assignments are acceptable (Bray, 2008). However, the author deemed this range reasonable for exploring differences across the classes based on organizational factors, keeping in mind that the assignment of hospitals to the classes is not 100% accurate (Lanza et al., 2007). The lenient criteria sample, therefore, was used for the bivariate and multinomial logistic regression analysis. (See appendix for posterior probabilities of the moderate and strict criteria samples.)

Table 6: Mean Posterior Probabilities, Lenient Criteria, Sample 1, 3-Class Model

Assigned Class	Class 1 (Advanced)	Class 2 (Intermediate)	Class 3 (Basic)
1	0.883999253	0.115938573	0.000062174
2	0.087172563	0.853101537	0.059725901
3	0.000399029	0.10754855	0.892052421

For the bivariate analysis, the item response probabilities (i.e., Rho estimates) in the latent class model remained relatively stable for every organizational factor (i.e., independent variable), indicating that the model fits the data well (Lanza et al., 2007). In the results below, odds ratios are reported for each organizational factor. The odds ratios indicate the effect that the response on the independent variable has on the odds of a hospital being classified as having an advanced, intermediate, or basic EMR infrastructure.

Also reported for each categorical independent variable are the class membership probabilities (gamma estimates) by response category. These class membership probabilities reflect the percentage of hospitals expected to be classified in each EMR category. Like odds ratios, grouping these class membership probabilities by response category on each categorical independent variable allows for comparing the likelihood of class membership across two groups of hospitals (i.e., those reporting "yes" on the independent variable and those reporting "no"). It is very important to note, however, that the odds ratios and class membership probabilities are not the same measure. Unlike the odds ratios, the class membership probability approach does not reflect relative changes in probability of membership in a specific class (e.g., advanced EMR) compared to membership in one reference class (e.g., basic EMR). Instead, it reflects absolute changes in probability across all three classes. Therefore, the differences in class membership probabilities might not appear as substantial in this analysis as those presented in the odds ratios. For example, a 2.0 odds ratio for the advanced class

compared to the basic class (reference group) for a given independent variable would not necessarily correspond to a class membership probability that is twice as high for the advanced class compared to the basic class.

Delivery System Capacity

The rationale for a relationship between delivery system membership and information system sophistication is that delivery systems have the incentive to assist with the collection and communication of patient information across providers in the system. Furthermore, delivery systems can pool resources for expensive endeavors such as information systems. However, results of previous studies have been mixed regarding the relationship between system affiliation and information system adoption/sophistication.

Delivery System Size and Revenues

This study explored whether the size of the delivery system is associated with information system sophistication, the assumption being that larger delivery systems likely would be associated with more sophisticated information systems. To measure system size, the number of acute-care hospitals affiliated with the system were counted. This count variable was then standardized and included in the model as a covariate.

Table 7: Delivery System Size Parameter Estimates

Covariate	**Class 1 Odds**	**Class 2 Odds**	**Class 1 Beta**	**Class 2 Beta**	**P value**
Number of Acute Care Hospitals in the System	**1.28**	**0.82**	**0.25**	**- 0.19**	**0.000**

The results were somewhat mixed. For every one unit increase (1 standard deviation) in system size, a hospital was 28% more likely to belong to the advanced infrastructure category (class 1) than the basic class (class 3). However, for every unit increase in system size, a hospital was approximately 20% more likely to be in the basic infrastructure category than the intermediate category. These results imply that larger delivery systems (i.e., systems with more acute care hospitals) tend to either have basic or advanced infrastructures, not intermediate ones.

Another measure of delivery system size is the amount of annual revenue generated by the system. To determine whether delivery system revenues were associated with IS infrastructure class membership, the annual revenues for the systems were standardized. The standardized revenue value for each system was then assigned to each acute care hospital in the system. It is acknowledged that this value does not reflect the amount of revenue attributable to the hospital itself. The variable is a system-level measure of size as reflected by the amount of financial resources received for services.

The results again were somewhat mixed. For every one unit increase in system revenues, a hospital was 46% more likely to belong to the advanced infrastructure category (class 1) than the basic class (class 3). However, for every unit increase in system revenues, a hospital was less likely to fall in the intermediate infrastructure category than the basic category. These results imply that systems with higher revenues tend to either have basic or advanced infrastructures, not intermediate ones.

Table 8: Delivery System Revenue Parameter Estimates

Covariate	Class 1 Odds	Class 2 Odds	Class 1 Beta	Class 2 Beta	P value
Annual Revenue for the System	**1.46**	**0.87**	**0.38**	**- 0.14**	**0.000**

Perhaps not surprisingly, the standardized system size and system revenue variables were highly correlated (0.9), as one would expect delivery systems with many organizations to have higher revenues than those systems with fewer organizations.

Hospital Capacity

Hospital size has been posited as a facilitator for information system adoption. A rationale for this relationship is that decision-makers in larger hospitals tend to see more potential for efficiencies gained with information systems and are more likely to have available resources for investing in information systems than are decision-makers in smaller hospitals. In this study, hospital size was measured by a standardized variable reflecting the number of staffed beds in the hospital.

Table 9: Hospital Size Parameter Estimates

Covariate	Class 1 Odds	Class 2 Odds	Class 1 Beta	Class 2 Beta	P value
Number of Staffed Beds	**2.53**	**2.36**	**0.93**	**0.86**	**0.000**

The results were significant and generally as expected. Hospitals are approximately two and a half times more likely to be in the advanced infrastructure category than in the basic infrastructure category for every unit increase (1 standard

deviation) in hospital size. Similarly, they are approximately two and a third times more likely to be in the intermediate infrastructure category than in the basic category for every unit increase in hospital size. This indicates that hospitals with basic infrastructures are smaller than those with intermediate and advanced infrastructures.

Information System Leadership Structure

Management support for an innovation has been posited as a key factor influencing the effectiveness of the innovation (Klein, Conn, & Sorra, 2001). In the case of information systems as innovations, management support often refers to support from non-IS managers, under the assumption that IS-managers inherently support information systems as innovations. The amount of non-IS management support for an innovation can be measured in a variety of ways. One way is to focus on the leadership resources dedicated to information systems planning, specifically the role that the CIO holds within the organization, as well as the structures in place to support decision making regarding information system investments.

Role of the Chief Information Officer (CIO) in the Hospital

Given that CIOs tend to be advocates for information systems, it is possible that hospitals with more influential CIOs would have more sophisticated information systems. One factor related to the amount of influence a CIO has, which has not received much attention in previous studies on information system adoption in hospitals, is the scope of the role of the CIO within the hospital. Specifically, CIOs with responsibilities extending

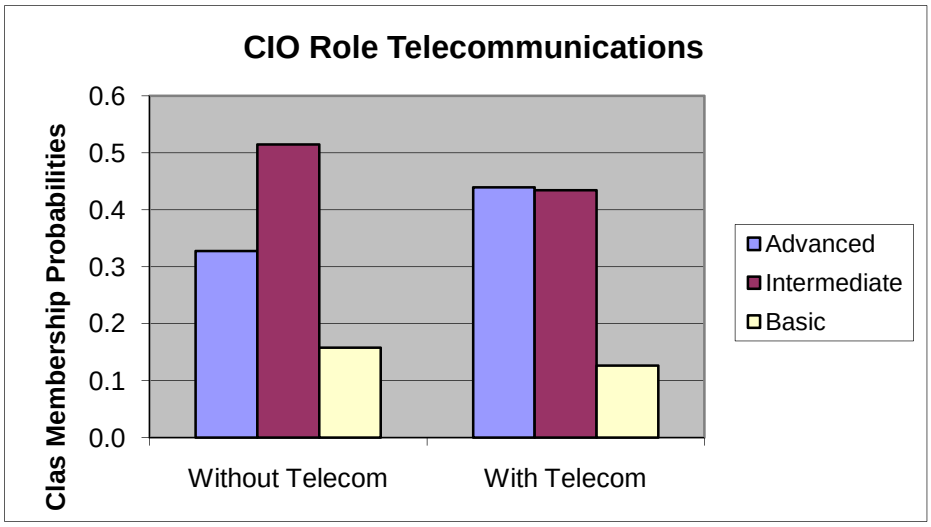
beyond traditional CIO responsibilities can be assumed to have more influence within the organization at the strategic level. Therefore, it is possible that hospitals with CIOs having broad responsibilities will be more likely to have sophisticated information systems. In this study, the scope of CIO responsibilities was measured by whether the CIO is responsible for telecommunications, as this is not a universal CIO responsibility.

CIOs having an expanded role including telecommunications did have a significant influence on whether a hospital was categorized with an advanced, intermediate, or basic electronic medical record system. Hospitals with CIOs having this expanded role were found to be 66% more likely to fall into the advanced information system infrastructure category than in the basic category. The likelihood of being in the intermediate category was not substantially higher than being in the basic category (6% higher). This result indicates that the expanded CIO role is a useful predictor for whether a hospital has an advanced infrastructure, but it does not differentiate well between those with intermediate and basic infrastructures. When the reference group was identified as the intermediate class (class 2) in the analysis, hospitals with expanded CIO roles were 57% more likely to fall into the advanced category than the intermediate category.

Table 10: CIO Role Parameter Estimates

Covariate	**Class 1 Odds**	**Class 2 Odds**	**Class 1 Beta**	**Class 2 Beta**	**P value**
CIO Role Telecommunications	1.66	1.06	0.51	0.05	0.000

Figure 2 depicts the probability of each class membership given whether the CIO has an expanded role into telecommunications.



	Advanced	*Intermediate*	*Basic*
Without Telecom	0.3277	0.5147	0.1576
With Telecom	0.4395	0.4340	0.1265

Figure 2: Probability of Class Membership by Expanded CIO Role

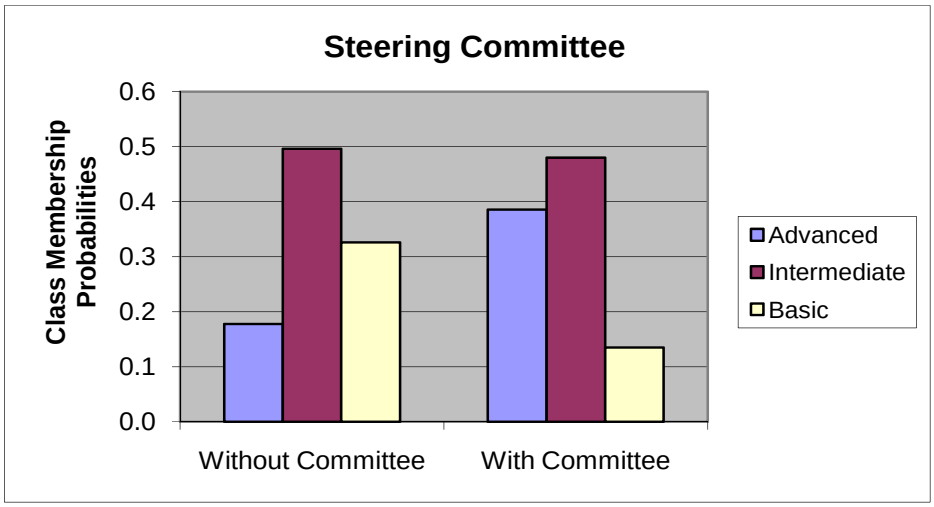
Information System Steering Committee

Since information systems require substantial investments and affect the roles and work flows involved with patient care, decisions about such systems have strategic implications. The leadership resources dedicated to strategic thinking about information systems likely affect an organization's ability to develop sophisticated systems. To assess the influence of these resources, a dummy variable was created to reflect the presence of an information system (IS) steering committee at the delivery-system level.

Table 11: IS Steering Committee Parameter Estimates

Covariate	**Class 1 Odds**	**Class 2 Odds**	**Class 1 Beta**	**Class 2 B**	**P value**
IS Steering Committee	5.24	2.34	1.66	0.85	0.000

Hospitals belonging to delivery systems with IS steering committees are greater than five times more likely to belong to the advanced infrastructure category than the basic category and greater than two times more likely to belong to the intermediate category than the basic category. When the intermediate category was used as the reference group in the analysis, hospitals with a steering committee were more than two times (odds ratio = 2.24) likely to be in the advanced category than the intermediate one. These are substantial differences and reflect the importance of such committees in predicting the sophistication level of a hospital's information system.



