Summer 2015

The Value of Integrated Information Systems for U.S. General Hospitals

Liuliu Fu
Old Dominion University, luna.foe@gmail.com

THE VALUE OF INTEGRATED INFORMATION SYSTEMS FOR U.S. GENERAL HOSPITALS

by

Liuliu Fu

A Thesis Submitted to the Faculty of
Old Dominion University in Partial Fulfillment of the
Requirement for the Degree of

DOCTOR OF PHILOSOPHY
INFORMATION TECHNOLOGY

July 2015

Approved by:

Ling Li (Director)

Li Xu (Member)

Erika Marsillac (Member)

Muge Akpinar-Elci (Member)

ABSTRACT

THE VALUE OF INTEGRATED INFORMATION SYSTEMS FOR U.S. GENERAL HOSPITALS

Each year, huge investments into healthcare information systems (HIS) are being made all over the world. Despite the enormous cost for the hospitals, the overall benefits and costs of the healthcare information systems have not been deeply assessed. In recent years, much previous research has investigated the link between the implementation of Information Systems and the performance of organizations. Although the value of Healthcare Information System or Healthcare Information Technology (HIS/HIT) has been found in many studies, some questions remain unclear. Do HIS/HIT systems influence different hospitals the same way? How to understand and explain the mechanism that HIS/HIT improves the performance of hospitals? To address these questions, our research will: 1) Identify the bottlenecks of the current healthcare system which affects the operation efficiency (mismatch between demand and service provided); 2) Adopt the institutional theory to explain the process of implementing HIS/HIT and the possible outcomes; 3) Conduct an empirical study, to expose issues of current healthcare system and the value of the HIS/HIT, and to identify the factors that affect the performance of different hospitals; and 4) Design a decision support system for hospitals.

Based on institutional theory, we explain the empirical findings from 2014 HIMSS database. To solve the mismatch between the patient needs and doctor's schedule, we will propose a business model for a new integrated information management system. It gives the physicians and patients a comprehensive picture needed to understand the type of different patients. A classification schema will be designed to provide recommendations for scheduling decision, and it is supported by the interactive system.

Dedication

To Dr.Ling Li and Dr.Li Xu, my advisor who lead my way and give me enjoyable seven years in Old Dominion University. To Dr.Erika Marsillac, Dr.Muge Akpinar-Elci, for reading and commenting on my work line by line.

To my parents.

To Zhiguo Huang, my husband, my best friend, my lover and my other half.

Thanks for supporting me all the times.

Words cannot express how much I love you all.

Acknowledgments

I would like to thank Dr. Menawat, Sunil and Dr.Newman, Robert in Eastern Virginia Medical School, who helped with this research for support, providing data, feedback and friendship.

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ABBREVIATION	DEFINITION
BOR	Bed Occupancy Rate
CCD	Continuity of Care Document
CDSS	Clinical Decision Support System
CFI	Confirmatory Fit Index
CMIN/DF	Chi Square/Degree of Freedom
CPOE	Computerized Physician Order Entry
EHR	Electronic Health Record
EMR	Electronic Medical Record
EPR	Electronic Patient Record
EVMS	Eastern Virginia Medical School
HIEI	Healthcare Information Exchange and Interoperability
HIMSS	Healthcare Information and Management System Society)
HIS	Health Information System
HIT	Health Information Technology
HL7	Health Level 7
IS	Information System
IT	Information Technology
MFI	Multiple Factor Integration
MRI	Magnetic Resonance Imaging
NHS	National Health Service
PMS	Performance Measurement System
QMR	Quantitative Magnetic Resonance
RFID	Radio-Frequency Identification
RMSEA	Root Mean Square Error Of Approximation
ROA	Return on Assets
ROI	Return on Investment

RTLS	Real-time Locating Systems
SMR	Standardized Mortality Ratio
SRMR	Standardized Root Mean Square Residual
SVM	Support Vector Machines
TMDM	Total Measurement Development Method
TMR	The Medical Record
TPM	Total Productive Maintenance
TQR	Total Quality Management
UHS	University Health Services
WHO	World Health Organization

CHAPTER 1

INTRODUCTION

1.1 Introduction: IT in U.S. General Hospitals

In the U.S., a hospital is often associated with a medical group and it is run by a set of general practitioners, including doctors, nurses, and laboratory technicians. Simultaneously, it has also been widely recognized that Information Technology (IT) market is growing dramatically in recent few years. Combining this, the key role that information plays in health care cannot be ignored. IT costs on healthcare have become a foremost concern of the U.S. government. Health Information Technology (HIT) or Health Information System (HIS), is defined as the computer applications for the practice of medicine (Orszag, 2008). HIS/HIT covers a wide range of applications, such as the Electronic Medical Record (EMR), the Electronic Health Record (EHR), Continuity of Care Document (CCD), Computerized Physician Order Entry (CPOE), decision support systems to assist clinical decision making, and computerized entry systems to collect and storage patient data. According to the report of the U.S. Congressional Budget Office, the Bush Administration established the position of National Coordinator for HIT in the Department of Health and Human Services in 2004, and set the goal of making EHR available to most Americans by 2014. The time to achieving the goal has been revised (Charles, Gabriel, & Searcy, 2015): in 2008, less than 10% of U.S. hospitals had adopted Basic EHR system; and however, this increased to 76% in 2014. Almost all hospitals (97%) have adopted a certified EHR technology in 2014, increasing by 35% comparing with 2011. Current data suggests that HIS/HIT has gained increasing recognition in the U.S. and it is playing a more and more important role for U.S. hospitals.

Not only the U.S. government, many leading business companies also realize the potential of HIS/HIT development. Google Health, introduced by Google in 2008 and cancelled in 2011, was a personal health information centralization service that allowed patients to import personal medical records, schedule appointments, and refill prescriptions (Sunyaev, Kaletsch, & Krcmar, 2010). As the most similar competitor of Google Health, HealthVault, developed by Microsoft, is a web-based platform where users can see, use, add and interact with other personal devices such as Windows, Windows phone, iPhone (Microsoft, 2015). Microsoft HealthVault allows individuals to manage personal health data via health apps and personal health devices. Intel is now making efforts on multiple perspectives to promote the development of HIS/HIT, including personalized medicine, mobility, devices and imaging, privacy and security, secure cloud (Intel, 2015). IBM’s Healthcare solution aims to enable advanced business models to reduce costs, to create new forms of cooperation, and to promote engagement among business and individuals to increase healthcare outcomes (IBM, 2015). Subsequently, HIS/HIT has gained visible achievements and is still evolving.

Government and business company efforts bring huge investments into healthcare information systems research in the U.S. and all over the world. Despite the enormous cost to the hospitals, the overall benefits and costs of HIS have not been deeply assessed (Friedman, Wyatt, & Faughnan, 1997). In recent years, much research efforts investigated the link between the implementation of information systems and the performance of organizations. Because hospitals are at the frontier of technology adoption, IT investment becomes one of the main costs of its spending (Parente & Van Horn, 2005). Many previous studies have indicated a positive relationship between the use of IT and hospital performance (Devaraj & Kohli, 2003; Lee & Wan, 2002), but the mechanisms by which IT impacts hospital performance are still not clear: Do HIS/HIT systems influence different hospitals the same way? How to understand and explain the mechanism that HIS/HIT improves the performance of hospitals?

1.2 Research Scope And Methodology

1.2.1 Research Scope

Due to the complexity of healthcare services and information systems, interpreting the process, costs, quality, performance, organization, structure, and efficiency are all relevant to investigate the outcomes of HIS/HIT systems. Multiple factors including healthcare service providers, consumers, policies and system design need to be considered. The Academy for Health Services Research and Health Policy (the Academy), the leading national organization serving the fields of health services and policy research, defined the scope of health services research as follows:

> *Health services research is the multidisciplinary field of scientific investigation that studies how social factors, financing systems, organizational structures and processes, health technologies, and personal behaviors affect access to health care, the quality and cost of health care, and ultimately our health and well-being. Its research domains are individuals, families, organizations, institutions, communities, and populations (Lohr & Steinwachs, 2002).*

The definition of health services research highlights the importance of examining the factors of multiple factors including social factors, financial factors and technical factors when conducting research in this field. Similarly, if we intend to study the outcomes and characteristics of health information systems, the organizational and social perspectives, and not only the financial and technical issues, must be considered. Human and organizational factors are as important as technology to HIS/HIT (Yusof, Kuljis, Papazafeiropoulou, & Stergioulas, 2008). For instance, implementing a new computerized system in a hospital relates to the human factors such as who use it, the knowledge of the users, the frequency and levels of using the system, age, background, value, beliefs, and also to the organizational factors such as type of the hospital, size (number of beds, number of full-time employees), leadership, government policies, location, culture, planning. These factors cannot be ignored as they interact with the implementation process and outcomes of HIS/HIT.

A search of Google Scholar using the key words “health information system” returns over 4 million results. With such a huge number, the results should be classified. The most common classification is quantitative versus qualitative research methods (Bryman, 2006; Neuman, 2005). The classification of these two categories doesn't require a research result to belong to one of them. In fact, there are quite some studies combining both of quantitative and qualitative methods to examine the healthcare and information system issues (B. Kaplan & Duchon, 1988; Morgan, 1998; Stoop & Berg, 2003). We will discuss the details of quantitative and qualitative methods in the following sessions.

1.2.2 Quantitative Research

Quantitative research methods are rooted in the natural sciences (Myers, 1997b). The objective is to measure a particular phenomenon using quantified datasets of a chosen sample from the population of interest. In general, using quantitative methods requires the inclusion of a large sample size in order to fully represent the population of interest. Sometimes quantitative research can be followed by qualitative research to further investigate the details of some findings, or it can follow qualitative research in order to prove the validity of proposed assumptions. Quantitative research methods are widely accepted in the field of social science. There are several examples of application of quantitative methods in HIS/HIT studies.

- *Mathematical modeling* (Bennett & Worthington, 1998; LaGanga & Lawrence, 2007; Zeng, Turkcan, Lin, & Lawley, 2010) means to construct and describe a system using mathematical concepts and equations.

- *Experimental method* in information system studies is a controlled procedure in which independent variables are manipulated by the researchers, and the dependent variable is measured to test the hypotheses (Franz, Robey, & Koeblitz, 1986; Fu, Maly, Rasnick, Wu, & Zubair; Korpela et al., 1998).
- *Survey* method (Baker, Wagner, Singer, & Bundorf, 2003; Schoen et al., 2012; Stinson & Mueller, 1980; Bill B Wang, Wan, Burke, Bazzoli, & Lin, 2005) studies the sampling of datasets from a population using collected survey data. A survey can be cross-sectional (collecting data from people for one time) or longitudinal (collecting information from the same people over time). The cross-sectional method simply measures the research subjects without manipulating the external environment. If multiple groups are selected, it can compare different population groups at a single point of time. In contrast, longitudinal survey method collects information from multiple time frames. It has a significant advantage over cross-section methods in identifying cause-and-effect relationships. However, longitudinal survey method also faces the challenges associated with following a study group over a long time period.

Quantitative methods are most suiTable when a researcher wants to know “how much”: the size and extent or duration of certain phenomena (Stoop & Berg, 2003). Especially when testing the cost, quality or performance of HIS/HIT systems, quantitative methods become a main choice of evaluation. For instance, to evaluate the financial performance of HIS/HIT systems, quantitative methods are suiTable to use. One of the main strengths of quantitative approaches is their reliability and objectivity. With a well-constructed analytical model, they are able to simplify a complex problem to a limited number of variables. This requires establishing the testing model prior to data collection, and the collected data to be precise and able to reflect the target population. Once the data collecting process is complete, data analysis becomes relatively less time consuming especially with the help of statistical software (e.g., SPSS, Matlab, Minitab, SAS, Excel). What one needs to note is that the research results are relatively independent of the researchers. For example, researchers cannot guarantee whether the outputs are statistically significant, or whether the model fit can be proved. There are also some weaknesses of quantitative methods. As the tested models are constructed before data collection, the researchers might miss some important factors of the phenomena, because the focus is “hypotheses testing” rather than “hypotheses generation” (R. B. Johnson & Onwuegbuzie, 2004). Therefore the tested model needs to be reasonable and with a valid theoretical background.

1.2.3 Qualitative Research

In contrast to quantitative ones, qualitative research methods were originally developed for the social sciences (Myers, 1997b) who are concerned with “developing explanations of social phenomena (Hancock, Ockleford, & Windridge, 1998)”. The purpose of utilizing qualitative methods is to gain an indepth understanding of underlying factors, and to uncover hidden trends. More importantly, they are able to provide insights and ideas for future quantitative research: to determine not only what is happening, or what might be important to measure, but why to measure and how people think or feel (B. Kaplan & Maxwell, 2005). Unlike quantitative methods that require large number of datasets in general, qualitative methods usually concentrate on a small number of cases. Examples of qualitative approaches in the field of information systems given by Myers are action research, case study research and ethnography (Myers, 1997b).

- *Action research* “seeks to bring together action and reflection, theory and practice, in participation with others, in the pursuit of practical solutions to issues of pressing concern to people, and more generally the flourishing of individual persons and their communities.” (Reason & Bradbury, 2001). By this definition, action research method for HIS/HIT has its concern on the perspective of human and organizational factors. Reason and Bradbury concluded that action research could be an ideal post-positivist social scientific research method in information system discipline (Reason & Bradbury, 2001).
- *Case study* research methods intend to implement up-close and detailed examination of a subject of the case. They are analyses of person, projects, periods, policies, decisions, events, institutions or other systems that are under the study by one or more methods (G. Thomas, 2011). By its nature, the case study approach can be applied on almost all perspectives of HIS/HIT research. Many cases are presented all over the

world, such as the United States (B. Kaplan & Duchon, 1988), Australia (Evered & Bögeholz, 2004), Netherland (Vennix & Gubbels, 1992), Taiwan (S.-W. Wang, Chen, Ong, Liu, & Chuang, 2006), Philippines (Jayasuriya, 1999), and Africa (Kamadjeu, Tapang, & Moluh, 2005).

- The word *ethnography* has its origin in Greek where ethnos means “folk, people, nation” and grapho means “I write” (Sukoharsono & SE). The goal of ethnography research is to improve people’s understanding of human thought and activities via investigation of human actions in context (Myers, 1997a). Therefore ethnography approaches in HIS/HIT research also focus on the social aspects of the field, for instance: organizational culture (Avison & Myers, 1995), power and managerial issues (Myers & Young, 1997), and to contribute to the design process drawing examples to build explanation system (Forsythe, 1995).

Unlike quantitative approaches which check comparatively large sample sizes, qualitative approaches examine specific cases. It is useful when investigating complex situations involving a limited number of cases, and it provides rich detail of the phenomena in specific contexts. Quantitative approaches require data standardization in order to process and compare statistical results; while qualitative approaches allow the researchers to explore the responses as they are, and to observe the behaviors, opinions, needs, and patterns without yet fully understanding whether the data are meaningful or not (Madrigal & McClain, 2012). As a result, they are able to help HIS/HIT researchers capture some important hidden factors which might be ignored with quantitative approaches. However, because of the flexibility of the collected data, it takes more time for data processing and data analysis. Moreover, the results interpretation and quality is easily influenced by researchers' personal knowledge and biases. Therefore, qualitative methods are combined quantitative methods in many HIS/HIT studies to overcome the weaknesses of each other.

1.3 Challenges

The evolutionary process in scientific research contains several steps in general: to understand the old system, to identify the weaknesses of the old systems, and to develop new systems to solve the issue of the old ones. Therefore, our research in HIS/HIT also needs to overcome two basic challenges along the process: challenges in understanding the existing systems, and challenges in designing a new system.

1.3.1 Challenges in understanding existing systems

It relates to identifying the influences from the physical, socioeconomic, and work environments (Steinwachs & Hughes, 2008). One of the most widely studied questions regarding the performance of current systems is: what matters? These factors can relate to multiple perspectives such as human, organization and technology. We find a lot of influential factors under different contexts, for example:

- Staff and clinic size, doctor waiting time, the use of appointment scheduler (new or follow-up patient) (Clague et al., 1997)
- Time interval until the next appointment, doctor number, keep record of follow-up patient, improve the communications, booking no routine patients for the 1st 45 minutes for each clinic, field-of-vision appointments before 1st appointment, redesign the appointment card to give patients more information about their next visit to clinic (Bennett & Worthington, 1998).
- Number of operators, registration windows, physicians nurses, medical assistants, check in rooms, specialty rooms (Swisher, Jacobson, Jun, & Balci, 2001).
- Appointment scheduling for no-shows. Solution: overbooking (LaGanga & Lawrence, 2007).
- Appointment scheduling, appointment supply and consumption process, no-shows, overbooking (LaGanga, 2011)
- Different appointment types, no shows, overbooking (Guo, Wagner, & West, 2004),
- Length of time patients had attended the clinic, patients' mode of transport to the clinic (S. Thomas, GLYNNE - JONES, & CHAIT, 1997).

Now the challenge is not only whether the factors matter or what factors matter, but also at which level they matter, and why they matter. Lau's review on HIS research summarized the factors of HIS studies into Information System Success Model (Delone & Mclean, 2004; Lau, Kuziemsky, Price, & Gardner, 2010), as shown in Table 1.1. It is clear that understanding HIS/HIT systems is multidisciplinary. As discussed earlier, the research scope of HIS/HIT covers the aspects of technology, organization, social and human. To evaluate the quality or performance of an existing health information system, we have to take elements from all perspectives into account: from technical factors (such as information quality, system easiness of use, system reliability and response time), to social factors (such as policy enforcement), to financial factors (such as different types of costs), but at the same time remain focused on the research questions.

HIS Quality	**HIS Use**	**Net Benefits**
System Quality • Functionality • Performance • Security **Information Quality** • Content • Availability **Service Quality** • Service	**Usage** • Use behavior/pattern • Self-reported use • Intention to use **Satisfaction** • Competency • User perception • Ease of use	**Care Quality** • Patient safety • Appropriateness and effectiveness • Health outcomes **Productivity** • Efficiency • Care coordination • Net cost **Access** • Service availability • Participation

Table 1.1 Evaluation Map of HIS Studies by Lau et.al

1.3.2 Challenges in designing a new system

Although a large number of studies aim to explore what was happening on their current systems (Bennett & Worthington, 1998; LaGanga, 2011; LaGanga & Lawrence, 2007; Lummus, Vokurka, & Rodeghiero, 2006; LYNAM, SMITH, & DWYER, 1994; S. Thomas et al., 1997; Zeng et al., 2010), there are also some tried to design an advanced system (Clague et al., 1997; Coffey, Harrison, Bedrosian, Mueller, & Steele, 1991; Guo et al., 2004; Hashimoto, 1996; Swisher et al., 2001). The establishment and development of advanced system is a continuous and time-consuming process. For instance, Hammond and Stead (1986) reviewed the development of a computerized information system call TMR (The Medical Record), for medical facilities during the period of 1968 to 1986 (Hammond & Stead, 1986). It took around 20 years for TMR to evolve from a local individual clinical decision support system, to a local multiple-user operating system, to a system running in multiple sites, to a networking and distributed system running across 2 states, 5 clinics, as shown in Table 1.2. Each stage solved a challenge in a particular aspect, such as data utilization issue, system scalability issue, data processing collection capability issues, and brought the system into an advanced level.

Time	Stage	System features
1968	The beginning	Clinical Decision Support System(CDSS) by IBM.
	Interactive questionnaires	Programs were run independently. The system provided few user aids.
1971	Obstetrics medical record	The system collected data through a mark-sense questionnaire.
	Time-shared operation system	An multiple-user operating system
1974	Primary care record	University Health Services Clinic (UHS)used the system primarily to record administrative data necessary for management and financial decisions. Records were over 20,000 patients by the end of 1974.
1977	The Medical Record(TMR)	TMR became a real operational system as UHS.
1983	Adaptation to an inpatient environment	TMR had been implemented in 10 sites, all of which were ambulatory care based.
1984	Data collection and report generation	The data collection capabilities of TMR were limited to the selection of a 153 parameter and the entry of a result. Data entry could be grouped by categories, and the user could be stepped through all entries for a given encounter.
1984	Microcomputer-based systems	30 megabyte Winchester disk, 4~6 video terminals, 2 100 cps printers, and the Micro/RSX operating system.
1985	Networking and geographically distributed system	System ran across 2 states, 5 clinics.

Table 1.2 Development of TMR by Hammond and Stead (1986)

Now we may question: at each stage, what issue(s) should we address to improve the current HIS/HIT systems? For this question, Haux (2006) summarized seven directions for HIS/HIT development as a guideline for our research (Haux, 2006):

- The 1st direction is *towards computer-based information processing tools*. It is recognized today that the information storage and processing has changed from paper-based to computer and networking based nowadays. From 2008 to 2013, the adoption rate of Basic EHR system grew from 10% to 60% (Charles et al., 2015). Such a dramatic shift happened in just five years. Our empirical research using HIMSS 2014 data also indicate that 58% of U.S. general hospitals are using EMR intensively (using EMR 75%~100% within a hospital), and 55% of them are using CPOE intensively. The research in this direction focuses on the computer-supported parts, for example: the impact of a computer-based health information support system (Gustafson et al., 1999), a registration HIS/HIT network in Netherlands (Metsemakers, Höppener, Knottnerus, Kocken, & Limonard, 1992), and personalized display of health information (Brown & Jensen, 2000).
- The 2nd direction is *from local to global information system architectures*. The international integration promotes the interchange of products, ideas, information and view. Globalization is the trend. HIS/HIT systems are facing the challenge of integrating different formats of healthcare information all over the world. There are some global health information

system standards, such as HL7 (Health Level 7) (Dolin et al., 2006), a set of standards to transfer clinical and administrative data between computer-base system applications of different regions. Studies of this direction examine the standardization of the system architecture, for example, implementation issue (Huang, Hsiao, & Liou, 2003), mapping from local clinical data warehouse to the global information model (Lyman et al., 2003), and IBM's health-care data model based on the HL7 model (Eggebraaten, Tenner, & Dubbels, 2007).

- The 3rd direction is *from healthcare professionals to patients and consumers*. The development of HIS/HIT systems should consider not only the healthcare providers or physicians as users, but also patients and consumers. Because patient satisfaction is one of the most important indicators of system quality (Lau et al., 2010), the patient-oriented factors such as the easiness of usage, patients' behavior, and privacy issues should be considered. There are lots of HIS/HIT studies in this direction in recent years, for example: there are studies on patient-centered health information system (Krist & Woolf, 2011), patient safety issue (Parente & McCullough, 2009) and patient interest in sharing personal health record (Zulman et al., 2011).
- The 4th direction is *from using data only for patient care to research*. Because of the research needs of HIS/HIT, the system should have a capability of providing data to researchers for future improvement.