	Advanced	*Intermediate*	*Basic*
Without Committee	0.1778	0.4961	0.3261
With Committee	0.3853	0.4799	0.1348

Figure 3: Probability of Class Membership by IS Steering Committee

Information System Planning Practices and Strategies

Based on contingency theory and the information systems literature, it is generally accepted that organizations should attempt to implement information systems that provide a "good fit" for the organization. The planning practices and strategies implemented by the IS leadership are key to achieving this fit.

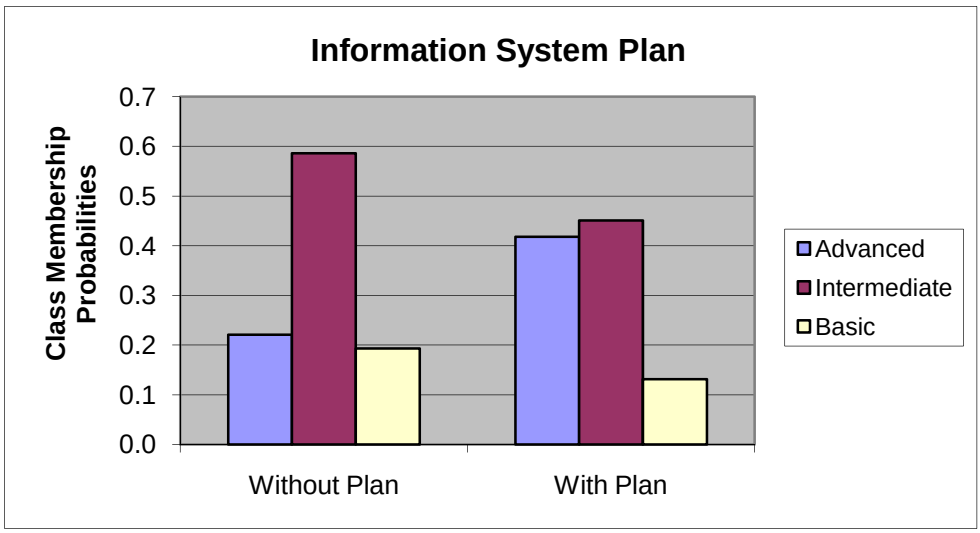
Having an Information System Plan

Organizations with a formalized information systems plan in place demonstrate an active approach to thinking about IS needs. The measure used to indicate the presence of an IS plan is a dichotomous (yes/no) variable at the health system level. Hospitals belonging to a health system with an IS plan were coded as having such a plan.

Table 12: Information System Plan Parameter Estimates

Covariate	**Class 1 Odds**	**Class 2 Odds**	**Class 1 Beta**	**Class 2 B**	**P value**
IS Plan	2.77	1.13	1.02	0.12	0.000

Logistic regression analysis indicates that hospitals with an IS plan were approximately two and three-quarters times more likely to belong to the advanced infrastructure category than the basic category, and 13% more likely to belong to the intermediate category than the basic category. The IS plan also differentiates the advanced and intermediate categories, as hospitals with a plan was nearly two and half times more likely (odds ratio = 2.46) to fall into the advanced category than the intermediate.



	Advanced	*Intermediate*	*Basic*
Without Plan	0.2208	0.5862	0.1930
With Plan	0.4177	0.4508	0.1316

Figure 4: Probability of Class Membership by IS Plan

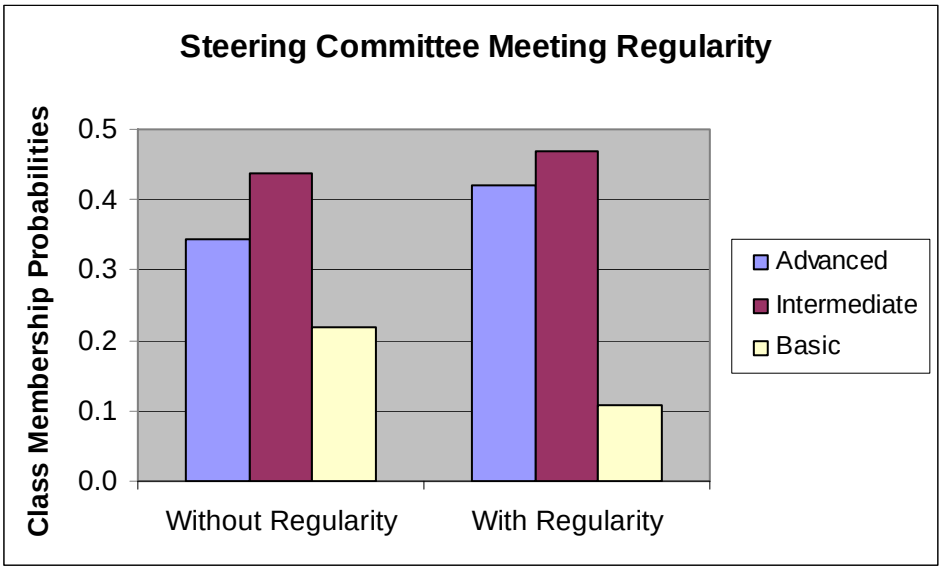
IS Steering Committee Meetings

The periodicity in which an IS committee meets could be an important indicator for how much attention is given to planning for a sophisticated EMR system. A dummy variable, therefore, was created to reflect the regularity of IS committee meetings at the delivery system level. This measure was intended to differentiate between committees that actively plan for information system investments and those that are more symbolic or passive in nature. Committees that reported meeting weekly or monthly were coded as meeting regularly (i.e., active committees). Those that reported meeting quarterly, "as needed," or "other" were coded as not meeting regularly.

Table 13: IS Committee Meetings Parameter Estimates

Covariate	**Class 1 Odds**	**Class 2 Odds**	**Class 1 Beta**	**Class 2 B**	**P value**
Regular Steering Committee Meetings	2.44	2.14	0.89	0.76	0.000

For the hospitals belonging to delivery systems with IS committees, those that report meeting regularly are nearly two and a half times (odds ratio = 2.44) more likely to belong to the advanced category than the basic category and over two times (odds ratio = 2.14) more likely to belong to the intermediate category than the basic category.



	Advanced	*Intermediate*	*Basic*
Without Regularity	0.3439	0.4385	0.2176
With Regularity	0.4210	0.4700	0.1090

Figure 5: Probability of Class Membership by IS Committee Meeting Regularity

While having regular committee meetings clearly differentiates the advanced and

intermediate categories from the basic category, the difference between advanced and intermediate hospitals is not as striking. Those with regular meetings are approximately 14% more likely to have an advanced infrastructure than an intermediate one.

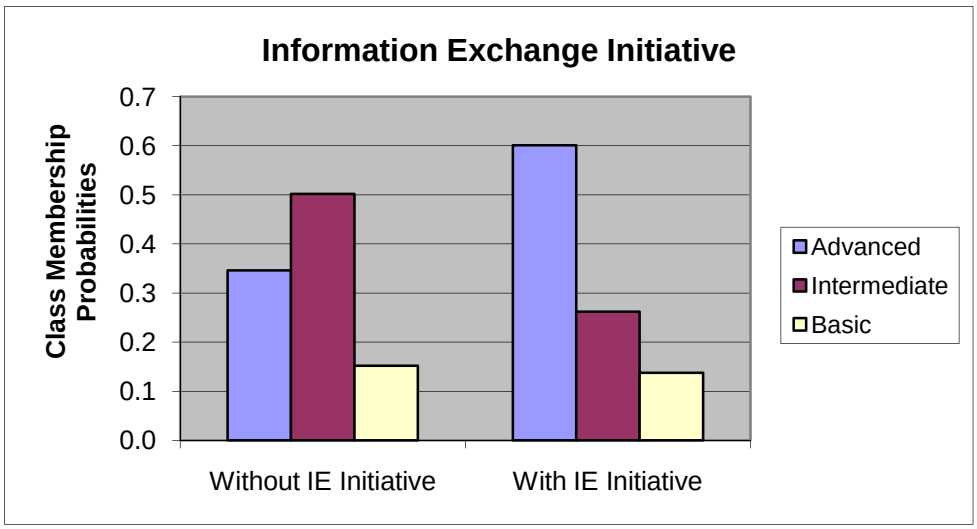
Information Exchange Initiatives

Information exchange (IE) initiatives refer to formal arrangements between multiple health care delivery organizations that involve sharing individual patient data to improve patient care. Such exchanges have been supported by funding from such federal agencies as the Centers for Medicare and Medicaid Services (CMS) and the Agency for Healthcare Research and Quality (AHRQ). For this study, a dichotomous variable was used to indicate hospitals reporting participation in any information exchange initiative. Only approximately 9% of the hospitals in the sample reported participation.

The analysis indicated that those participating in an exchange initiative were nearly twice as likely to fall into the advanced category than in the basic category. It is expected that hospitals would need advanced IS infrastructures to be able to have the capability to participate in an IE initiative. However, hospitals participating in IE initiatives were less likely to fall into the intermediate category than in the basic category, a result that is not easily explained.

Table 14: Information Exchange Initiative Parameter Estimates

Covariate	**Class 1 Odds**	**Class 2 Odds**	**Class 1 Beta**	**Class 2 B**	**P value**
Information Exchange Initiative	1.92	0.58	0.65	-0.55	0.000



	Advanced	*Intermediate*	*Basic*
Without IE Initiative	0.3461	0.5020	0.1519
With IE Initiative	0.6007	0.2621	0.1372

Figure 6: Probability of Class Membership by IE Participation

Disaster Recovery Planning

The September 11th terrorist attacks in New York increased awareness about the importance of disaster preparedness and recovery for various types of organizations. With respect to health care delivery organizations, the Katrina disaster was perhaps just as influential because the large amount of patient medical information that was lost illustrated the vulnerability of paper records to certain natural disasters. In essence, the Katrina disaster provided an opportunity for many health care organization leaders to rethink their patient record systems (Boom et al., 2007).

For the present study two measures of disaster recovery planning were explored.

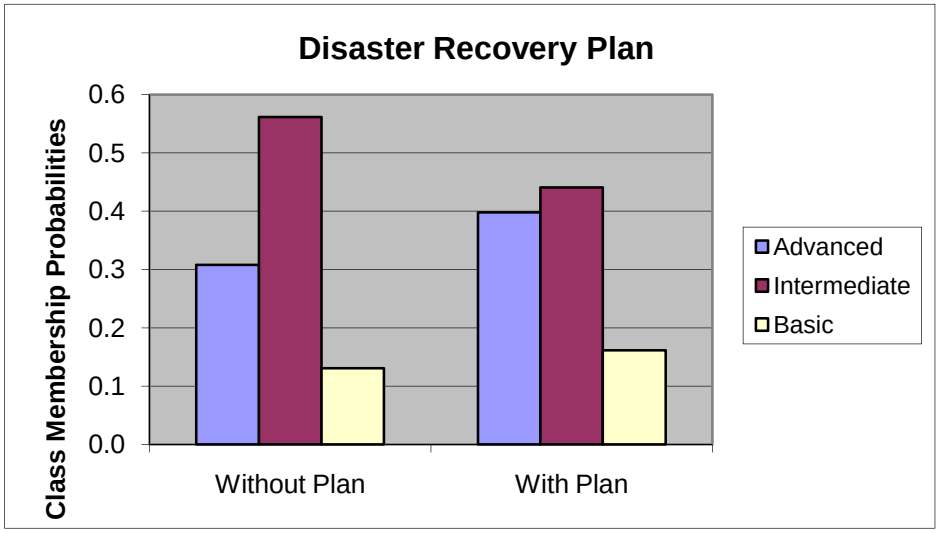
The first was a dichotomous variable indicating whether the delivery system to which the hospital belongs has a formal disaster recovery plan. The results of this analysis were statistically significant; however, they indicated that the presence of a plan was not a particularly useful predictor of IS infrastructure class membership. Those with a plan were 4% more likely to fall into the advanced class than in the basic class and less likely to fall into the intermediate category than in the basic one.

A second measure explored was whether the delivery system has a backup facility for disaster recovery. Arguably, having a backup facility in place is evidence of a more active approach to disaster planning than having a disaster recovery plan because the facility requires a direct monetary investment. Results indicated that hospitals belonging to delivery systems with a backup facility for disaster recovery were over two and half times more likely to fall into the advanced infrastructure category than in the basic category, but approximately 18% more likely to fall into the basic category than the intermediate category. Analysis using the intermediate class as the reference group indicated that hospitals with the backup facility were over three times as likely (odds ratio = 3.06) to fall into the advanced category than in the intermediate one.