- The 5th direction is *from technical to strategic information management priorities*. This means that HIS/HIT system should be able to provide appropriate recommendation for management, administration and patient care, to assist managerial and strategic decision making. Some decision support systems may be used to determine the how urgent a patient case would be (Y. Wang, Cong, Song, & Xie, 2010). Some help to suggest interpretation of patient's symptoms, such as QMR (Quantitative Magnetic Resonance) system (R. A. Miller, 2009). Many challenges exist in constructing an effective decision support system for healthcare, such as the effectiveness of its interventions, the human-computer interface design, information presentation, recommendation filtering, and so on (Sittig et al., 2008).
- The 6th direction is *inclusion of new types of data*. We are living in an era of information explosion where the amount of information as well as the types of information is increasing at a rapid speed. It brings information overload, and brings challenges to information management. The HIS/HIT studies should consider expanding the capability of new types of data, such as image and video.
- The 7th direction is *inclusion of new technologies*, such as RFID (Radio-Frequency Identification) (Fry & Lenert, 2005; Nouei, Kamyad, Soroush, & Ghazalbash, 2015; Oztekin, Pajouh, Delen, & Swim, 2010), smartphone (Choi et al., 2011; Ko et al., 2010; Putzer & Park, 2010) and RTLS (Real-time Locating Systems) (Boulos & Berry, 2012; Schrooyen et al., 2006).

> The inclusion of new technologies brings many new features to current HIS/HIT systems, improves the systems quality and performance. Despite the advantages of including new technologies to HIS/HIT systems, there are also some challenges in system design such as data standard issue, hardware integration, and costs issue.

As mentioned, no matter what direction(s) we choose, we will encounter some challenges during the process of constructing and promoting the new generation of health information system to the next stage. For example, different hospitals may adopt different databases to store and manage patients' information. When data are transferred from one database to another, there are likely to have internet scalability issue, identification and addressing issue, heterogeneity issue (such as different standards), and service paradigm issues because of lack of comprehensive data (Haller, Karnouskos, & Schroth, 2009). Ma (2011) discussed the challenges from the perspective of data feathers (Ma, 2011): 1) Non-uniformity. Data formats such as humidity, audio, video, and temperature are different from each other; 2) Inconsistency. Due to the distortion of space-time mapping, there is inconsistent information; 3) Inaccuracy, which is often generated from the variety of sampling methods and different capabilities of the sensors; 4) Discontinuities, which is often caused by the dynamic network transmission capacity; 5) Incomprehensiveness, which often comes from the limitations of sensors; and 6) Incompleteness, such as partial loss of information, which is caused by dynamic network environment. The issues surrounding data processing will bring errors to the healthcare systems. If we examined the process that how data goes through the system, there are errors from entering and retrieving information and errors in the communication and coordination process (Ash, Berg, & Coiera, 2004). The research of Weber (Weber, 2009) focused on regulatory challenges, such as institutional issues and governance principles, for instance, the stakeholders' co-action, enhanced communication, coordination and cooperation in a kind of forum, to frame a central institutional point for the regulation of system issues. Institutional factors also play an important role in the implementation of international network structures especially for HIS/HIT systems, as even hospitals usually follow the federal regulation more intensively than other business organizations.

The challenges of HIS/HIT system construction are multi-disciplinary. The technology aspects of studies examine the issues such as system architecture, data management, algorithm optimization, and algorithm implementation, etc, while institutional aspects explore the social and human factors. On the other hand, from the view of a HIS/HIT system application scope, there are common challenges faced by all situations in general, and are also application-specific challenges which are case-specified and may matter only for certain scenarios. The attribution schema of these challenges must utilize cross classification method, as shown in Table 1.3.

	Technical Challenges	Institutional Challenges
Common Challenges	- Identification and addressing - Heterogeneity - Data Non-uniformity - Data Inconsistency - Inaccuracy - Incompleteness - Incomprehensiveness	- Institutional issues - governance principles - cultural issues
Application-specific Challenges	- System scalability - Service paradigm - Intra-net of things - Discontinuities	- The knowledge level of target users group - The knowledge level of physicians - Hospital type

Table 1.3 2*2 Matrix of Different Type of Challenges for IS Implementation

1.4 Research question and Objective of the study

The value of Healthcare Information System or Healthcare Information Technology (HIS/HIT) has been reported in many studies. Many factors have been proven to be related with the performance of HIS/HIT systems. But the challenge is not only whether the factors matter or what factors matter, but also at which level they matters, why they matter, and how they work. More studies need to focus on the intersection of technology and social perspectives. Now some questions remain unclear: Do HIS/HIT systems influence different hospitals the same way? How to better understand and explain the mechanism by which HIS/HIT improves the performance of hospitals? To address these questions, our research will:

1) Identify the bottleneck of the current healthcare system which affects the operation efficiency.
2) Adopt institutional theory to explain the process of implementing HIS/HIT and the possible outcomes.
3) Conduct an empirical study, including both a case study and empirical data analysis, to expose the issues of current healthcare systems and the value of the HIS/HIT, and to identify the factors that affect the performance of different hospitals.
4) Design a decision support system for current hospitals.

We will propose a business model for a new integrated information management system. It gives the clinic physicians and patients a whole picture to understand the work flow. A scheduling schema will be designed to reduce the operational cost, and it is supported by the interactive system. Finally, we will finish the prototype of the system. The system with a decision support module is proposed as a solution to improve the efficiency of the current healthcare system.

The rest of this paper is organized as follows: the background information and an overview of the relevant research areas are presented in two chapters, including the state-of-the-art healthcare systems, issues, and system measurement methods. In particular, the existing issues and gap between the current and integrated systems are introduced in Chapter 1, which are the starting point of this research. Chapter 2 reviews the studies of information transparency theory and institutional theory on healthcare, as well as the measurement of healthcare systems, providing a solid theoretical background to establish our study. In Chapter 3, we conduct an empirical study using HIMSS 2014 data. A measurement framework is designed to identify the value of Information Systems for healthcare. Chapter 3 exposes the value of IS in different healthcare environments. The explanations based on information transparency theory and institutional theory introduced in chapter 2 are consistent with our findings. Chapter 4 provides a case study as a supporting example to illustrate the issues of current health information system. In addition, Chapter 5 describes the details of the system design, in which the system framework, the database architecture, and the algorithm for scheduling are elaborated. Finally Chapter 6 summarizes the research findings and contributions, presents the limitations of our research and suggests future work.

CHAPTER 2

LITERATURE REVIEW

2.1 Current system

A healthcare system, sometimes referred as "health care system" or "health system", is the integration of people, institutions and resources that provide health care services. According to the World Health Organization (WHO)'s definition (Organization, 2007):

> *A health system consists of all organizations, people and actions whose primary intent is to promote, restore or maintain health. This includes efforts to influence determinants of health as well as more direct health-improving activities. A health system is therefore more than the pyramid of publicly owned facilities that deliver personal health services. It includes, for example, a mother caring for a sick child at home; private providers; behavior change programmers; vector-control campaigns; health insurance organizations; occupational health and safety legislation. It includes inter-sectoral action by health staff, for example, encouraging the ministry of education to promote female education, a well-known determinant of better health.*

The WHO's definition highlights the fact that there are not only factors of technology, but also factors of human and organization in a healthcare system. All these factors simultaneously determine the outcome of a health care system.

In our research, we narrow the broad scope of “system” and define healthcare information systems as computerized systems that facilitate the information sharing and processing within healthcare facilities. Healthcare information systems are fundamentally different from industrial and consumer products which are concerned about market share protection (Mandl & Kohane, 2012). They need to be able to be implemented across the platforms, and thus there is a requirement for standardization. In general, it has special needs in terms of security, database design and standards issue.

As discussed in Chapter 1, evaluating, designing and implementing HIS/HIT systems covers a wide scope. The key is to integrate the technology factors (e.g., information integration and knowledge management) and social factors (e.g., management, psychology and policy). This multi-disciplinary research has drawn interests from many fields including those working in the fields of information system, computer science, business management, medical science and others. For example: Wilton and McCoy (1989) introduced a distributed database which established data links between different applications running in a local network (Wilton & McCoy, 1989). Both patient information and reference materials were included in their database. Lamoreaux (1996) described a database architecture in a medical center in Virginia which integrated the patient treatment file, outpatient clinic file and fee basis file all together (Lamoreaux, 1996). Johonson, Khenina and Paul (1997) discussed the generic database design for patient management information (S. B. Johnson, Paul, & Khenina, 1997), and indicated that the database design needed to allow efficient access to clinical management events from patient, even, location and provider. Teumoto (2000) developed a rule instruction system to automatically discover the knowledge from an outpatient healthcare system (Tsumoto, 2000), similar to Khoo, Chan and Niu (2000)'s knowledge extraction and discovery system while using the graphical pattern of a medical database (Khoo, Chan, & Niu, 2000). Chandrashekar et al (2006) talked about the considerations when designing a reusable medical database, including the contract issue between the clinical applications and the storage component, multi-modality support, centralizing external dependencies, communication models, and performance considerations (Chandrashekar, Gautam, Srinivas, & Vijayananda, 2006). Xu, Wermus and Bauman (2011) introduced an integrated medical supply information system which integrated the demand, service provided, health care service provider's information, inventory storage data and support tools all together (Xu, Wermus, & Bauman, 2011). A recent study by Honglin et al proposed multiple factor integration (MFI) method to calculate the similarity map for sentence aligning for medical database (H. L. Wu, Liu, Dong, & Wang, 2013).

With the emergence of these advanced HIS/HIT systems, some well-developed ones have gained wide adoption. Electronic Medical Record (EMR), Electronic Health Record (EHR) and Electronic Patient Record (EPR) are three of the main types adopted. All three systems aim to represent the data electronically and are often used interchangeably. However, fundamental differences exist among these three systems. EMR is the electronic medical information file that is generated during the process of diagnosis. EMR is normally designed according to the diagnosis process in a medical facility, and it is rarely extended outside the scope of a hospital, clinic or medical center. On the other hand, EHR is the systematic collection of electronic health information about patients, which can go beyond the scope of a single medical facility. Thus EHR integrates information across different facilities and systems, and EMR can serve as a type of data source for the EHR (Habib, 2010; Kierkegaard, 2011). The scope and purpose of EHR are given by ISO TR 20514: “a repository of information regarding the health status of a subject of care in computer processable form, stored and transmitted securely, and accessible by multiple authorized users. It has a standardized or commonly agreed logical information model which is independent of EHR systems. Its primary purpose is the support of continuing, efficient and quality integrated health care and it contains information which is retrospective, concurrent and prospective.” And finally, EPR refers to “An electronic record of periodic health care of a single individual, provided mainly by one institution” (Executive, 1998), as defined by National Health Service(NHS). The definition of EPR is patient centric. It is the health record of a person along his/her life. NHS has classified EPR into six levels. The research of HIS/HIT may focus on any of the six levels.

Level 1 - Patient Administration System and Departmental Systems

Level 2 - Integrated patient administration and departmental systems

Level 3 - Clinical activity support and noting

Level 4 - Clinical knowledge, decision support and integrated care pathways

Level 5 - Advanced clinical documentation and integration

Level 6 - Full multi-media EPR on line

From the perspective of information location, content, source, maintainer and user, we compare EMR, EHR and EPR in Table 2.1:

	EMR	EHR	EPR
Purpose	Managerial process control on a medical domain	Information sharing	Personal health management
Information allocation	Health facilities	Public health department	Individual person
Information content	Medical record	Medical record and public health record	Medical record and personal health record
Information control	Health practitioner or related stuff can gain access	Health practitioner, related stuff in the health facilities, and government stuff can gain access	Can get access only after get permission by the record owner
Information resource	Single health facilities	Multiple health facilities	Single Health facility and individuals
Information maintainer	Health facility	Government	Individual

Table 2.1 Comparison among EMR, EHR and EPR

Although these well-developed systems have gained wide acceptance and have been implemented by most healthcare facilities today, many studies have discussed the issues regarding the implementation of the EMR/EHR/EPR as well as the problems of the system design. For example: Some studies discussed the accuracy issues of quantitative EMR data (Corson et al., 2004; Goldberg, Shubina, Niemierko, & Turchin, 2010; Szeto, Coleman, Gholami, Hoffman, & Goldstein, 2002; Wagner & Hogan, 1996). Particularly, Wagner and Hogan indicated that the main cause of errors was the failure to capture the patient's mistake when misreporting about medications, and the second most important cause for the error was the failure to capture medication changes from outside clinicians. Linda et al (2004) found that only small amount of nurses reported that EHRs had resulted in a decreased workload, while the majority of nurses preferred bedside documentation (Moody, Slocumb, Berg, & Jackson, 2004). Bygholm (2000) found the implementation issues of EPR systems from a case study (Bygholm, 2000), and it was argued that there was a need to distinguish different types of end-user support when various type of activity were involved.