Table 15: Disaster Recovery Planning Parameter Estimates

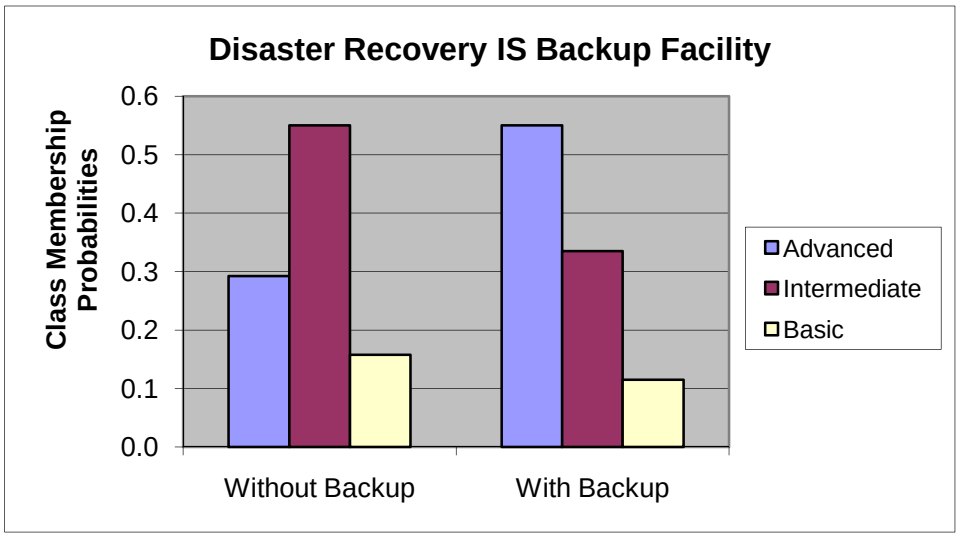
Covariate	**Class 1 Odds**	**Class 2 Odds**	**Class 1 Beta**	**Class 2 Beta**	**P value**
Recovery Plan	1.05	0.63	0.05	-0.45	0.002
Recovery Plan IS Backup Facility	2.58	0.83	0.95	-0.18	0.000

While approximately 61% of hospitals in the sample belong to delivery systems reporting a disaster recovery plan, a much smaller percentage (35%) reported having a backup facility for disaster recovery. Based on the results of this analysis, hospitals belonging to systems investing in backup facilities appear to be the ones most likely to have advanced IS infrastructures.



	Advanced	*Intermediate*	*Basic*
Without Plan	0.3078	0.5617	0.1305
With Plan	0.3980	0.4407	0.1613

Figure 7: Probability of Class Membership by Disaster Recovery Plan



	Advanced	*Intermediate*	*Basic*
Without Backup	0.2924	0.5501	0.1575
With Backup	0.5503	0.3349	0.1148

Figure 8: Probability of Class Membership by Disaster Recovery IS Backup Facility

Vendor Selection Strategy

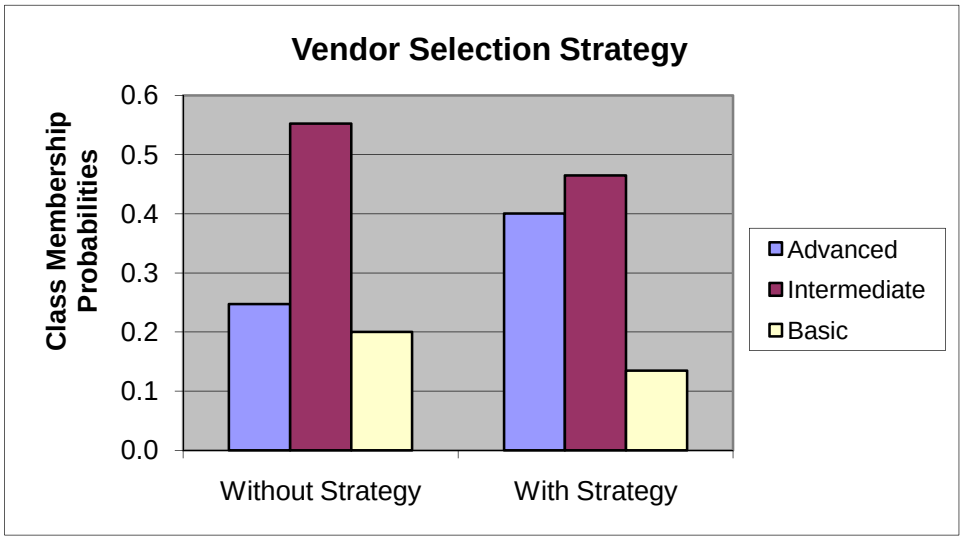
One of the tasks associated with information systems development is identifying a strategy for selecting IS vendors. Presumably, this is a task that CIOs and other IS steering committee members would consider very carefully. The vendor has implications on several factors, such as cost, functionality, and interoperability of system components. Analysis was conducted to determine if the presence of a formal vendor selection strategy influenced the level of IS sophistication. Then each strategy – single vendor, best of breed, and best of suite (cluster) – were analyzed.

Hospitals reporting the presence of any vendor selection strategy were approximately two and a third times (odds ratio = 2.41) more likely to be in the advanced infrastructure class than the basic class and 25% more likely to be in the intermediate class than the basic class.

Table 16: Vendor Selection Parameter Estimates

Covariate	**Class 1 Odds**	**Class 2 Odds**	**Class 1 Beta**	**Class 2 B**	**P value**
Vendor Selection Strategy	2.41	1.25	0.88	0.22	0.000

Having a strategy also differentiates the advanced from the intermediate categories well, as those hospitals with a strategy were nearly two times more likely (odds ratio = 1.92) to fall into the advanced category than the intermediate one.



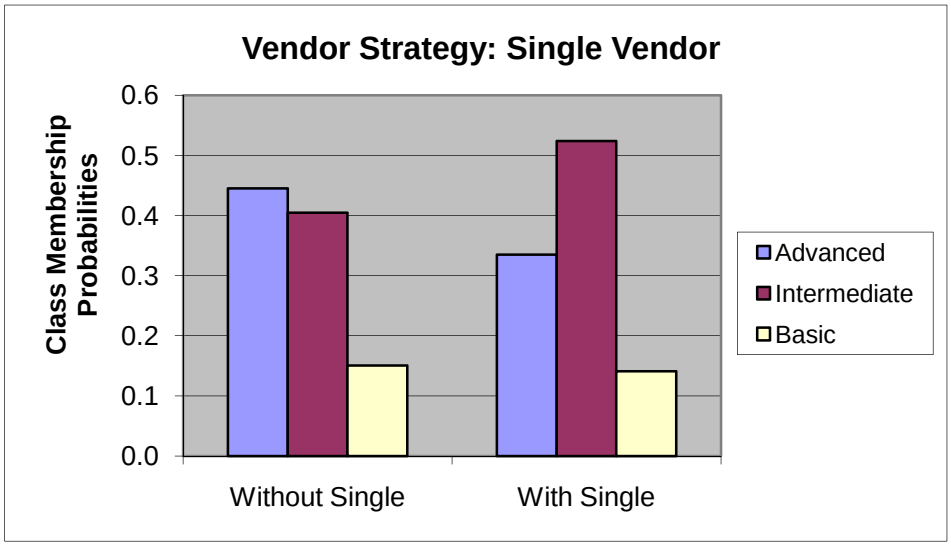
	Advanced	*Intermediate*	*Basic*
Without Strategy	0.2472	0.5524	0.2004
With Strategy	0.4006	0.4646	0.1348

Figure 9: Probability of Class Membership by Vendor Selection Strategy

Those reporting that they were migrating toward the single-vendor strategy were 38% more likely to be in the intermediate category than the basic category. However, they were 20% more likely to be in the basic category than the advanced category. Furthermore, those with this strategy were 1.71 times as likely to fall into the intermediate category than in the advanced category. These results suggest the difficulty of finding a single vendor to meet the needs of the various components found in the advanced infrastructure category.

Table 17: Single-Vendor Strategy Parameter Estimates

Covariate	**Class 1 Odds**	**Class 2 Odds**	**Class 1 Beta**	**Class 2 B**	**P value**
Single-Vendor Strategy	0.80	1.38	- 0.22	0.32	0.002



	Advanced	*Intermediate*	*Basic*
Without Single	0.4450	0.4045	0.1506
With Single	0.3350	0.5238	0.1412

Figure 10: Probability of Class Membership by Single-Vendor Strategy

Those reporting migration toward a best-of-breed strategy were 48% more likely to be in the advanced category than the basic category and nearly two and a half times more likely to be in the intermediate than the basic category. Furthermore, those migrating toward this strategy were over 1 and a half times more likely (odds ratio = 1.63) to fall into the intermediate category than the advanced category. This might be due to the increased number of interfaces needed between system components in the advanced category compared to the intermediate category. Developing these interfaces between products from various vendors can be costly (Rao, 2006).

Latent class analysis with the best-of-breed variable used as a covariate did not yield class membership probabilities by response category, likely because of the small number of hospitals reporting having the best-of-breed strategy (184 out of 1636). Therefore, it is not possible to graph these probabilities as has been done for the other dichotomous independent variables.

Table 18: Best-of-Breed Strategy Parameter Estimates

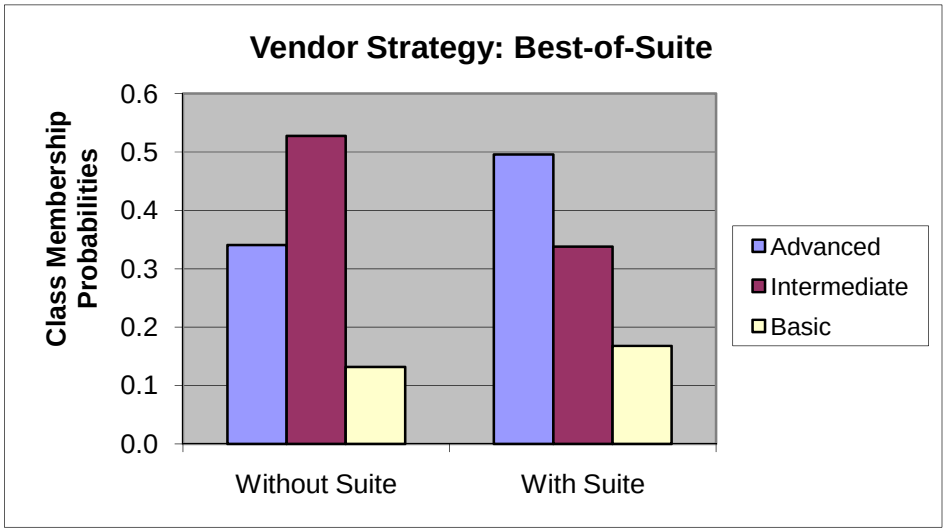
Covariate	**Class 1 Odds**	**Class 2 Odds**	**Class 1 Beta**	**Class 2 B**	**P value**
Best-of-Breed Strategy	1.48	2.42	0.39	0.88	0.016

Those reporting migration toward best-of-suite (cluster) were 15% more likely to be in the advanced category than the basic, but less likely to be in the intermediate category than in the basic. Hospitals pursuing this strategy were two and a quarter times more likely (odds ratio = 2.26) to be in the advanced category than in the intermediate,

and approximately two times likely (odds ratio = 1.97) to be in the basic than the intermediate. This result is consistent with that of the best-of-breed approach discussed above. Specifically, hospitals with the most sophisticated systems requiring integration across multiple system components see the need to minimize the costs of developing interfaces between components from various vendors. The best-of-suite approach minimizes these integration costs. The best-of-breed strategy, on the other hand, tends to lead to higher integration costs.

Table 19: Best-of-Suite Strategy Parameter Estimates

Covariate	**Class 1 Odds**	**Class 2 Odds**	**Class 1 Beta**	**Class 2 B**	**P value**
Best-of-Suite	**1.15**	**0.51**	**0.14**	**- 0.68**	**0.000**



	Advanced	*Intermediate*	*Basic*
Without Suite	0.3407	0.5276	0.1317
With Suite	0.4954	0.3380	0.1677

Figure 11: Probability of Class Membership by Best-of-Suite Strategy

Based on these results, it is clear that having a vendor selection strategy is related to the sophistication level of a hospital's IS system and that the specific strategy can be a useful predictor of which class of IS infrastructure a hospital has. The logic behind these relationships is worth further exploration and testing.