As a short conclusion to this section, existing healthcare systems have gained long term success, while there remain many unsolved issues regarding the implementation and use of such systems. More research needs to be done to improve the usability and data quality of healthcare systems. There is demand for a further investigation of current system's weaknesses and the development of integrated healthcare systems. We will discuss the evaluation framework of HIS/HIT systems in section 2.5. In chapter 5, we will propose a health information system design with decision support module using support vector machine. In the following two sections, we will discuss institutional theory, as theoretical support for the research.

2.2 Institutional Theory on Healthcare

According to Scott’s (2001) definition, institutions are “multi-faceted, durable, social structures, made up of symbolic elements, social activities, and material resources” (Scott, 2008b). The process in which an organization attains a stable state is called “institutionalization”. Hospitals are institutions with social structure associated with activities and resources provided by different agents and service providers. Thus we can adopt institutional theory as a meaningful tool to understand and explain the implementation process of HIS/HIT systems. Institutional theory describes how institutions are created, maintained, changed, and dissolved. It examines the environment with “positions, policies, programs, and procedures of modern organizations (Meyer & Rowan, 1977).” The influence of institutional environment is emphasized. It argues that such influence from inside the institution is normally more profound than some external influences, such as market pressures (Meyer & Rowan, 1977). In our case, we look at the field of healthcare. A hospital, as a type of professional institution, is more likely to receive regulation pressure from the states or the government, but not market pressure. Some may suspect that laws and regulations (for example, mandating to adopt EMR) are external pressure rather than internal institutional pressure. Edelman et al. (2008) insists laws and mandated regulations to be treated as “at least in part endogenous, constructed in and through the organizational fields that it seeks to regulate” rather than exogenous pressure (Edelman, Uggen, & Erlanger, 1999; Scott, 2008a). DiMaggio and Powell recently added that institutional pressure would increase the homogeneity of organizational structures, and that such isomorphism is amplified under three conditions: 1) when they were highly dependent on their institutional environment; 2) when there were high uncertainty or ambiguous goals; and 3) when the organization relied on professionals intensively (Powell & DiMaggio, 2012). These three conditions are met for a hospital. All organizations are operating in both market and institutional environments, but the extent of pressure posed by each is different for various types of organizations (Meyer & Scott, 1991; Meyer, Scott, Rowan, & Deal, 1985). Hospitals operate in environments with high institutional but low market pressure (Scott, 2008a). For example, the national healthcare IT strategies are mandated by the governments (Dobbin, 1994).

Intuitional theory has been applied in the field of healthcare previously (Blair, Fottler, & Savage, 2001; Covaleski, Dirsmith, & Michelman, 1993; Dacin, Goodstein, & Scott, 2002; Jensen, Kjærgaard, & Svejvig, 2009; Scott, 2000; Shoib, Nandhakumar, & Currie, 2009). Particular focus has been spent on information systems research in the context of healthcare(Jensen et al., 2009; Shoib et al., 2009). Orlikowski and Barley (2001) suggested that institutional view provides to IT research “a vantage point for conceptualizing the digital economy as an emergent, evolving, embedded, fragmented, and provisional social production that is shaped as much by cultural and structural forces as by technical and economic ones”(Orlikowski & Barley, 2001). With the help of organizational studies, IT studies can retain a more systematic understanding of how technologies are embedded in the complex social environment.

There are two types of institutionalization studies on IT artefact, as classified by Shoib et al.: those focusing mainly on the effects of institutionalism, and those focusing on the process of institutionalism (Shoib et al., 2009). In the first type, Sherer presented several propositions about the implementation of electronic health records over several years (Sherer, 2010). Zinn et al. examined the influential factors to nursing home's Total Quality Management (TQR) using institutional theory and resource dependence (Zinn, Weech, & Brannon, 1998). Lowe studied a large public hospital in the central North Island, New Zealand, and reported the changes caused by the implementation of a sophisticated system of case-mix budgeting, including the changes in working practices and those during clinical procedures (LOWE, 2000). The latter type requires more longitudinal, process-oriented, and case-based effort than the previous one. For instance, Jensen et al. did a case study about the implementation of an Electronic Patient Record (EPR) system in a clinical setting (Jensen et al., 2009). As an example of process-orientated research, they examined how an EPR system travelled from the organizational field to individual doctors using institutional theory together with sense-making theory. Detailed exploration was given to doctors' experiences and their reactions to the EPR implementation. Another example of process-oriented research is Currie and Guah's 4-year study on the UK National Health Service (NHS) program (Currie & Guah, 2007), in which interpretations were given based on historical and empirical data from six NHS organizations.

As a short summary, institutional theory is a suitable tool to explain the process and outcomes of the implementation of HIS/HIT in U.S. hospitals. With the help of institutional theory, we may have a clearer look at the changes of the hospital performance in a complex social network.

2.3 The Measurement of the Healthcare System

Institutional theory views performance as the results that created organizational structures intend to affect (Scott, 1987). Performance measurement is defined as “the process of quantifying the efficiency and effectiveness of action”, or “a metric used to quantify the efficiency and/or effectiveness of an action”, or “the set of metrics used to quantify both the efficiency and effectiveness of actions” (AD Neely, 1994; Andy Neely, Gregory, & Platts, 1995). Here three main issues are covered: “quantification”, “efficiency and effectiveness”, and “metrics”. Quantification means that the results of performance measurement need to be countable and comparable. Efficiency and effectiveness are the measuring objects. Metrics emphasize that performance measurement is multidimensional.

In most cases, the process of measuring performance requires the uses of statistical tools to determine results. Today many performance measurement systems have gained great achievements. For example, the Balanced Scorecard, first proposed in 1992, provides a comprehensive framework to translate a company’s strategic objectives into a related set of performance measures (R. S.

Kaplan & Norton, 1995, 2005), including the financial perspective, customer perspective, internal business perspective, and innovation and learning perspective. Neely's "Performance Prism" system looks at five interrelated facets of the prism: stakeholder satisfaction, stakeholder contribution, strategies, process and capabilities (Adams & Neely, 2000; Andy Neely, Adams, & Crowe, 2001; A. D. Neely, Adams, & Kennerley, 2002). More detailed measuring perspectives are defined under each facet. The Performance Pyramid developed by Lynch and Cross contains a hierarchy of financial and non-financial performance measures. The four-level pyramid system shows the link between strategies and operations, translating the strategic objectives top down, and rolling measures bottom up (Cross & Lynch, 1988). Dixon et al. (1990) developed the Performance Measurement Questionnaire (PMQ) system to determine the degree that the existing performance measures supported the improvements, and to identify what the organization needed for improvement (Dixon, 1990). For team-based structures, Jones and Schilling (2000) proposed the approaches of the Total Productive Maintenance (TPM) process in which a practical guide for developing a team's vital measurement system is provide (Jones & Schilling, 2000). Later after the proposition of TPM, the 7-step TPM process (Leflar, 2001) and Total Measurement Development Method (TMDM) (Gomes, Yasin, & Lisboa, 2006) were developed. By studying the processes and strategies with organizations, these systems function as a part of the management process giving insights on what should be achieved and whether the outputs meet intended goals.

Since performance measurement is multidimensional, a Performance Measurement System (PMS) can differ when the situation and context change. Despite the variety of PMSs, some universal steps and requirements need to be followed when designing a meaningful measurement system. Three general steps are included when designing a performance measurement system: defining strategic objectives, deciding what to measure, and installing performance measurement system into management thinking (Keegan, Eiler, & Jones, 1989). Wisner and Fawcett later added more operational details into the procedure, expanding the three steps to a nine-step flow diagram (Wisner & Fawcett, 1991). For common standards, Bourne et al. gave some examples of these rules (Bourne, Mills, Wilcox, Neely, & Platts, 2000):

1) A PMS should include a mechanism to review and revise their goals and standards (Ghalayini & Noble, 1996).
2) A PMS should include a process to develop individual measures when the situation changes (Dixon, 1990; Brian H. Maskell, 1991; Brian H Maskell, 1992; McMann & Nanni Jr, 1994).
3) A PMS should include a process for periodical review, and this process needs to correspond with the changing environments (Dixon, 1990; Lingle & Schiemann, 1996; Wisner & Fawcett, 1991).
4) A PMS should be used for questioning strategic assumptions (Bourne et al., 2000).

Particularly for the measurement of healthcare related systems, Purbey et al. adopted Beamon’s evaluation criteria for supply chain performance (Beamon, 1999), coming up with a set of measurement characteristics for healthcare processes: inclusiveness, universality, measurability, consistency, and applicability (Purbey, Mukherjee, & Bhar, 2007). Due to the complexity of healthcare systems, there are various aspects implicating the system performance. Looking at the review of Van Peursem et al., three measurement groups are included for health management performance: 1) Economy, efficiency and effectiveness; 2) Quality of care; and 3) Process (Van Peursem, Prat, & Lawrence, 1995). These measurement aspects focused on the quality of management, not the quality of medical practice. The first aspect mentioned here (economy, efficiency and effectiveness) is normally referred to as the three e's and it has been devised for public sector organizations (Brignall & Modell, 2000; Mayston, 1985; Midwinter, 1994). A PMS for HIS/HIT can also be classified as financial or non-financial (Micheli & Kennerley, 2005; Schur, Albers, & Berk, 1994; Van Peursem et al., 1995). Table 2.2 summarizes the studies on healthcare system performance and their measurements according to financial and non-financial categories:

Financial Measurement	Non-financial Measurement
- Return on Investment (ROI) (Menachemi, Burkhardt, Shewchuk, Burke, & Brooks, 2005) - Medicaid inpatient revenue (Ginn & Lee, 2005) - Total income/revenue (Akashi, Yamada, Huot, Kanal, & Sugimoto, 2004) - Cost, market share grow, Return on Assets (ROA), ROI, operating profit (L. Li, Benton, & Leong, 2002) - ROA, operating margin, market share, sales growth, current ratio, debt ratio, cash flow to debt ratio, cumulative depreciation ratio (Je'McCracken, McIlwain, & Fottler, 2001) - Net operating revenue, market share, total margin, total revenue(Lamont, Marlin, & Hoffman, 1993) - ROA, operating margin, net cash flow, adjusted net patient revenue (Bill Binglong Wang, Wan, Clement, & Begun, 2001)	- Patient satisfaction (Boulding, Glickman, Manary, Schulman, & Staelin, 2011; Carr-Hill, 1992; Pascoe, 1983; Press, Ganey, & Malone, 1991) - Patient safety (Bill Binglong Wang et al., 2001) - For three clinical areas: hip/knee surgery, cardiac care, and obstetric care, hospitals were rated as better than expected (fewer deaths/ complications), as expected, or worse than expected. (Hibbard, Stockard, & Tusler, 2005) - Standardised mortality ratio (SMR) (Jarman et al., 2010; Kahn, Kramer, & Rubenfeld, 2007; Molyneux et al., 2009; Shortell & LoGerfo, 1981) - Bed Occupancy Rate (BOR) (Akashi et al., 2004) - Mortality, readmission, and complication (DesHarnais, McMahon Jr, Wroblewski, & Hogan, 1990) - Percent occupancy (Lamont et al., 1993)

Table 2.2 Healthcare System Studies with Financial and Non-Financial Measurements

2.4 Research Framework and Hypotheses

Many influential factors on the performance of health care facilities have been identified. Li and Benton (2002) found that the intermediate infrastructural operations had significant effect on the cost, quality, and financial performance in a hospital environment (L. Li et al., 2002). Their further work in 2006 revealed that the size and the location of the hospital are related to the nurse management decisions and computer and information technology decisions, which further more affect the cost and the quality of the hospital service. In this conceptual model, we believe that there are determinative relationship among the execution of IS, the service provided by the hospital and the performance of the hospital. The size of the hospital and the IS plan setting moderate the relationship among the relationship among IS execution, service provided and the performance.