Multinomial Logistic Regression

While analyzing the relationship between individual factors and class membership is informative, conducting multivariate analysis is useful for understanding the relative importance of the factors in relation to class membership. Some factors that may appear to have meaningful relationships with class membership in the bivariate analysis are not useful predictors in a multivariate model.

All of the factors discussed in the bivariate analysis were included in the multinomial logistic model using the same sample. First, the analysis was run using the forward entry stepwise method in SPSS 16.0 with main effects only (i.e., no interaction effects were included) . Under the forward selection approach, the model excludes factors that are not statistically significant. Odds ratios {Exp(B)} are most useful for interpreting the effect size of each factor. For factors with odds ratios less than 1.0, it is often clearest to interpret the inverse odds ratio (Lanza et al., 2007). Results of the analysis were compared to the validation sample to determine whether the identified effects were stable or, instead, unique to the sample.

The Pearson and deviance "goodness-of-fit" statistics yield conflicting results for

the model, which is somewhat unusual. A well fitting model yields nonsignificant results on these statistics (Garson). However, the deviance statistic is generally preferred in logistic regression (Menard, 2002), and the deviance is non-significant in this analysis, indicating a good model fit. This finding is supported by the significant log likelihood ratio (-2LL), which indicates that the observed values of the dependent variable can be adequately predicted by the observed values of the independent variables (Garson). Results using the validation sample were very similar. (See Appendix for validation sample results.)

Table 20: Significance Tests for the Model, Lenient Criteria, Sample 1 without Interaction Terms

Model Fitting Information

Model	Model Fitting Criteria			Likelihood Ratio Tests		
	AIC	BIC	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	1.890E3	1.900E3	1.886E3			
Final	1.751E3	1.790E3	1.735E3	151.604	6	.000

Goodness-of-Fit

	Chi-Square	df	Sig.
Pearson	2115.139	1916	.001
Deviance	1732.932	1916	.999

The pseudo-R^2 statistics, intended to measure the strength of association in the model, were not out of the ordinary. Unlike the R^2 in ordinary least squares (OLS)

regression, pseudo-R^2 statistics for logistic regression do not measure amount of variance explained (Pampel, 2000), and the overall usefulness of pseudo-R^2 values has been questioned (Menard, 2002). However, pseudo-R^2 has been used as a measure when comparing two or more nested models. Furthermore, it is reassuring that analysis on the validation sample resulted in similar pseudo-R^2 results. (See Appendix for validation sample results.)

Table 21: Psuedo-R^2 Statistics, Lenient Criteria, Sample 1, without Interaction Terms

Pseudo R-Square	
Cox and Snell	.143
Nagelkerke	.168
McFadden	.080

The parameter estimates indicate that, as expected, many of the factors included in the bivariate analysis were not useful predictors in the multinomial logistic model and, therefore, were not included in the final model. According to the model, three factors are important predictors of EMR system sophistication: (1) the annual revenue for the delivery system (included in the model as a standardized variable), (2) having a backup facility for disaster recovery, and (3) pursuing a best-of-suite vendor strategy. These factors represent capacity at the delivery-system level (annual revenue), information systems planning at the delivery-system level (backup facility), and information system strategy at the hospital level (vendor strategy).

With respect to delivery system capacity as measured by annual system revenue,

the results indicate that the systems with higher revenues tend to have less sophisticated EMR systems. For every unit increase in system revenue, hospitals are approximately four times more likely to fall into the basic class than the advanced class (odds ratio = 4.08) and nearly three times more likely to fall into the basic class than the intermediate class (odds ratio = 2.88). These results show a consistent inverse relationship between systems revenues and the sophistication level of the EMR system, implying that larger delivery systems are less likely to have hospitals with sophisticated EMR systems. This finding runs contrary to the belief that large health systems have more resources, and therefore slack resources, to dedicate to the development of sophisticated information systems. However, it could support the argument that large systems face an increased challenge of coordination across units within the system, which hinders implementation of complex projects, such as information systems that are interoperable across organizations within the delivery system.

Hospitals in delivery systems with backup facilities for disaster recovery tend to have more sophisticated EMR systems. Those that report *not* having a backup facility for disaster recovery are nearly three times more likely to fall into the intermediate EMR class than the advanced class (odds ratio = 2.81), eight and a half times more likely to fall into the basic EMR class than the advanced class (odds ratio = 8.51), and approximately three times more likely to fall into the basic class than the intermediate class (odds ratio = 3.03).

Hospitals reporting pursuit of a best-of-suite vendor strategy tend to have either

advanced or basic EMR systems. Hospitals that do not report pursuing a best-of-suite strategy are nearly two times more likely to fall into the intermediate class than the advanced class (odds ratio = 1.96) or the basic class (odds ratio = 1.91). However, pursuing a best-of-suite strategy is not a statistically significant predictor of whether a hospital falls into the advanced class compared to the basic class.

Table 22: Parameter Estimates for Multinomial Logistic Regression Model, Lenient Criteria, Sample 1, without Interaction Terms

Parameter Estimates

classmembshp[a]		B	Std. Error	Wald	df	Sig.	Exp(B)	95% Confidence Interval for Exp(B)	
								Lower Bound	Upper Bound
2	Intercept	-.785	.141	31.102	1	.000			
	[RECOVERYPLANISBACKUP=.00]	1.033	.144	51.807	1	.000	2.809	2.120	3.722
	[RECOVERYPLANISBACKUP=1.00]	0[b]	.	.	0	.	.	.	.
	[vendorstrategysuite=1.00]	.671	.153	19.349	1	.000	1.956	1.451	2.638
	[vendorstrategysuite=2.00]	0[b]	.	.	0	.	.	.	.
	zannualrevenue	.348	.205	2.890	1	.089	1.416	.948	2.115
3	Intercept	-2.440	.267	83.465	1	.000			
	[RECOVERYPLANISBACKUP=.00]	2.142	.283	57.212	1	.000	8.519	4.890	14.842
	[RECOVERYPLANISBACKUP=1.00]	0[b]	.	.	0	.	.	.	.

Table 22 (continued)

[vendorstrategysuite =1.00]	.022	.241	.009	1	.926	1.023	.638	1.640
[vendorstrategysuite =2.00]	0[b]	.	.	0	.	.	.	.
zannualrevenue	1.406	.267	27.718	1	.000	4.079	2.417	6.885

a. The reference category is: 1.00.

b. This parameter is set to zero because it is redundant.

Analysis using the validation sample generally yields similar results. Parameter estimates for having (1) a backup facility for disaster recovery and (2) a best-of-suite vendor strategy indicate relationships comparable to the original analysis. There are two notable differences in the results, however. First, whereas the original analysis identified annual revenue as an important factor, the validation analysis identified the number of hospitals in the health-care-delivery system as an important factor instead. The directions of the relationships are similar across the analyses, with larger capacity delivery systems having less sophisticated EMR systems. As discussed in the bivariate analysis, these variables are highly correlated, as both measure of delivery system capacity—one in terms of dollars generated for services and the other in terms of number of hospitals. Therefore, this discrepancy between the original analysis and the validation analysis is not considered substantial.

Table 23: Parameter Estimates for Multinomial Logistic Regression Model, Lenient Criteria, Validation Sample, without Interaction Terms

Parameter Estimates

classmembshp[a]		B	Std. Error	Wald	df	Sig.	Exp(B)	95% Confidence Interval for Exp(B)	
								Lower Bound	Upper Bound
2	Intercept	-1.067	.167	40.791	1	.000			
	zparhospcount	.396	.142	7.730	1	.005	1.486	1.124	1.964
	[scmeetregular=.00]	.392	.145	7.330	1	.007	1.480	1.114	1.965
	[scmeetregular=1.00]	0[b]	.	.	0	.	.	.	.
	[vendorstrategysuite =1.00]	.583	.160	13.255	1	.000	1.791	1.309	2.451
	[vendorstrategysuite =2.00]	0[b]	.	.	0	.	.	.	.
	[RECOVERYPLANISBACKUP=.00]	.545	.145	14.058	1	.000	1.724	1.297	2.292
	[RECOVERYPLANISBACKUP=1.00]	0[b]	.	.	0	.	.	.	.
3	Intercept	-2.354	.253	86.274	1	.000			
	zparhospcount	1.101	.161	46.471	1	.000	3.007	2.191	4.126
	[scmeetregular=.00]	.354	.210	2.859	1	.091	1.425	.945	2.150
	[scmeetregular=1.00]	0[b]	.	.	0	.	.	.	.
	[vendorstrategysuite =1.00]	.034	.216	.025	1	.875	1.035	.677	1.580
	[vendorstrategysuite =2.00]	0[b]	.	.	0	.	.	.	.
	[RECOVERYPLANISBACKUP=.00]	1.695	.242	49.185	1	.000	5.445	3.391	8.743

Table 23 (continued)

[RECOVERYPLANISBACKUP=1.00]	0[b]	.	.	0	.	.	.	.

a. The reference category is: 1.00.

b. This parameter is set to zero because it is redundant.

The second difference is that the validation analysis yielded statistically significant estimates for the regularity of IS steering committee meetings, a measure of how active the steering committee is. The results indicate that hospitals belonging to systems *without* regular IS steering committee meetings were approximately one and half times (odds ratio = 1.48) more likely to belong to the intermediate class than the advanced class. However, the variable is not a statistically significant predictor for whether a hospital falls into the basic class instead of the advanced class. While this difference in the results between the original analysis and the validation is notable, it is not alarming. Given the similar findings with respect to the backup facility and the best-of-suite strategy, the models are generally consistent. The measure of IS steering committee meeting regularity is one that could be further explored in future, however.

Introducing Interaction Effects into the Model

The original logistic model identified two strategic variables (backup facility for disaster recovery and best-of-suite vendor strategy) and health system capacity (revenues in sample 1 and number of organizations in the validation sample) as key predictors of EMR sophistication. To test whether general organizational characteristics (delivery

system capacity and hospital capacity) interact with IS-specific characteristics, interaction effects between these three variables and the strategic variables were entered into the model.

The goodness of fit statistics for the revised model were similar to those of the original model, with the model chi-square (-2LL) being significant and the deviance statistic not being significant. The pseudo-R2 statistics are higher for the revised model, indicating that it might be preferable to the original model.

Table 24: Significance Tests and Psuedo-R^2 for the Model, Lenient Criteria, Sample 1 with Interaction Terms

Model Fitting Information

Model	Model Fitting Criteria			Likelihood Ratio Tests		
	AIC	BIC	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	1.890E3	1.900E3	1.886E3			
Final	1.734E3	1.793E3	1.710E3	176.096	10	.000

Goodness-of-Fit

	Chi-Square	df	Sig.
Pearson	2222.191	1912	.000
Deviance	1708.440	1912	1.000

Pseudo R-Square

Cox and Snell	.164
Nagelkerke	.192
McFadden	.093

The more reliable point of comparison than the pseudo R^2 statistics is the

difference in model chi-square between the model with the interaction effects and the one without. Generally, speaking the lower the model log likelihood (-2LL), the better the model fit (Garson, n.d.). The model containing interaction effects has a final log likelihood of 1.710E3, while the original model log likelihood equaled 1.735E3. Calculating the difference between these log likelihood values and the difference between the degrees of freedom for the two models provides a model chi-square that can be compared to the critical value on a chi-square table to determine if the difference is significant. In this case, the value of 25 with 4 degrees of freedom is larger than the critical value of 9.49 at the 0.05 level, meaning that the model with interaction effects is significantly different (i.e., better) than the original model (i.e., the reduced model).

The parameter estimates of the full model indicate that the significance of having a backup facility and a best-of-suite vendor strategy remain substantively unchanged. However, the delivery system capacity measure (annual revenue) becomes not significant as a stand-alone factor, indicating that delivery system size alone does not influence the EMR sophistication of the hospital. Furthermore, one interaction effect is significant: annual revenue by disaster recover facility between the advanced class and the basic class. This interaction effect indicates that hospitals without a disaster recovery facility are more likely to belong to the basic class if the delivery system with which they are associated generates higher revenue (i.e., is larger) than the delivery systems of other hospitals. Put another way, the result implies that delivery systems that generate high revenues relative to other systems but do not invest in disaster recovery facilities tend

have less sophisticated EMR systems.

Table 25: Parameter Estimates for Multinomial Logistic Regression Model, Lenient Criteria, Sample 1, with Interaction Terms

Parameter Estimates

classmembshp[a]		B	Std. Error	Wald	df	Sig.	Exp(B)	95% Confidence Interval for Exp(B)	
								Lower Bound	Upper Bound
2	Intercept	-.818	.148	30.533	1	.000			
	[RECOVERYPLANISBACKUP=.00]	1.081	.192	31.746	1	.000	2.948	2.024	4.294
	[RECOVERYPLANISBACKUP=1.00]	0[b]	.	.	0	.	.	.	.
	[vendorstrategysuite=1.00]	.771	.190	16.491	1	.000	2.162	1.490	3.136
	[vendorstrategysuite=2.00]	0[b]	.	.	0	.	.	.	.
	zannualrevenue	.112	.315	.126	1	.722	1.119	.603	2.074
	[vendorstrategysuite=1.00] * zannualrevenue	.460	.415	1.228	1	.268	1.585	.702	3.578
	[vendorstrategysuite=2.00] * zannualrevenue	0[b]	.	.	0	.	.	.	.
	[RECOVERYPLANISBACKUP=.00] * zannualrevenue	.148	.425	.121	1	.728	1.159	.504	2.665
	[RECOVERYPLANISBACKUP=1.00] * zannualrevenue	0[b]	.	.	0	.	.	.	.

Table 25 (continued)

3	Intercept	-2.792	.338	68.313	1	.000			
	[RECOVERYPLANISBACKUP=.00]	2.590	.360	51.719	1	.000	13.328	6.580	26.995
	[RECOVERYPLANISBACKUP=1.00]	0[b]	.	.	0	.	.	.	.
	[vendorstrategysuite=1.00]	-.102	.289	.125	1	.724	.903	.512	1.591
	[vendorstrategysuite=2.00]	0[b]	.	.	0	.	.	.	.
	zannualrevenue	-.078	.749	.011	1	.917	.925	.213	4.010
	[vendorstrategysuite=1.00] * zannualrevenue	-1.197	.643	3.466	1	.063	.302	.086	1.065
	[vendorstrategysuite=2.00] * zannualrevenue	0[b]	.	.	0	.	.	.	.
	[RECOVERYPLANISBACKUP=.00] * zannualrevenue	2.751	.802	11.766	1	.001	15.657	3.251	75.401
	[RECOVERYPLANISBACKUP=1.00] * zannualrevenue	0[b]	.	.	0	.	.	.	.

a. The reference category is: 1.00.

b. This parameter is set to zero because it is redundant.

In summary, introducing interaction effects improves the overall model and indicates that delivery system capacity interacts with the disaster recovery variable. While analysis of the original sample indicates that delivery system capacity is not a good predictor of EMR sophistication alone, the validation sample yielded contrary results in

this regard. (See Appendix for the validation sample results with interaction effects.)

Limitations

Since cross-sectional data provide just a "snapshot," there are limitations with respect to this analysis. First, causality cannot be determined because it is not possible to determine if the independent variables were present prior to the dependent variable (i.e., the EMR sophistication level). While relationships between organizational factors and the level of EMR sophistication are identified, it is not possible to determine whether the factors cause the sophistication level. However, results from this study do appear to be relatively consistent with previous studies and anecdotal evidence (e.g., informal case studies and consultants' advice) regarding best practices for IS development. Furthermore, the relationships found in this study provide a foundation for future work related to EMR sophistication, vendor strategies, and disaster recovery planning.

Second, the cross-sectional data also do not allow the researcher to identify whether the length of time that a given practice or strategy has been in place affects the association between the factor and the level of EMR sophistication. Similarly, it is not possible to determine whether hospitals that have been developing EMR infrastructures for a longer period of time have more sophisticated systems than those that have been developing the infrastructure for a shorter period.

Another limitation of this study is the possibility of common methods bias (CMB), which occurs when the independent variables and dependent variables are measured by the same survey instrument. One source of CMB is including an

introduction in the questionnaire that informs the respondent about what the researcher is attempting to measure, which can lead to artificially high internal consistency of items (i.e., “item priming effects”). Another source of CMB occurs when respondents attempt to force consistency among their responses to provide the appearance of rationality. This can lead to findings of statistical relationships that otherwise would not exist or that would be weaker (i.e., “consistency motif or consistency effect”). CMB is a common concern among information systems studies; however, there is debate in the literature about how substantially CMB affects correlations between the variables measured (Schwarz, Schwarz, & Rizzuto, 2008). It is perhaps less of a concern if the data analysis yields unexpected results (e.g., no correlation or correlations in unexpected directions). Furthermore, CMB is perhaps most problematic in studies that assess a user’s perceptions about the usefulness of a particular technology or his/her ability to use a particular technology, which is not the case in this study.

Chapter 5: Discussion

The aims of this study were to increase understanding about sophistication in the context of electronic medical record systems in U.S. hospitals and to assess whether EMR sophistication is associated with specific IS leadership structures, planning practices, or strategies. This chapter is intended to synthesize the findings related to these aims. Specifically, it will summarize the results related to the stage model and latent class model approaches to measuring EMR sophistication, emphasizing the strengths and limitations of each approach. Furthermore, it will discuss the implications of the bivariate and multinomial logistic regression results, focusing on how these results could inform managers and policy makers interested in clinical information systems usage. Finally, the chapter discusses future research needs as evidenced by the results of this research.

Assessment of EMR Sophistication

Comparing the Stage Model and the Latent Class Model

The stage model for measuring EMR sophistication is an attractive approach because stage models have been used in theory development and research for various organizational issues. Furthermore, stage models facilitate a clear conceptualization of the phenomena at hand. However, stage models have limitations as well, including the threat of oversimplification or omission of contextual factors that hinder the generalizability of a stage progression.

In this study, the scalogram analysis did not yield favorable results for the stage model. It is important to emphasize, however, that these results do not invalidate every stage model of EMR sophistication, only the model as hypothesized and measured in this study. Along these lines, it is possible that the conceptual model guiding the selection of variables for the stage model is valid, but that one or more of the measures used in the analysis were inadequate for determining whether pure stages exist. Nevertheless, based on this study, researchers, managers, and policy makers interested in understanding the state of electronic medical records systems in U.S. hospitals should be weary of a lock-step, stage approach to describing EMR sophistication.

The latent class analysis approach used in this study allowed for the identification of a descriptive pattern of EMR sophistication without imposing a normative bias related to the order with which the IS components "should" be implemented. By not defining the order of implementation of the components *a priori*, the latent class model allowed for a description of EMR sophistication classes that could account for the contextual differences across the various health care delivery organizations in the sample.

It was assumed in this study that these contextual differences, such as the information system planning structures and strategies at the delivery-system and hospital levels, are important influences on the sophistication of the EMR system in a given hospital. In other words, these differences hinder the validity of a rigid stage-model description. Perhaps somewhat ironically, the fact that the LCA results yielded several information system components with neither near-zero nor near-100% affirmative

responses – a recognized limitation of the LCA findings – further support the importance of contextual factors. In other words, it is extremely difficult to identify groups of hospitals that have identical combinations of IS components comprising their EMR infrastructure. The complexity of the overall health care delivery system in the U.S. and of individual health care organizations contributes to the low likelihood of finding uniformity across such organizations, particularly with respect to such complex endeavors as developing an EMR system infrastructure.

Despite the fact that the LCA analysis yielded less than a perfect fit for the latent classes, the results do provide a useful classification of EMR infrastructures. The reliability of these results is strengthened by the fact that they remained relatively stable across the sensitivity analyses with respect to criteria for determining whether a hospital has a particular IS component in place. In other words, the subjectivity in determining whether the implementation of a component is "in process" or whether the component is "live and operational" does not substantially influence the characteristics of the EMR sophistication classes found in this study.

Finally, it should be noted that the LCA results are not entirely at odds with the stage model that was tested. In fact, the LCA analysis supported one important assumption of the stage model – that information systems in ancillary departments provide the foundation for the EMR system. Furthermore, while the stage model, as hypothesized and measured, has substantial limitations as a descriptive model, it could prove to be a useful normative model, either in its current form or with modifications. In

other words, while this study supports the descriptive characterization of three EMR sophistication classes, not six stages, this characterization does not necessarily depict the ideal or optimal path for developing sophisticated EMR systems. A stage model might prove more useful in that regard as a guide for hospitals that have yet to begin a full-scale effort to develop an EMR system. Of course, normative stage models potentially suffer from the same contextual limitations as descriptive stage models. The usefulness of any normative stage model for developing a sophisticated EMR likely will depend on how successfully it accounts for contextual factors.

Implications of the Latent Class Model

The latent class analysis yielded a three-class model that characterizes the state of EMR sophistication in U.S. hospitals. The characteristics of each class are defined by the information system components that hospitals in the class tend to report having. These defining characteristics have important implications for understanding EMR sophistication.

First, the characteristics indicate that there are levels of EMR sophistication, as indicated by the labels “basic,” “intermediate,” and “advanced.” This finding of levels is consistent with other studies (DesRoches et al., 2008; HIMSS Analytics, 2006) and is notable because it supports the notion that EMR system sophistication is cumulative in nature. Prior to conducting the LCA, it was unknown how the IS components would group. For example, it was plausible that the components could have grouped primarily

based on the department in which they are used. Under this scenario, for example, the radiology information system and PACS, might have formed the defining characteristics of a class (i.e., a radiology class). Instead, it appears that, sophisticated systems are built upon foundational system components, with greater sophistication requiring usage of technologies by those providing direct patient care.

It is important to note that while these levels are cumulative, they do not necessarily indicate a stage-like progression. Because of the cross-sectional nature of the study, it does not allow for the determination of whether a hospital advances from one level of sophistication to the next. Only a "snapshot" of these EMR sophistication classes is provided. It is possible that hospitals in the "intermediate" class might progress into the class identified as "advanced." However, it is also possible that the characteristics of these classes could change over time, with some IS components falling out of favor and others emerging, thus changing the combinations of IS components across the population of hospitals (i.e., the essence of the classes).

Second, regardless of whether hospitals progress through the levels of sophistication, the levels do support the notion that hospitals belong to complex hierarchical systems composed of subsystems (e.g., departments) with "the lower levels governing the fast, 'high-frequency' dynamics . . . [and] . . . the higher level interactions governing the slow, 'low-frequency' dynamics . . ." (Simon, 1962). In other words, as evidenced by the LCA results, information systems that are contained within one department, such as laboratory information systems or pharmacy management systems,

are extremely common across the population of acute care hospitals. Presumably, these departments successfully implement their systems because those individuals primarily involved with the implementation decisions work in the same department. They interact with each other frequently and, therefore, are able to develop a common understanding of departmental needs and barriers. Those at the executive level within the hospital and the delivery system interact much less frequently with those who work in the departments. The "vision" of an EMR system, comprised of many system components, which executives may strive for is more ambitious and complex to implement and, therefore, is likely to take more time achieve, if it is ever achieved at all. Again, because of the cross-sectional nature of this study, it is impossible to say for certain whether, or how quickly, IS implementation tends to spread throughout the organization.

Finally, building upon the concepts discussed in the previous paragraph, the results support the notion that integration of system components is a key factor in EMR sophistication. The levels of classes require varying amounts of integration across system components and involve varying numbers of departments and types of users. The ancillary department systems (laboratory, Pharmacy, and radiology) must be integrated with the order entry system even in the "basic" level of EMR infrastructure. This integration enables one-way information transmission (e.g., via order entry) to individuals in these ancillary departments. Intermediate systems require more integration, enabling two-way information transmission primarily among individuals in ancillary departments for order entry *and* decision support. The need for integration

increases further when more system components are introduced and more users become involved (e.g., nurses and physicians). Advanced sophistication enables two-way communication – order entry, documentation, and decision support – for nurses and physicians at the bedside. While this study did not measure levels of integration (i.e., how well integrated the components are), the results imply that integration takes place in clusters of departments and/or users.

IS Leadership Structures, Planning Practices, Strategy, and EMR Sophistication

With respect to assessing factors influencing the sophistication of EMR systems, this study focused on the information system leadership structures, planning practices, and strategies. The rationale for this focus is that organizational characteristics alone, such as size, do not provide insight into the practices and strategies that health care organizations use regarding information systems. These practices and strategies indicate the resources used with respect to EMR development and, therefore, the extent to which the EMR system is a priority for the organization.