As early as 1992, DeLone and McLean developed a series of dependent variable measurements in information systems research with six major dimensions or categories: system quality, information quality, use, user satisfaction, individual impact, and organizational impact (DeLone & McLean, 1992). After 10 years, they reviewed and analyzed more than 150 articles using the model (DeLone & McLean, 2002). A revised version of the model, known as the Information System Success Model, was proposed and became a standard to specify and justify the measurement of information system studies (Delone & Mclean, 2004). The Information System Success Model consists of six correlated instruments presenting the dynamic process within an information system. Specifically, Lau et al applied this structure in their review of the field of health information systems, and viewed the six instruments as three layers, as shown in Figure 2.1 (Lau et al., 2010). System quality, information quality and service quality are on a first layer to represent the general quality of a HIS/HIT system. The second layer contains the usage of the HIS/HIT and user satisfaction, both of which represent the actual HIS/HIT system utilization of the hospitals. The third layer is net benefits, which is the final outcome of the HIS/HIT implementation. Three dimensions are included for net benefits: care quality, productivity, and access.

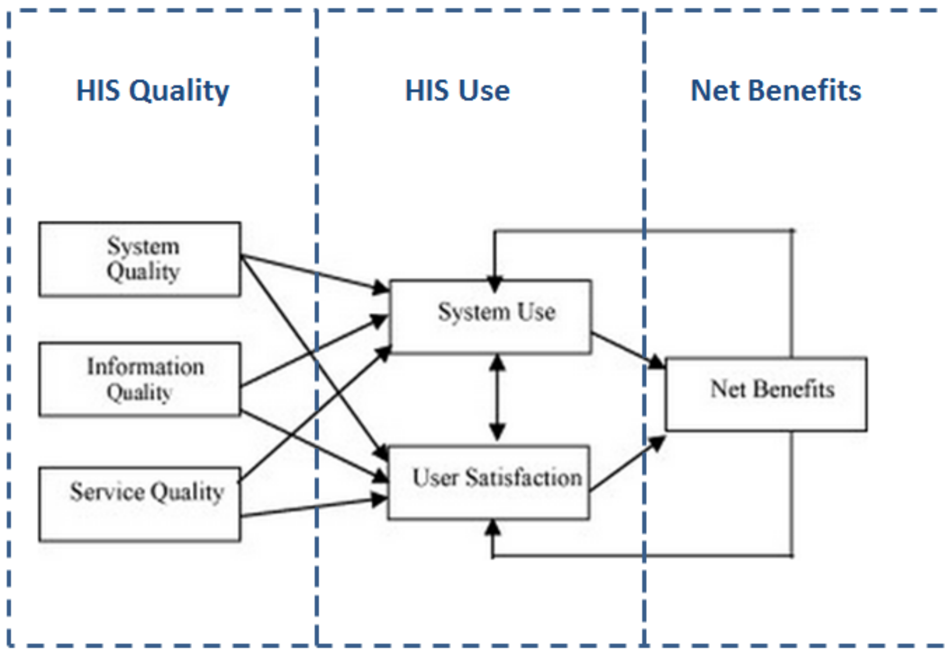

Figure 2.1 Information System Success Model in HIS/HIT

Based on the frameworks of DeLone and McLean and Lau et al, we propose our HIS/HIT evaluation framework in Figure 2.2. We define IT implementation as the first layer, referring to the system quality in Information System Success Model in HIS/HIT. IT implementation includes three perspectives: whether the healthcare system mandated that physicians utilize a

CPOE (Computerized Physician Order Entry) system; whether the hospital is using HL7 CCD (Continuum of Care Document) transactions to share patient data with other organization; and the utilization percentage range of the hospital's current electronic medical record (EMRP, Electronic Medical Record Percentage). These three factors of IT implementation cover the IS implementation status from the perspective of the patient side, the physician side and among different hospitals. They describe the functionality and premier quality of HIS/HIT healthcare systems.

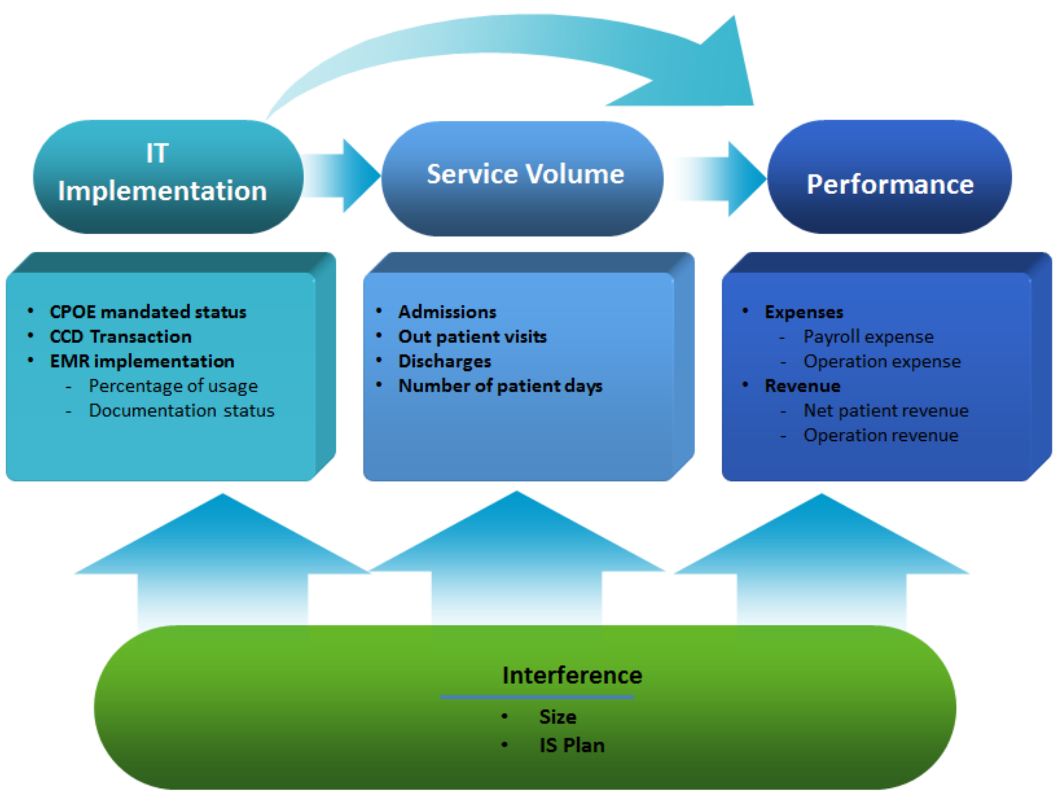

Figure 2.2 HIS/HIT Evaluation Framework

For the second layer, Service Volume is the actual work load carried by the hospitals. It refers to the “system use” in Information System Success Model. Because there are different type of patients and services, we measure the services from four perspectives due to the complexity of the hospital operation: AHA Admissions is the number of admissions which includes the number of adult and pediatric admissions only (excluding births). This number includes all patients admitted during the a 12-month reporting period, including neonatal and swing admissions; Out patient visits (NoOp) is the number of outpatient visits at each Acute-Care Hospital in the most recent fiscal year; Discharges (Disch) is the total number of patients discharged from the hospital in a calendar year; and Number of patient days (PatD) is the number of calendar days of care provided for hospital inpatient treatment under the terms of the patient’s health plan, excluding the day of discharge. Thus IT utilization is measured by not only the number of patients served, but also by the days patients were served.

Finally, the performance is the third layer: the net benefits associated with the implementation of HIS/HIT. To measure performance, we reviewed both spending and revenue of the hospital, where spending includes payroll expense and operation expense; and revenue contains net patient revenue and operation revenue.

In the Information System Success Model, three instruments are included to represent the first layer, the HIS quality. The three instruments are: system quality, information quality, and service quality. In our research, we will only examine the system quality aspect for the data collection and following analysis.

According to the findings of Lau et al, 25 out of 26 review papers of HIS/HIT systems about system quality focused on the functionality of the system, and only one of them looked at the security issue, as shown in Figure 2.3. Thus we will concentrate on functionality and take it as one of the influential instrument of healthcare information system performance. The term “functionality” represents the range of operations that runs on a HIS/HIT system. Example of functionality include: the implementation of CPOE (Ammenwerth, Schnell-Inderst, Machan, & Siebert, 2008), the adoption of EMR and EHR (Hsiao et al., 2009). To specify the data processing and quantify the data, we will check the usage status of some important HIS/HIT systems, such as CPOE. Therefore the term “implementation” is used rather than “functionality” to represent the HIS quality of layer 1. Similarly, we adopt the element “use” to capture how intense the HIS/HIT systems might be operated by the hospitals. The amount of patient cases taken can be used to estimate the service volume, such as outpatient visits and number of admitted patients per year. And finally, the net benefits will be represented as “performance”. We are examing the financial performance, from the aspects of both cost and revenue. The measurement of performance has been discussed in section 2.4.

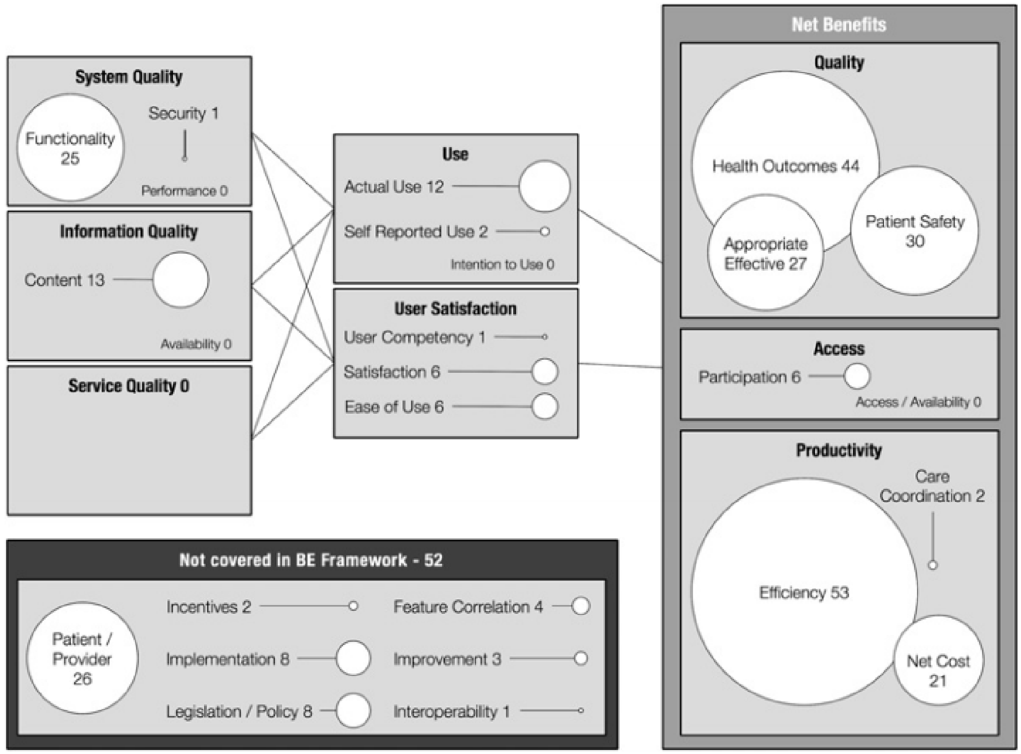

Figure 2.3 Distribution of Health Information Systems by Categories

Based on the Information System Success model, we propose the first two hypotheses. Because institutional theory describes the development process of an institution, we assume that the operational status of big and small hospitals will differ, as well as their profitable status. We will test H1 and H2 and all the other hypotheses for all hospitals and for small and big hospitals individually. Moreover, we are measuring the financial performance of hospitals from two aspects: costs and revenue. Better performance means lower average costs and higher average revenue. As a result, six models will be tested: the cost model for all hospitals, the cost model for big hospitals, the cost model for small hospitals, the revenue model for all hospitals, the revenue model for big hospitals, and the revenue model for small hospitals. We will check the model fit and the hypotheses for each of the six models. The first two hypotheses are stated as follows:

H1: The level of *IT Implementation* has an effect on the *service volume*.