Logistic regression allows for the prediction of which EMR class a hospital will belong to given its IS practices. Due to the cross-sectional data used in this study, it is not possible to determine whether the practices included in the model cause hospitals to belong to their respective classes. In other words, while it is possible that the IS planning structures and strategies influence the sophistication of the EMR system, it is also possible that the sophistication of the EMR system influences the IS planning structures

and strategies. Also possible is that the influence runs in both directions.

The two practices identified by the model – (1) having a backup facility for disaster recovery and (2) pursuing a best-of-suite vendor strategy – are interesting findings because they represent very specific strategies related to EMR systems planning. In other words, measures of having an information system steering committee, having an IS strategic plan, and having any vendor-selection strategy do not differentiate hospitals with respect to their EMR system sophistication, perhaps because most hospitals have these general practices in place (93%, 73%, and 84%, respectively, in the sample analyzed). The specific strategies developed by these committees and executed by the organization appear to be the difference-makers with respect to predicting EMR sophistication.

Thirty-five percent of hospitals belong to delivery systems that report having a backup facility for disaster recovery. These hospitals are more likely to have advanced EMR systems than intermediate or basic, and more likely to have intermediate systems than basic. More than half (51%) of all hospitals in the sample associated with a delivery system having a backup facility for disaster recovery belong to the advanced EMR class.

The relationship between disaster recovery planning and information systems has become a more prominent issue for health care organizations since Hurricane Katrina (Boom et al., 2007) exposed the danger of relying solely on paper records. According to the results of this study, it appears that delivery systems with hospitals having sophisticated EMR systems tend to invest in backup facilities for their information

systems. It is not possible to determine from this analysis whether sophisticated EMR systems were developed as part of the disaster recovery strategy, or whether disaster recovery facilities were invested in to protect the organization from damage to existing EMR systems. Regardless, it appears that hospitals with sophisticated EMR systems are leaders in disaster recovery investment as well. Furthermore, based on the full model (i.e., with interaction effects), it appears that larger delivery systems that do not invest in disaster recovery backup facilities are most likely to have basic EMR systems.

With respect to vendor strategy, nearly half (47%) of those pursuing a best-of-suite approach belong to the advanced class. Having this strategy significantly differentiates hospitals with advanced EMR systems from those with intermediate systems. This result is consistent with the perceived strengths of this vendor strategy, specifically that it facilitates integration across various components. Since the advanced EMR class contains more IS components than the intermediate class, the need for and potential cost of integration increases. Interestingly, however, having the strategy does not significantly differentiate hospitals in the advanced class from those in the basic. It is possible that hospitals in the advanced and basic classes have relatively similar splits with regard to the percentage pursuing a best-of-suite strategy, perhaps because many in the basic class are migrating toward a best-of-suite strategy to facilitate the development of more sophisticated EMR systems. Of course, this explanation is only speculation and cannot be supported by the findings of the study. More data would be needed about the timing and rationale for pursuing this vendor strategy in order to study whether this trend

is occurring.

In summary, the findings of this study support the assumptions that (1) specific information system planning practices and strategies are predictors of EMR sophistication and (2) general delivery-system and hospital capacity characteristics tend to interact with the planning practices and strategies as predictors of EMR sophistication. With respect to whether the general delivery-system and hospital capacity characteristics themselves are strong predictors of EMR sophistication, the results are mixed. Analysis of the original dataset indicates that the general delivery-system and hospital capacity characteristics alone are not valid predictors, while analysis of the validation sample led to contrary findings in this regard. Therefore, while the size and financial resources of the delivery system, as well as the size of the particular hospital, are important for understanding the sophistication of the hospital's EMR system, these characteristics do not tell the whole story. The IS planning practices and strategies are important too.

Future Research

The results of this study indicate the need for further research focused on measuring EMR sophistication, as well as the relationship between IS strategy and EMR system sophistication. Specifically, the influence of disaster recovery planning and vendor strategy selection on EMR systems should be pursued. For all of these areas, it would be useful to develop longitudinal data sets to assess how EMR system sophistication changes over time, as well as how the passing of time affects the influence of strategy on EMR sophistication.

With respect to measuring EMR sophistication, it would be useful to know whether the characteristics of the EMR classes are stable over time. Furthermore, knowing whether hospitals move between classes of sophistication over time would helpful for determining whether hospitals tend to progress across the levels of sophistication. Also, improving upon the available measures for some EMR components is necessary. Ensuring that respondents have and adhere to common definitions of the components is crucial, given the lack of consensus in the field about what constitutes an EMR system. Doing so will likely require multiple measures for some components, particularly clinical decision support (CDSS), a component with varying levels of functionality. Finally, developing robust measures of integration for the IS components is needed. The level of integration has direct bearing on the level of sophistication of the overall system, as greater integration enables greater functionality and overall usefulness of the EMR system.

With respect to disaster recovery planning, knowing more about the underlying relationship between disaster recovery planning and EMR system development would be useful. Specifically, are hospitals developing sophisticated EMR systems as a component of their disaster recovery plan? Or have hospitals with sophisticated EMR systems decided to protect their information system assets by investing in backup facilities? If hospitals have tended to develop EMRs as part of an overall disaster recovery strategy, how have these hospitals leveraged resources for these purposes? Have they been successful in framing EMR development as a disaster recovery strategy in order to

achieve buy-in from various stakeholders?

Finally, vendor-selection strategy is a key decision faced by information system decision makers that needs to be better understood. Currently, such decision-makers are at risk of following the latest fad without evidence that the given strategy is optimal for their organization's circumstances. The best-of-suite strategy is currently being touted by some as the optimal strategy for most organizations. However, little is known about whether the strategy is effective or sustainable over time. Furthermore, the effectiveness of the strategy might be dependent upon various hospital characteristics (e.g., patient volume) and the vendors selected. Given the substantial total cost of implementing EMR systems, it is necessary that hospital administrators have reliable information on which to base the important vendor-selection decision.

Conclusion

Although there is still debate about whether electronic medical record systems will improve the quality of care patients receive, it appears that the U.S. health care system is moving toward electronic systems and automation. As this trend continues, understanding how to assess the relative sophistication level of a given hospital's EMR system will be important to researchers, policymakers, and administrators alike. Furthermore, health care administrators, in particular, would benefit from reliable information about the information system structures and strategies that tend to facilitate more successful use of information systems. Given that sophisticated EMR systems carry more potential for increasing the efficiency and quality of care delivery than do

basic systems, administrators most likely will strive for sophisticated systems in their own organizations. Based on the findings of this study, it appears that some information system leadership structures (e.g., steering committees) and practices (e.g., developing a strategic plan) are common across delivery systems. However, the specific strategies that are developed and utilized by the IS leadership are not uniform. These specific strategies are the “nuts and bolts” of information system planning and, as such, could be a key factor in determining whether a hospital is able to develop a sophisticated EMR system.

REFERENCES

Advisory Board Company. (2001). *Computerized Physician Order Entry: Lessons From Pioneering Institutions*. Washington DC: Advisory Board Company.

Ahmad, A.T., P. Bentley, T.D., Kuehn, L., Kumar, R.R., Thomas, A., & Mekhjian,H.S. (2002). Key attributes of a successful physician order entry system implementation in a multi-hospital environment. *Journal of the American Medical Informatics Association, 9*(1), 16-24.

Ash, J. S., Gorman, P. N., Lavelle, M., Payne, T. H., Massaro, T. A., Frantz, G. L., et al. (2003). A cross-site qualitative study of physician order entry. *Journal of the American Medical Informatics Association, 10*(2), 188-200.

Ash, J. S., Gorman, P. N., Seshadri, V., & Hersh, W. R. (2004). Computerized physician order entry in U.S. hospitals: Results of a 2002 survey. *Journal of the American Medical Informatics Association, 11*(2), 95-99.

Ash, J. S., Stavri, P. Z., & Kuperman, G. J. (2003). A consensus statement on considerations for a successful CPOE implementation. *Journal of the American Medical Informatics Association, 10*(3), 229-234.

Becker, S., & Arenson, R. (1994). Costs and benefits of picture archiving and communication systems. *Journal of the American Medical Informatics Association,*

1(5), 361-371.

Bhattacherjee A, Hikmet N, Menachemi N, & et al. (2007). The differential performance effects of healthcare information technology adoption, *Information Systems Management*, *24*(1), 5.

Boom, J. A., Dragsbaek, A. C., & Nelson, C. S. (2007). The success of an immunization information system in the wake of hurricane Katrina. *Pediatrics*, *119*(6), 1213-1217.

Bray, B. (2008). Email to G. David Garson 7/16/2008. (Bray is assistant director, the Methodology Center, the Pennsylvania State University, originators of PROC LCA.)

Burke, D. E., & Menachami, N. (2004). Opening the black box: Measuring hospital information technology capability. *Health Care Management Review*, *29*(3), 207-217.

Burke, D. E., & Menachemi, N. (2004). Opening the black box: Measuring hospital information technology capability. *Health Care Management Review*, *29*(3), 207-217.

Burke, D. E., Wang, B. B. L., Wan, T. T. H., & Diana, M. L. (2002). Exploring hospitals' adoption of information technology. *Journal of Medical Systems*, *26*(4), 349-355.

Burke, L., & Weill, B. (2009). *Information Technology for the Health Professions* (3rd ed.). Upper Saddle River, N.J.: Pearson Prentice Hall.

Centers for Medicare & Medicaid Services. (2007). *MLN matters.* Retrieved 05/17/2007 from http://www.cms.hhs.gov/mlnmattersarticles/downloads/mm5558.pdf

Chaudhry, B., Wang, J., Wu, S. Y., Maglione, M., Mojica, W., Roth, E., et al. (2006). Systematic review: Impact of health information technology on quality, efficiency, and costs of medical care. *Annals of Internal Medicine, 144*(10), 742-752.

Cooper, R. B., & Zmud, R. W. (1990). Information technology implementation research - a technological diffusion approach. *Management Science, 36*(2), 123-139.

Cutler, D. M. (2005). US adoption of computerized physician order entry systems. *Health Affairs, 24*(6), 1654-1663.

Davis, M. (2006). Personal communication 11/21/2006. (Davis is Executive Vice President, HIMSS Analytics.)

Davis, M. (2007). Personal communication 06/12/2007. (Davis is Executive Vice President, HIMSS Analytics.)

Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1989). User acceptance of computer technology: A comparison of two theoretical models. *Management Science, 35*(8), 982-1003.

DesRoches, C. M., Campbell, E. G., Rao, S. R., Donelan, K., Ferris, T. G., Jha, A., et al. (2008). Electronic health records in ambulatory care -- A national survey of

physicians. *The New England Journal of Medicine, 359 (1),* 50-60.

Edwards, A. (1948). On Guttman's scale analysis. *Educational and Psychological Measurement, 8*, 313-318.

Edwards, A. (1957). *Techniques of Attitude Scale Construction*. Englewood Cliffs, NJ: Prentice Hall.

Garets, D. a. D., Mike. (2006). Electronic medical records vs. electronic health records: Yes, there is a difference. *HIMSS Analytics White Paper*. Retrieved 04/13/2007 from http://www.himssanalytics.org/docs/WP_EMR_EHR.pdf

Garg, A., Adhikari, N. J., McDonald, H., Rosas-Arellano, M. P., Devereaux, P. J., Beyene, J., et al. (2005). Effects of computerized clinical decision support systems on practitioner performance and patient outcomes: A systematic review. *JAMA: The Journal of the American Medical Association, 293*(10), 1223-1238.

Garson, G. D. (n.d.) "Logistic regression" from S*tatnotes: Topics in multivariate analysis*. Retrieved 06/23/2008 from http://www2.chass.ncsu.edu/garson/pa765/statnote.htm.

Garson, G. D. (2006). *Public Information Technology and E-Governance: Managing the Virtual State*. Sudbury, MA: Jones and Bartlett.

Goodenough, W. H. (1944). A technique for scale analysis. *Educational and*

Psychological Measurement, 4, 179-190.

Griffin, D. (2006). *Hospitals: What They Are And How They Work* (3rd ed.). Sudbury, MA: Jones & Bartlett Publishers.

Guttman, L. (1944). A basis for qualitative data. *American Sociological Review, 9*(2), 139-150.

Guttman, L. (1950). The basis for scalogram analysis. In S. A. Stouffer (Ed.), *Measurement and Prediction* (pp. 60-90). Princeton: Princeton University Press.

Guttman, L. (1947). On festinger's evaluation of scale analysis. *Psychological Bulletin, 44*(5), 451-465.

Hagland, M. (2005). Interoperability conundrum. *Healthcare Informatics, ,* 1-8.

Halvorson, G. (2007). *Health Care Reform Now: A prescription for change*. San Francisco: John Wiley & Sons, Inc.

Hartzband, P., & Groopman, J. (2008). Off the record – avoiding the pitfalls of going electronic. *The New England Journal of Medicine, 358*(16), 1656-1658.

HIMSS. (2008). *RHIO / HIE.* Retrieved September 11, 2008, from http://www.himss.org/asp/topics_rhio.asp

HIMSS Analytics. (2006). EMR sophistication correlates to hospital quality data.

Retrieved 11/21/2006 from http://www.himss.org/content/files/UHCresearch.pdf.

HIMSS Analytics. (2007). *HIMSS analytics sorted by term.* Unpublished manuscript.

Institute of Medicine. (1999). *To Err Is Human: Building a Safer Health System*. Washington DC: National Academy Press.

Institute of Medicine. (2001). *Crossing the Quality Chasm: A New Health System for the 21st Century*. Washington DC: National Academy Press.

Jaana, M., Ward, M. M., Pare, G., & and Sicotte, C. (2006). Antecedents of clinical information technology sophistication in hospitals. *Health Care Management Review, 31*(4), 289.

Jha, A.K., Ferris, T.G., Donelan, K., DesRoches, C., Shields, A., Rosenbaum, S., Blumenthal,D. (2006). How common are electronic health records in the united states? A summary of the evidence. *Health Affairs, 25*(6), w496-w507.

Klein, K. J., Conn, A. B., & Sorra, J. S. (2001). Implementing computerized technology: An organizational analysis. *Journal of Applied Psychology, 86*(5), 811-824.

Kohane, I. S., Greenspun, P., Fackler, J., Cimino, C., & Szolovits, P. (1996). Building national electronic medical record systems via the world wide web. *Journal of the American Medical Informatics Association, 3*(3), 191-207.

Kuperman, G. J., & Gibson, R. F. (2003). Computer physician order entry: Benefits,

costs, and issues. *Annals of Internal Medicine, 139*(1), 31-39.

Lanza, S. T., Collins, L. M., Lemmon, D. R., & Schafer, J. L. (2007). PROC LCA: A SAS procedure for latent class analysis. *Structural Equation Modeling, 14*(4), 671-694.

Mahoney, C. D., Berard-Collins, C. M.)., Coleman, R., Amaral, J. F., & Cotter, C. M. (2007). Effects of an integrated clinical information system on medication safety in a multi-hospital setting. *American Journal of Health-System Pharmacy, 64*(18), 1969-1977.

Mccutcheon, A. L. (1987). *Latent Class Analysis*. Beverly Hills, CA: Sage Publications.

McIver, J. P., & Carmines, E. G. (1981). *Unidimensional scaling*. Beverly Hills: Sage Publications.

Mehrotra, A., Pearson, S. D., Coltin, K. L., Kleinman, K. P., Singer, J. A., Rabson, B., et al. (2007). The response of physician groups to P4P incentives. *American Journal of Managed Care, 13*(5), 249--257.

Menachami, N., Burkhardt, J., Shewchuck, R., Burke, D., & Brooks, R., G. (2006). Hospital information technology and positive financial performance: A different approach to finding an ROI. *Journal of Healthcare Management, 51*(1), 40-59.

Menachemi, N., Ford, E. W., Chukmaitov, A., & Brooks, R. G. (2006). Managed care

penetration and other factors affecting computerized physician order entry in the ambulatory setting. *American Journal of Managed Care, 12*(12), 738-744.

Menard, S. W. (2002). *Applied Logistic Regression Analysis* (2nd ed.). Thousand Oaks, CA.: Sage Publications.

Menzel, H. (1953). A new coefficient for scalogram analysis. *Public Opinion Quarterly, 16*(2), 268-280.

Miller, R. H., & Sim, I. (2004). Physicians' use of electronic medical records: Barriers and solutions. *Health Affairs, 23*(2), 116-126.

Monegain, B. (2008). Medicare awards nearly $25M in hospital P4P pilot. *Healthcare IT News*, June 23, 2008.

Morgan, G. (1997). *Images of Organization* (2nd ed.). Thousand Oaks, CA: Sage Publications.

Office of the National Coordinator for Health Information Technology. *Value of HIT.* Retrieved June 19, 2008, from www.os.dhhs.gov/healthit/valueHIT.html

Ohsfeldt, R. L., Ward, M. M., Schneider, J. E., Jaana, M., Miller, T. R., Lei, Y., et al. (2005). Implementation of hospital computerized physician order entry systems in a rural state: Feasibility and financial impact. *Journal of the American Medical Informatics Association, 12*(1), 20-27.

Pampel, F. C. (2000). *Logistic Regression: A Primer* (132nd ed.). Thousand Oaks: Sage Publications.

Paré, G., & Sicotte, C. (2001/10). Information technology sophistication in health care: An instrument validation study among Canadian hospitals. *International Journal of Medical Informatics, 63*(3), 205-223.

Poon, E. G., Blumenthal, D., Jaggi, T., Honour, M. M., Bates, D. W., & Kaushal, R. (2004). Overcoming barriers to adopting and implementing computerized physician order entry systems in U.S. hospitals. *Health Affairs, 23*(4), 184-190.

Rao, S. (2006). Enterprise applications: Best of breed vs. best of suit. *SAP Insight.* Retrieved 04/03/2008 from http://i.i.com.com/cnwk.1d/html/itp/sap_BestofBreedvsBestofSuiteInsight.pdf

Rogers, E. M. (2003). *Diffusion of Innovations*. New York: Free Press.

Rummel, R. J. (1970). *Applied Factor Analysis.* Evanston: Northwestern University Press.

Schoen, C., Davis, K., How, S. K. H., & Schoenbaum, S. C. (2006). U.S. health system performance: A national scorecard. *Health Affairs, 25*(6), w457-475.

Schwarz, A., Schwarz, C., & Rizzuto, T. (2008). Examining the "urban legend" of common methods bias: Nine common errors and their impact. *Proceedings of the*

41st Hawaii International Conference on System Sciences, 441.

Shapiro, S. E., Lasarev, M. R., & McCauley, L. (2002). Factor analysis of gulf war illness: What does it add to our understanding of possible health effects of deployment? *American Journal of Epidemiology, 156*(6), 578-585.

Shortliffe, E. H., & Cimino, J. J. (Eds.). (2006). *Biomedical Informatics: Computer Applications in Health Care and Biomedicine* (3rd ed.) Springer.

Simon, H. A. (1962). The architecture of complexity. *Proceedings of the American Philosophical Society, 106*(6) 467-482.

Stead, W. W. (2007). Rethinking electronic health records to better achieve quality and safety goals. *Annual Review of Medicine, 58*, 35-47.

Thompson, D. M. (2006). Performing latent class analysis using the CATMOD procedure. *Proceedings of the Thirty-First Annual SAS® Users Group International Conference*, Cary, NC. , *201-31*

Vermunt, J. K. (2008). Latent class and finite mixture models for multilevel data sets. *Statistical Methods for Medical Research, 17,* 33-51.

Vermunt, J. K., & Magidson, J. (2005). Factor analysis with categorical indicators: A comparison between traditional and latent class approaches. In *New Developments in Categorical Data Analysis for the Social and Behavioral Sciences* (pp. 41-62).

Mahwah, New Jersey: Lawrence Erlbaum Associates.

Walker, J. M. (2005). Electronic medical records and health care transformation 10.1377/hlthaff.24.5.1118. *Health Affairs, 24*(5), 1118-1120.

Wang, B. B., Wan, T. T. H., Burke, D. E., Bazzoli, G. J., & Lin, B. Y. J. (2005). Factors influencing health information system adoption in American hospitals. *Health Care Management Review, 30*(1), 44-51.

Yarbrough, A. K., & Smith, T. B. (2007). Technology acceptance among physicians: A new take on TAM. *Medical Care Research and Review, 64*(6), 650-672.

Zmud, R. W., & Apple, L. E. (1992). Measuring technology incorporation infusion. *Journal of Product Innovation Management, 9*(2), 148-155.

APPENDICES

Table 26: Frequencies of Stage Model Indicators for Lenient Criteria Dataset

The FREQ Procedure

LabIS	Frequency	Percent	Cumulative Frequency	Cumulative Percent
.	41	2.51	41	2.51
1	14	0.86	55	3.36
2	1581	96.64	1636	100.00

RadIS	Frequency	Percent	Cumulative Frequency	Cumulative Percent
.	54	3.30	54	3.30
1	65	3.97	119	7.27
2	1517	92.73	1636	100.00

Pharm	Frequency	Percent	Cumulative Frequency	Cumulative Percent
.	36	2.20	36	2.20
1	8	0.49	44	2.69
2	1592	97.31	1636	100.00

OrderEntry	Frequency	Percent	Cumulative Frequency	Cumulative Percent
.	31	1.89	31	1.89
1	74	4.52	105	6.42
2	1531	93.58	1636	100.00

CMV	Frequency	Percent	Cumulative Frequency	Cumulative Percent
.	91	5.56	91	5.56
1	1338	81.78	1429	87.35
2	207	12.65	1636	100.00

Table 26 (continued)

CDR	Frequency	Percent	Cumulative Frequency	Cumulative Percent
.	33	2.02	33	2.02
1	333	20.35	366	22.37
2	1270	77.63	1636	100.00

CPOE	Frequency	Percent	Cumulative Frequency	Cumulative Percent
.	32	1.96	32	1.96
1	853	52.14	885	54.10
2	751	45.90	1636	100.00

CDSS	Frequency	Percent	Cumulative Frequency	Cumulative Percent
.	31	1.89	31	1.89
1	535	32.70	566	34.60
2	1070	65.40	1636	100.00

eMAR	Frequency	Percent	Cumulative Frequency	Cumulative Percent
.	33	2.02	33	2.02
1	666	40.71	699	42.73
2	937	57.27	1636	100.00

NursDoc	Frequency	Percent	Cumulative Frequency	Cumulative Percent
.	60	3.67	60	3.67
1	628	38.39	688	42.05
2	948	57.95	1636	100.00

PACS	Frequency	Percent	Cumulative Frequency	Cumulative Percent
1	860	52.57	860	52.57
2	776	47.43	1636	100.00

Table 26 (continued)

BarcodeRFID	Frequency	Percent	Cumulative Frequency	Cumulative Percent
.	78	4.77	78	4.77
1	1220	74.57	1298	79.34
2	338	20.66	1636	100.00

PhysDoc	Frequency	Percent	Cumulative Frequency	Cumulative Percent
.	61	3.73	61	3.73
1	1025	62.65	1086	66.38
2	550	33.62	1636	100.00

Table 27: Frequencies of Stage Model Indicators for Strict Criteria

The FREQ Procedure

LabIS	Frequency	Percent	Cumulative Frequency	Cumulative Percent
.	41	2.51	41	2.51
1	38	2.32	79	4.83
2	1557	95.17	1636	100.00

RadIS	Frequency	Percent	Cumulative Frequency	Cumulative Percent
.	54	3.30	54	3.30
1	117	7.15	171	10.45
2	1465	89.55	1636	100.00

Pharm	Frequency	Percent	Cumulative Frequency	Cumulative Percent
.	36	2.20	36	2.20
1	19	1.16	55	3.36
2	1581	96.64	1636	100.00

Table 27 (continued)

OrderEntry	Frequency	Percent	Cumulative Frequency	Cumulative Percent
.	31	1.89	31	1.89
1	121	7.40	152	9.29
2	1484	90.71	1636	100.00

CMV	Frequency	Percent	Cumulative Frequency	Cumulative Percent
.	91	5.56	91	5.56
1	1358	83.01	1449	88.57
2	187	11.43	1636	100.00

CDR	Frequency	Percent	Cumulative Frequency	Cumulative Percent
.	33	2.02	33	2.02
1	417	25.49	450	27.51
2	1186	72.49	1636	100.00

CPOE	Frequency	Percent	Cumulative Frequency	Cumulative Percent
.	32	1.96	32	1.96
1	1241	75.86	1273	77.81
2	363	22.19	1636	100.00

CDSS	Frequency	Percent	Cumulative Frequency	Cumulative Percent
.	31	1.89	31	1.89
1	632	38.63	663	40.53
2	973	59.47	1636	100.00

eMAR	Frequency	Percent	Cumulative Frequency	Cumulative Percent
.	33	2.02	33	2.02
1	983	60.09	1016	62.10
2	620	37.90	1636	100.00