H2: *Service volume* is positively related with *Performance*, leading to higher revenue and lower cost.

Looking at Information System Success model, IT implementation should be only related with IT utilization, and IT utilization is the mediator between IT implementation and performance. Because the impact of IT implementation to performance has been widely studied, we will also test whether such relationship differs for big and small hospitals.

H3: *IT implementation* is positively related with *performance,* leading to higher revenue and lower cost.

As we are examining different hospital groups for big and small ones, size may be a factor that interferences the implementation and utilization status of

HIS/HIT systems. Moreover, before certain HIS/HIT systems are adopted, some hospitals may have set up a comprehensive plan to solve particular problems, such as reducing medical errors, reducing the number of software vendors and switching toward a paperless environment; but some hospitals may just follow the government regulations. Little work has been done to study hospital efforts in planning of HIS/HIT. Thus we will also add IS plan effort as another moderator. The last two hypotheses are presented as follows:

H4: *Size* interferes the relationship among *IT implementation*, *service volume* and *performance*.

H5: *IS Plan* interferes the relationship among *IT implementation*, *service volume* and *performance*.

Now we may fit into the testing framework with five hypotheses. The moderating effects of size are to be tested by looking at the relationships between size and service volume, size and performance, and size and IT implementation. Only when size is significantly related with both the service volume/IT implementation and performance at the same time, will we say that size is a moderator of service volume/IT implementation. The same testing procedure is followed for IS plan. The testing framework and hypotheses are summarized in Figure 2.4.

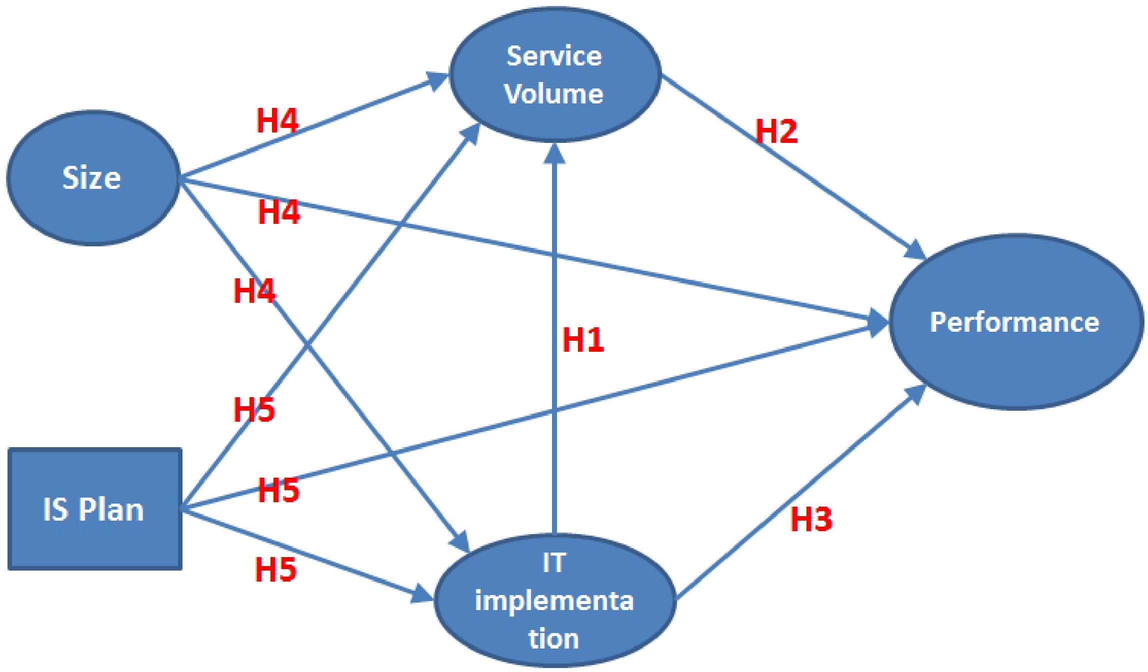

Figure 2.4 Testing Framework for Hypotheses

CHAPTER 3

EMPIRICAL STUDY WITH HIMSS DATA: THE VALUE OF IT

3.1 Data Description

The HIMSS (Healthcare Information and Management System Society) is a non-profit organization in existence since 1961. The main goal of HIMSS is to promote better health through Information Technology (IT). Our research uses the HIMSS 2014 analytics database. It contains the information for 5436 U.S. hospitals and 659 Canadian hospitals. Our current stage focuses on only the U.S. ones.

To identify the implementation of IT in U.S. hospitals, as well as the impact of IT on these hospitals, we specifically focus on several research questions as follows:

- What are the influential factors of hospital performance?
- Do Information Systems play a role to improve hospital performance? If so, what's the mechanism allowing IS to influence the performance?
- For different types of hospitals, does IS affect the performance differently? If so, why?

IS (Information System) in this research is defined as a system that processes or interprets information among hospitals in order to benefit information transmission, exchange and sharing, such as CPOE (Computerized Physician Order Entry), CCD (Computer Information Systems) and EMR

(Electronic Medical Record). Some other diagnosing systems such as MRI (Magnetic Resonance Imaging) are not included in our definition of IS.

The statistics for the original sample are summarized in the following Tables and Figure: Table 3.1 shows the number of different types of hospitals; Table 3.2 shows the number of different size of hospitals by number of beds; and Figure 3.1 illustrates the number of hospitals by state.

Type of Hospital	**Data point number of each type**
Academic	209
Acute Psychiatric	2
Acute Rehabilitation	1
Cardiology	16
Critical Access	1332
Eye, Ear, Nose & Throat	5
General Medical	**49**
General Medical & Surgical	**3115**
Long Term Acute	376
Oncology	12
Orthopedic	24
Other Specialty	176
Pediatric	95
Pediatric, Women's Health	7
Women's Health	17

Table 3.1 Type of Hospitals.

# of beds each hospital	# of hospitals
Less than 100	2890
101~200	972
201~300	602
301~400	399
401~500	234
501~600	148
601~700	71
701~800	47
801~900	32
901~1000	23
More than 1001	18

Table 3.2 Number of Hospitals by Size (Number of Beds)

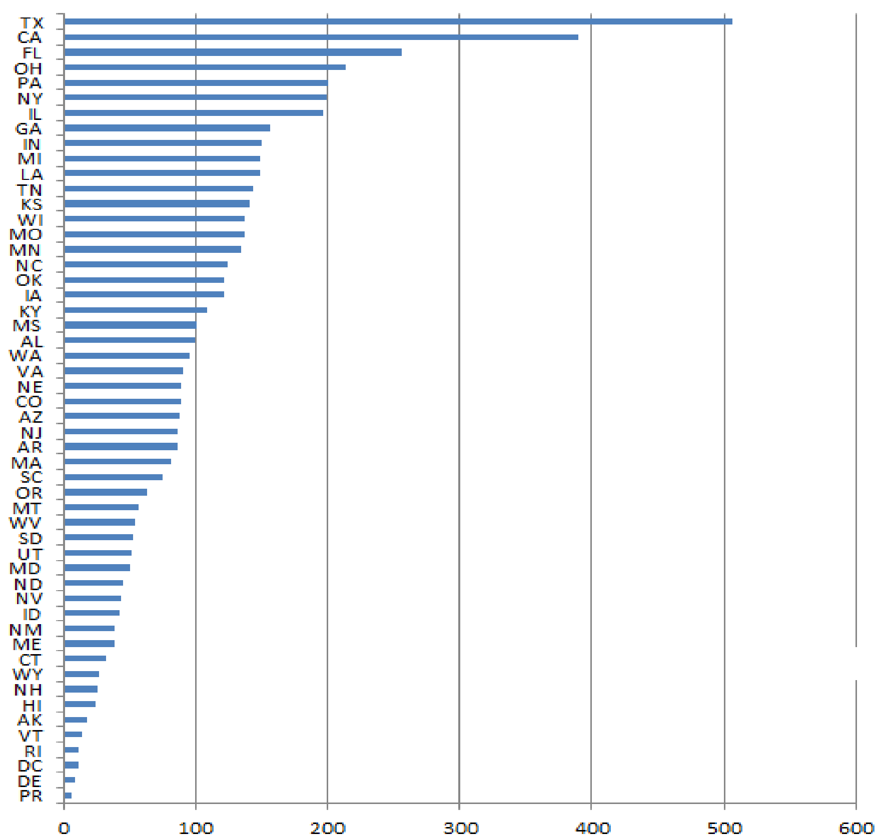

Figure 3.1 Number of Hospitals by State

In terms of IT implementation, we looked at the statistics on how hospitals conduct IT implementation plans and utilized different IT systems. Descriptive statistics for hospital IS implementation status are as follows:

68.4% (3718 out of 5436) data points have the percentage range of all medical orders entered by physicians using CPOE. The distribution is as Table 3.3:

CPOE adoption rate	#of hospitals	percentage
76-100%	2046	55%
51-75%	646	17%
26-50%	584	16%
1-25%	442	12%

Table 3.3 CPOE Adoption Status

82.7% (4494 out of 5436) data points have the percent range of the hospital's current medical record that is electronic (includes digital and/or scanned data). The distribution is as Table 3.4:

EMR percentage	# of hospitals	percentage
76-100%	2614	58%
51-75%	863	19%
26-50%	496	11%
1-25%	520	12%

Table 3.4 EMR Adoption Status

80.6% (4381 out of 5436) data points have adoption status of CCD. The distribution is as Table 3.5:

	# of hospitals	percentage
Using CCD	1708	39%
Not using CCD	2673	61%

Table 3.5 CCD Adoption Status

3.2 Model Construction

There are two types of moderators: Size and IS Plan. Size is represented by the number of beds and the number of full time employees of the hospital. The IS Plan means whether a hospital has set up a conductible plan in the following five areas:

ISPlan_id1	Integration issues
ISPlan_id2	Reducing the number of software vendors
ISPlan_id3	Migrating toward a paperless environment
ISPlan_id4	Decreasing medical errors
ISPlan_id5	Computerized patient record

Table 3.6 IS Plan Detail

If a hospital has conducted an IS plan in a particular area, we assign a score of 1, or the score is 0 for the particular IS Plan id. The total score of the five areas ranging from 0 to 5 measures the degree of how a hospital makes an effort to set up IS Plans.

The full analysis model is represented in Figure 3.2. Performance is to measured from cost and revenue. Cost is a latent varibale represented by the avegarge payroll expense (payroll expense divided by number of full time employees) and average operatinal cost (operatinal cost divided by number of full time employees). Similarly, revenue is an other latent variable and it is represented by average patient revenue (patient revenue divided by number of full time employees) and average operational revenue revenue (operational revenue divided by number of full time employees). The variables to represent each instruments are sumarrized in Table 3.7.