Table 27 (continued)

NursDoc	Frequency	Percent	Cumulative Frequency	Cumulative Percent
.	60	3.67	60	3.67
1	833	50.92	893	54.58
2	743	45.42	1636	100.00

PACS	Frequency	Percent	Cumulative Frequency	Cumulative Percent
1	860	52.57	860	52.57
2	776	47.43	1636	100.00

BarcodeRFID	Frequency	Percent	Cumulative Frequency	Cumulative Percent
.	78	4.77	78	4.77
1	1227	75.00	1305	79.77
2	331	20.23	1636	100.00

PhysDoc	Frequency	Percent	Cumulative Frequency	Cumulative Percent
.	61	3.73	61	3.73
1	1213	74.14	1274	77.87
2	362	22.13	1636	100.00

Table 28: *Latent Class Analysis, Moderate Criteria, Sample 1, 3-Class Model*

```
Number of subjects:                    1636

Number of measurement items:             13
Response categories per item:             2 2 2 2 2 2 2 2 2 2 2 2 2
Number of groups in the data:             1
Number of latent classes:                 3
Rho starting values were randomly generated (seed = 861551).

No parameter restrictions were specified (freely estimated).

The model converged in 177 iterations.

Maximum number of iterations: 5000
Convergence method: maximum absolute deviation (MAD)
Convergence criterion:  0.000001000
```

Table 28 (continued)

```
Log-likelihood:     -8721.56
G-squared:           1337.17
AIC:                 1419.17
BIC:                 1640.57
Degrees of freedom:     8150

Test for MCAR
      Log-likelihood:     -8052.97
      G-squared:            781.11
      Degrees of freedom:    55702

Gamma estimates (class membership probabilities):
Class:                      1          2          3
                       0.3842     0.4381     0.1778

Rho estimates (item response probabilities):
  Response category  1:
Class:                1          2          3
  LabIS   :       0.0000     0.0099     0.0935
  RadIS   :       0.0152     0.0321     0.2790
  Pharm   :       0.0033     0.0081     0.0295
  CMV     :       0.7683     0.9354     0.9669
  CDR     :       0.0506     0.2114     0.8118
  NursDoc :       0.0970     0.6832     0.9325
  eMAR    :       0.2488     0.7422     0.8434
  OrderEntry:     0.0082     0.0292     0.2916
  CDSS    :       0.2040     0.3357     0.8765
  CPOE    :       0.4943     0.8299     0.9845
  PhysDoc :       0.4304     0.9211     0.9613
  PACS    :       0.4356     0.4978     0.7892
  BarcodeRFID:    0.6991     0.8740     0.7636

  Response category  2:
Class:                1          2          3
  LabIS   :       1.0000     0.9901     0.9065
  RadIS   :       0.9848     0.9679     0.7210
  Pharm   :       0.9967     0.9919     0.9705
  CMV     :       0.2317     0.0646     0.0331
  CDR     :       0.9494     0.7886     0.1882
  NursDoc :       0.9030     0.3168     0.0675
  eMAR    :       0.7512     0.2578     0.1566
  OrderEntry:     0.9918     0.9708     0.7084
  CDSS    :       0.7960     0.6643     0.1235
  CPOE    :       0.5057     0.1701     0.0155
  PhysDoc :       0.5696     0.0789     0.0387
  PACS    :       0.5644     0.5022     0.2108
  BarcodeRFID:    0.3009     0.1260     0.2364
```

Table 29: *Latent Class Analysis, Strict Criteria, Sample 1, 3-Class Model*

```
Number of subjects:                   1636

Number of measurement items:            13
Response categories per item:            2 2 2 2 2 2 2 2 2 2 2 2 2
Number of groups in the data:            1
Number of latent classes:                3
Rho starting values were randomly generated (seed = 861551).

No parameter restrictions were specified (freely estimated).

The model converged in 173 iterations.

Maximum number of iterations: 5000
Convergence method: maximum absolute deviation (MAD)
Convergence criterion:  0.000001000

=============================================
Fit statistics:
=============================================

Log-likelihood:     -8771.75
G-squared:           1373.31
AIC:                 1455.31
BIC:                 1676.71
Degrees of freedom:     8150

Test for MCAR
      Log-likelihood:     -8085.09
      G-squared:            780.00
      Degrees of freedom:    55702

                             Parameter Estimates

Gamma estimates (class membership probabilities):
Class:                      1          2          3
                       0.3395     0.4557     0.2048

Rho estimates (item response probabilities):
  Response category  1:
Class:                      1          2          3
  LabIS   :       0.0000     0.0134     0.0876
  RadIS   :       0.0168     0.0336     0.2641
  Pharm   :       0.0060     0.0077     0.0313
  CMV     :       0.7769     0.9166     0.9628
  CDR     :       0.0511     0.1899     0.7694
  NursDoc :       0.0891     0.6848     0.9232
  eMAR    :       0.2853     0.7567     0.8413
```

Table 29 (continued)

```
 OrderEntry:       0.0168     0.0253     0.2865
  CDSS    :       0.2418     0.2970     0.8666
  CPOE    :       0.5545     0.8452     0.9812
  PhysDoc :       0.4497     0.9239     0.9598
  PACS    :       0.4630     0.4654     0.7638
  BarcodeRFID:       0.7158     0.8481     0.7696

  Response category  2:
Class:                      1          2          3
  LabIS   :       1.0000     0.9866     0.9124
  RadIS   :       0.9832     0.9664     0.7359
  Pharm   :       0.9940     0.9923     0.9687
  CMV     :       0.2231     0.0834     0.0372
  CDR     :       0.9489     0.8101     0.2306
  NursDoc :       0.9109     0.3152     0.0768
  eMAR    :       0.7147     0.2433     0.1587
  OrderEntry:       0.9832     0.9747     0.7135
  CDSS    :       0.7582     0.7030     0.1334
  CPOE    :       0.4455     0.1548     0.0188
  PhysDoc :       0.5503     0.0761     0.0402
  PACS    :       0.5370     0.5346     0.2362
  BarcodeRFID:       0.2842     0.1519     0.2304
```

Table 30: *Mean Posterior Probabilities, Moderate Criteria, Sample 1, 3-Class Model*

Class 1	0.856703597	0.142126044	0.001170359
Class 2	0.106466618	0.805087016	0.088446365
Class 3	0.002483942	0.140433962	0.857082096

Table 31: *Mean Posterior Probabilities, Strict Criteria, Sample 1, 3-Class Model*

Class 1	0.843009606	0.154303756	0.002686637
Class 2	0.106965357	0.794170681	0.098863962
Class 3	0.005049573	0.132103651	0.862846776

Table 32: *Significance Tests and Psuedo-R2, Lenient Criteria, Validation Sample, without Interaction Terms*

Model Fitting Information

Model	Model Fitting Criteria			Likelihood Ratio Tests		
	AIC	BIC	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	1.971E3	1.981E3	1.967E3			
Final	1.833E3	1.882E3	1.813E3	154.249	8	.000

Goodness-of-Fit

	Chi-Square	df	Sig.
Pearson	2074.001	1910	.005
Deviance	1810.373	1910	.948

Pseudo R-Square

Cox and Snell	.146
Nagelkerke	.169
McFadden	.078

Table 33: Significance Tests, Psuedo-R2, and Parameter Estimates, Lenient Criteria, Validation Sample, with Interaction Terms

Model Fitting Information

Model	Model Fitting Criteria			Likelihood Ratio Tests		
	AIC	BIC	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	1.971E3	1.981E3	1.967E3			
Final	1.723E3	1.840E3	1.675E3	292.357	22	.000

Goodness-of-Fit

	Chi-Square	df	Sig.
Pearson	1965.976	1896	.129
Deviance	1672.265	1896	1.000

Pseudo R-Square

Cox and Snell	.259
Nagelkerke	.298
McFadden	.148

Parameter Estimates

classmembshp[a]		B	Std. Error	Wald	df	Sig.	Exp(B)	95% Confidence Interval for Exp(B)	
								Lower Bound	Upper Bound
2	Intercept	-1.055	.177	35.728	1	.000			
	znofstaffedbeds	-.014	.073	.039	1	.843	.986	.855	1.136
	zparhospcount	-2.860	.838	11.663	1	.001	.057	.011	.296
	[scmeetregular=.00]	.292	.254	1.321	1	.250	1.339	.814	2.204
	[scmeetregular=1.00]	0[b]	.	.	0	.	.	.	.

Table 33 (continued)

[vendorstrategysuite =1.00]	.357	.206	3.002	1	.083	1.428	.954	2.138
[vendorstrategysuite =2.00]	0[b]	.	.	0	.	.	.	.
[RECOVERYPLANISBACKUP=.00]	.715	.267	7.189	1	.007	2.044	1.212	3.447
[RECOVERYPLANISBACKUP=1.00]	0[b]	.	.	0	.	.	.	.
zannualrevenue	3.262	.807	16.315	1	.000	26.090	5.360	127.001
[scmeetregular=.00] * zparhospcount	-.152	.544	.078	1	.780	.859	.296	2.494
[scmeetregular=1.00] * zparhospcount	0[b]	.	.	0	.	.	.	.
[vendorstrategysuite =1.00] * zparhospcount	1.178	.835	1.993	1	.158	3.248	.633	16.674
[vendorstrategysuite =2.00] * zparhospcount	0[b]	.	.	0	.	.	.	.
[RECOVERYPLANISBACKUP=.00] * zparhospcount	2.734	.953	8.224	1	.004	15.389	2.376	99.680
[RECOVERYPLANISBACKUP=1.00] * zparhospcount	0[b]	.	.	0	.	.	.	.
[RECOVERYPLANISBACKUP=.00] * zannualrevenue	-2.363	.855	7.632	1	.006	.094	.018	.503
[RECOVERYPLANISBACKUP=1.00] * zannualrevenue	0[b]	.	.	0	.	.	.	.

Table 33 (continued)

	[vendorstrategysuite =1.00] * zannualrevenue	-1.557	.835	3.473	1	.062	.211	.041	1.084
	[vendorstrategysuite =2.00] * zannualrevenue	0[b]	.	.	0	.	.	.	.
3	Intercept	-3.023	.554	29.792	1	.000			
	znofstaffedbeds	-.352	.145	5.905	1	.015	.703	.529	.934
	zparhospcount	-.513	2.310	.049	1	.824	.598	.006	55.379
	[scmeetregular=.00]	-.820	.329	6.230	1	.013	.440	.231	.839
	[scmeetregular=1.00]	0[b]	.	.	0	.	.	.	.
	[vendorstrategysuite =1.00]	-.685	.354	3.752	1	.053	.504	.252	1.008
	[vendorstrategysuite =2.00]	0[b]	.	.	0	.	.	.	.
	[RECOVERYPLANISBACKUP=.00]	3.577	.584	37.526	1	.000	35.775	11.390	112.369
	[RECOVERYPLANISBACKUP=1.00]	0[b]	.	.	0	.	.	.	.
	zannualrevenue	-.459	2.123	.047	1	.829	.632	.010	40.488
	[scmeetregular=.00] * zparhospcount	-3.347	.667	25.176	1	.000	.035	.010	.130
	[scmeetregular=1.00] * zparhospcount	0[b]	.	.	0	.	.	.	.
	[vendorstrategysuite =1.00] * zparhospcount	-2.432	.979	6.170	1	.013	.088	.013	.599
	[vendorstrategysuite =2.00] * zparhospcount	0[b]	.	.	0	.	.	.	.

Table 33 (continued)

[RECOVERYPLANISBACKUP=.00] * zparhospcount	7.013	2.335	9.025	1	.003	1111.417	11.448	107901.126
[RECOVERYPLANISBACKUP=1.00] * zparhospcount	0[b]	.	.	0	.	.	.	.
[RECOVERYPLANISBACKUP=.00] * zannualrevenue	-1.381	2.112	.427	1	.513	.251	.004	15.790
[RECOVERYPLANISBACKUP=1.00] * zannualrevenue	0[b]	.	.	0	.	.	.	.
[vendorstrategysuite=1.00] * zannualrevenue	.763	1.377	.307	1	.579	2.145	.144	31.848
[vendorstrategysuite=2.00] * zannualrevenue	0[b]	.	.	0	.	.	.	.

a. The reference category is: 1.00.

b. This parameter is set to zero because it is redundant.