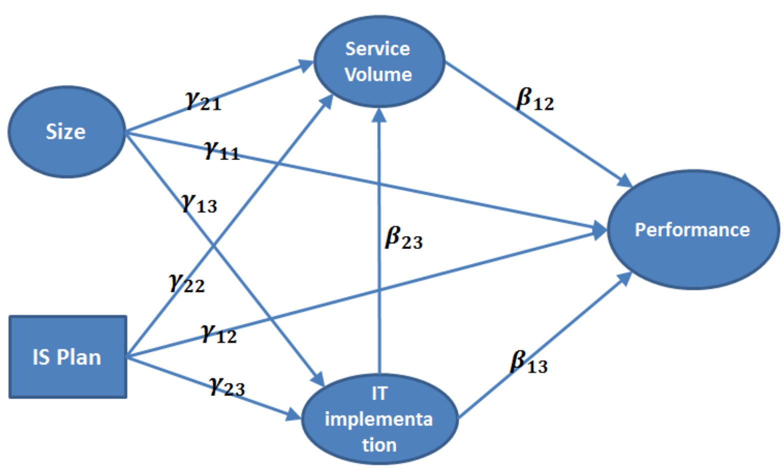

Figure 3.2 Framework of Analysis

Element Category	Variable Name	Element Name	Description
Performance	Pay	PayrollExpense	Payroll expense for a 12-month period, this includes all salaries and wage expenses.
	Oexp	TotalOperExpense	The total amount of money the Acute-Care Hospital spends on operations such as staffing, property expenses, etc. for the most recent fiscal year.
	Orev	NetOperRevenue	Net operating revenue includes revenues associated with the main operations of the hospital (net inpatient+ net outpatient revenue). It does not include dividends, interest income or non-operating income.
	PatRvn	NetPatientRevenue	Net Patient Revenue in hospitals, is gross inpatient revenue plus gross outpatient revenue minus related deductions from revenue.
Service Volume	AHA	AHAAdmissions	Number of Admissions which includes the number of adult and pediatric admissions only (excluding births). This number includes all patients admitted during a 12-month reporting period, including neonatal and swing admissions.
	NoOp	NofOutpatientVisits	Number of outpatient visits at each Acute-Care Hospital in the most recent fiscal year.
	Disch	NofTotDischarge	The total number of patients discharged from the hospital in a calendar year
	PatD	NofTotPatientDays	The number of calendar days of care provided for hospital inpatient treatment under the terms of the patient's health plan, excluding the day of discharge
Size	Size	NofBeds	Number of Licensed Beds
	NoFTE	NofFTE	Total number of FTEs

Table 3.7 Data Elements and Instruments

Table 3.7 Continued

IT Implementation	CPOE	CPOEMandated	Yes = healthcare system mandated that physicians utilize CPOE system
	CCD	CCD_Transaction	Yes = the hospital is using HL7 CCD (continuum of care document) transactions to share patient data with other organizations?
	EMRP	ElectronicMedRecPerc	The percent range of the hospital's current medical record that is electronic (includes digital and/or scanned data) (see tab AS-Perc Ranges)
IS Plan		ISPlan_id1	Integration issues
		ISPlan_id2	Reducing the number of software vendors
		ISPlan_id3	Migrating toward a paperless environment
		ISPlan_id4	Decreasing medical errors
		ISPlan_id5	Computerized patient record
	ISPlan	ISPlan_Score	The value ranging from 1~5 to measure the IS Plan degree

The general form of the structural equation is (L. X. Li, 1997):

$$y = \beta y + \gamma x + \varepsilon$$

Where:

$y =$ a p*1 vector of depedent variables measured without error

$\beta =$a p*p matrix of coefficients relating p depent variables to one another

$x =$ a q*1 vector of indepedent variables measured without error

$\gamma =$ a p*q matrix of coefficients relating q indepent variables to the p dependent variables

$\varepsilon =$ a p*1 vector of errors in the equation

In our case, the structural equations for the hypothesized relationships are written as follows:

$$\begin{bmatrix} Performace \\ ServiceVolumn \\ ITImplementation \end{bmatrix} = \begin{bmatrix} 0 & \boldsymbol{\beta_{12}} & \boldsymbol{\beta_{13}} \\ 0 & 0 & \boldsymbol{\beta_{23}} \\ 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} Performace \\ ServiceVolumn \\ ITImplementation \end{bmatrix}$$

$$+ \begin{bmatrix} \boldsymbol{\gamma_{11}} & \boldsymbol{\gamma_{12}} \\ \boldsymbol{\gamma_{21}} & \boldsymbol{\gamma_{22}} \\ \boldsymbol{\gamma_{31}} & \boldsymbol{\gamma_{32}} \end{bmatrix} \begin{bmatrix} HSize \\ ISPlan \end{bmatrix} + \begin{bmatrix} \boldsymbol{\varepsilon_1} \\ \boldsymbol{\varepsilon_2} \\ \boldsymbol{\varepsilon_3} \end{bmatrix}$$

3.3 Data Preparation

There are 3164 General Medical & Surgical Hospitals in the U.S., as shown in Table 3.8. In our research, we only looked at General Medical and General Medical & Surgical Hospitals. To begin, 120 elements potentially related to the hospital performance were selected and grouped into six categories. These six categories are: performance by cost, performance by revenue, service volume, IT implementation status, size, and IS plan status.

Type of Hospital	Data point number of each type
Academic	209
Acute Psychiatric	2
Acute Rehabilitation	1
Cardiology	16
Critical Access	1332
Eye, Ear, Nose & Throat	5
General Medical	**49**
General Medical & Surgical	**3115**
Long Term Acute	376
Oncology	12
Orthopedic	24
Other Specialty	176
Pediatric	95
Pediatric, Women's Health	7
Women's Health	17

Table 3.8 Type of Hospitals

Since missing data exist, we selected the datasets with no missing data for each of the instruments (Performance, Service volume, Size, IS implementation, IS plan) and variables, as shown in Table 3.8. Because larger hospitals are more likely to provide a comprehensive report, the ratio of the large hospitals (#bed>100) in our 522 data sample is much bigger than that of the original 3164 hospital dataset.

There are 4 ranges of element “ElectronicMedRecPerc”, recoded as EMR score 4, 3, 2 and 1 respectively (Table 3.9). Now all the variable elements are represented in numerical values.

EMR percentage	Recode
76-100%	4
51-75%	3
26-50%	2
1-25%	1

Table 3.9 Coding for EMR Adoption Status

3.4 Model Fit Analysis

To examine how the IT investment affects the hospital performance, and how such effect differs for different type of hospitals, we separate our data sample into two groups: the big hospitals with more than 100 beds, and small hospitals with equal to or less than 100 beds. Six models were tested to check the model's fit for hypotheses: the cost model for all hospitals, the cost model for big hospitals, the cost model for small hospitals, the revenue model for all hospitals, the revenue model for big hospitals, and the revenue model for small hospitals. By comparing the fit results of the three groups, any differing effect of IT can be revealed.

3.4.1 The Cost Model for All Hospitals

First of all, we examined the cost model which contain 522 datasets, both the large(#beds>100) and small hospitals (#beds=<100). The average payment and average operational expense are the total payroll expense and total operational expense divided by number of full time employees. The result of the complete model is provided in Figure 3.3 (covariance links are added according to the initial output). Insignificant paths were highlighted according to the p value of each path load.

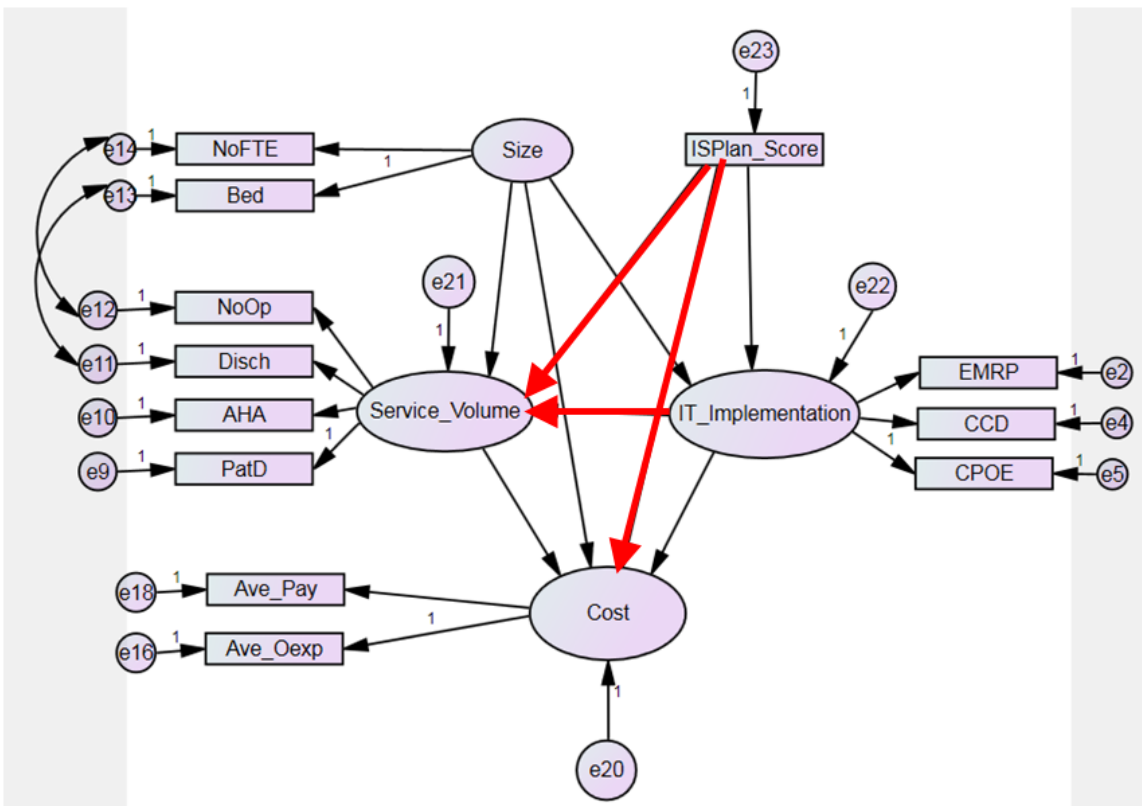

Figure 3.3 Insignificant Paths in the Complete Cost Model for All Hospitals

Hu and Bentler indicate that model fit is acceptable when CMIN/DF is below 5 and preferably below 3 (Hu & Bentler, 1999). Lei and Wu (2007) later provided a comprehensive summary of common fit indices(Lei & Wu, 2007). In their example analyses, they used the standardized root mean square residual (SRMR), the root mean square error of approximation (RMSEA), the likelihood ratio chi-square goodness of fit statistic, and sometimes the confirmatory fit index (CFI). According to their model fit criteria, our proposed model is acceptable (Table 3.10). Absolute fit is evidenced by the CMIN/DF of 2.033 being below the preferable cut-off of 3, and the SRMR of 0.0379 being below the suggested cut-off of 0.08, and the CFI of 0.992 being higher than the suggested cut-off of 0.95, and the RMSEA of 0.045 being below the suggested cut-off of 0.06 (Lei & Wu, 2007).

Default model
Standardized RMR = .0379

Model	NPAR	CMIN	DF	P	CMIN/DF
Default model	34	89.434	44	.000	2.033
Saturated model	78	.000	0		
Independence model	12	5479.007	66	.000	83.015

Model	NFI Delta1	RFI rho1	IFI Delta2	TLI rho2	CFI
Default model	.984	.976	.992	.987	.992
Saturated model	1.000		1.000		1.000
Independence model	.000	.000	.000	.000	.000

Model	RMSEA	LO 90	HI 90	PCLOSE
Default model	.045	.031	.058	.738
Independence model	.397	.388	.406	.000

Table 3.10 Model Fit Results of the Complete Cost Model for All Hospitals

However, when looking at the individual regression weights, some of the path parameters were not significant (Table 3.11):

			Estimate	S.E.	C.R.	P	Label
IT_Implementation	<---	ISPlan_Score	.034	.009	3.732	***	
IT_Implementation	<---	Size	.000	.000	2.574	.010	
Service_Volume	<---	Size	250.755	6.148	40.787	***	
Service_Volume	<---	ISPlan_Score	-190.591	351.282	-.543	.587	
Service_Volume	<---	IT_Implementation	247.609	3301.550	.075	.940	
Cost	<---	IT_Implementation	39769.382	13180.738	3.017	.003	
Cost	<---	Size	-770.079	249.232	-3.090	.002	
Cost	<---	Service_Volume	3.097	.964	3.212	.001	
Cost	<---	ISPlan_Score	552.996	1337.658	.413	.679	
CPOE	<---	IT_Implementation	1.000				
PatD	<---	Service_Volume	1.000				
AHA	<---	Service_Volume	.204	.002	82.290	***	
Disch	<---	Service_Volume	.203	.002	83.585	***	
NoOp	<---	Service_Volume	3.056	.203	15.030	***	
Bed	<---	Size	1.000				
NoFTE	<---	Size	6.345	.176	36.013	***	
Ave_Oexp	<---	Cost	1.000				
Ave_Pay	<---	Cost	.364	.052	6.970	***	
EMRP	<---	IT_Implementation	1.417	.248	5.703	***	
CCD	<---	IT_Implementation	.624	.122	5.108	***	

Table 3.11 Paths of Complete Cost Model for All Hospitals

To represent the model modification, we delete the path from the one with largest P value according to the suggested fit index (Lei & Wu, 2007). The model fit statistics for each step are summarized in Table 3.12:

Model fit statistics	Indicator Cut-Off	Model A (Complete model)	Model B (IT_Implementation=> Service_Volume)	Model C (delete ISPlan_Score => Cost)	Model D (ISPlan_Score=>Service_Volume)
CMIN/Df	< 3	2.033	1.988	1.948	1.909
SRMR	<.05	.0379	.0379	.0374	.0369
CFI	>.95	.992	.992	.992	.992
RMSEA	<.05	.045	.044	.043	.042
Number of insignificant paths (ordered from the biggest p-value)		3 paths: IT_Implementation=> Service_Volume ISPlan_Score => Cost ISPlan_Score =>Service_Volume	2 paths: ISPlan_Score => Cost ISPlan_Score=>Service_Volume	1 path: ISPlan_Score=>Service_Volume	0 path

Table 3.12 Adjust from the Complete Model

The adjusted cost model with all paths significant is shown in Figure 3.4:

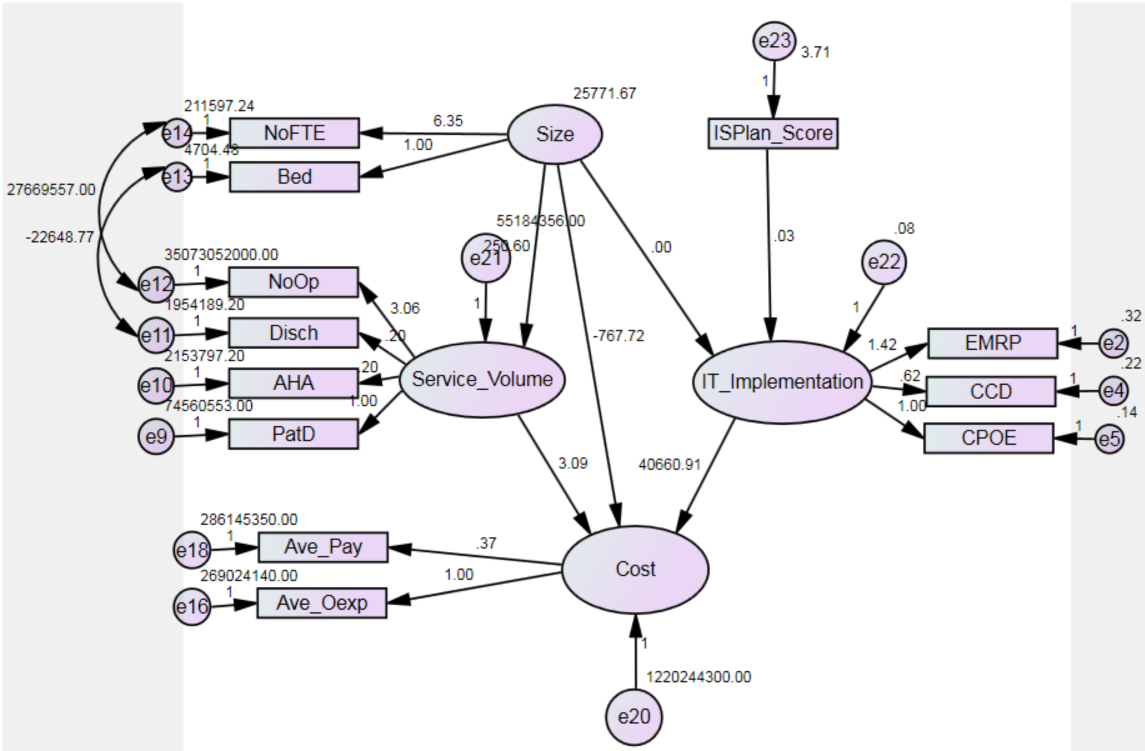

Figure 3.4 Result of the Adjusted Cost Model for All Hospitals

The final structural equations for the hypothesized relationships are written as follows:

$$\begin{bmatrix} Cost \\ ServiceVolume \\ ITImplementation \end{bmatrix} = \begin{bmatrix} 0 & 3.09 & 40660.908 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} Cost \\ ServiceVolume \\ ITImplementation \end{bmatrix}$$

$$+ \begin{bmatrix} -767.72 & 0 \\ 250.604 & 0 \\ 0 & .034 \end{bmatrix} \begin{bmatrix} Size \\ ISPlan \end{bmatrix} + \begin{bmatrix} \boldsymbol{\varepsilon_{11}} \\ \boldsymbol{\varepsilon_{12}} \\ \boldsymbol{\varepsilon_{13}} \end{bmatrix}$$

In the cost model for all hospitals, H1 is rejected, that is, It implementation has no significant affect to IT utilization. H2 and H3 were rejected: the service volume and the implementation are two significant factors which increase the hospital cost. We also accepted H4 that size is negatively related with cost and positively related with service volume and IT implementation. In other words, bigger hospitals tend to implement HIS/HIS systems more intensively, have higher service volume and are receiving lower average cost. H5 is also rejected based on the fact that IS plan is only directly related with IT implementation. That is, if well planned, HIS/HIT systems are more likely to implement well.

3.4.2 The Cost Model for Small Hospitals

For the second scenario, we examined the cost model of 138 small hospitals (Figure 3.5). The original complete model is acceptable; however, 7 paths were not significant (Table 3.13). The number of insignificant paths is more than those of the mixed model. This result suggests that other uncertainties may exist which lead to the costs of small hospitals.

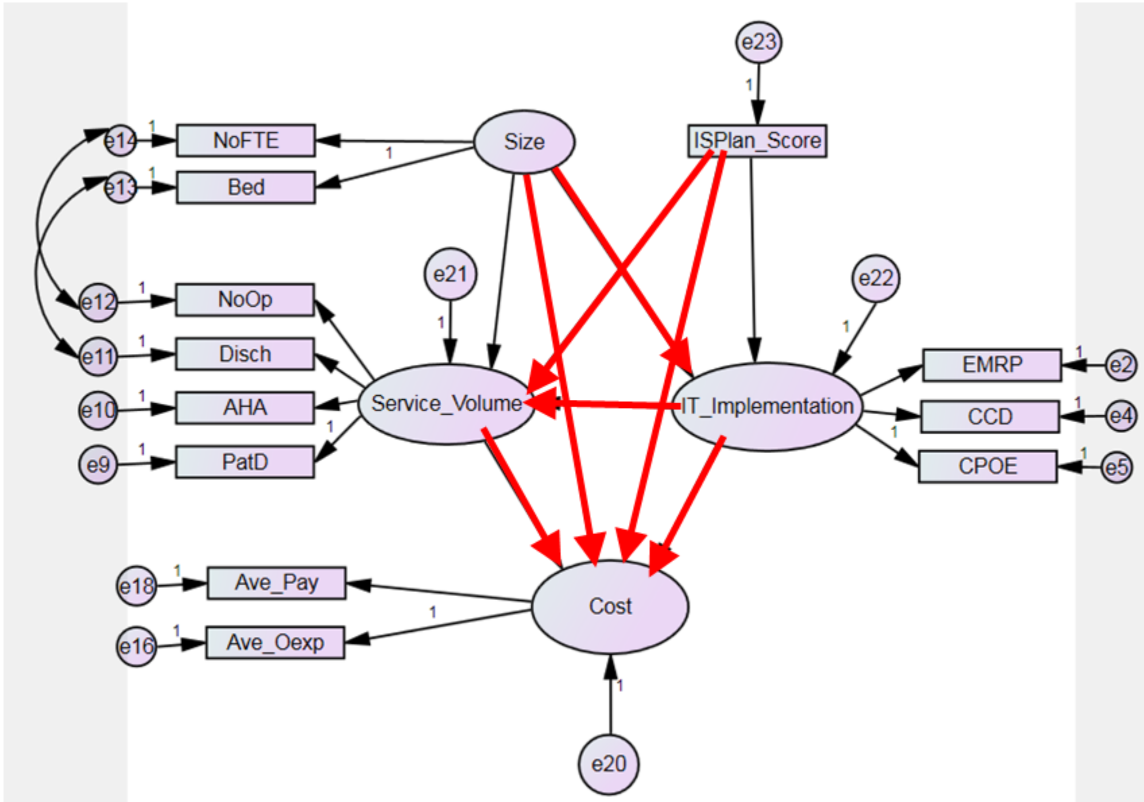

Figure 3.5 Insignificant Paths in the Complete Cost Model for Small hospitals

			Estimate	S.E.	C.R.	P	Label
IT_Implementation	<---	ISPlan_Score	.059	.018	3.337	***	
IT_Implementation	<---	Size	.000	.003	.021	.983	
Service_Volume	<---	Size	348.473	54.811	6.358	***	
Service_Volume	<---	ISPlan_Score	-184.021	160.312	-1.148	.251	
Service_Volume	<---	IT_Implementation	2186.463	1824.945	1.198	.231	
Cost	<---	IT_Implementation	73830.156	52221.930	1.414	.157	
Cost	<---	Size	4480.650	6393.619	.701	.483	
Cost	<---	Service_Volume	-10.047	19.724	-.509	.610	
Cost	<---	ISPlan_Score	-1766.244	4646.879	-.380	.704	
CPOE	<---	IT_Implementation	1.000				
PatD	<---	Service_Volume	1.000				
AHA	<---	Service_Volume	.286	.024	12.044	***	
Disch	<---	Service_Volume	.287	.029	9.787	***	
NoOp	<---	Service_Volume	4.090	.892	4.583	***	
Bed	<---	Size	1.000				
NoFTE	<---	Size	9.066	1.293	7.010	***	
Ave_Oexp	<---	Cost	1.000				
Ave_Pay	<---	Cost	.397	.067	5.962	***	
EMRP	<---	IT_Implementation	1.260	.407	3.095	.002	
CCD	<---	IT_Implementation	.477	.208	2.294	.022	

Table 3.13 Paths of the Complete Cost Model for Small Hospitals

Following the same processing procedure as was used for the model of all hospitals in the section 3.4.1, we removed the insignificant paths one by one from the one with largest P value until all the paths were significant (Figure 3.6). In the cost model with small hospitals, only H4 was accepted. Size interferes the relationship among IT implementation and the cost, but now bigger size means more costs for small hospitals. The relationship between service volume and cost disappears.

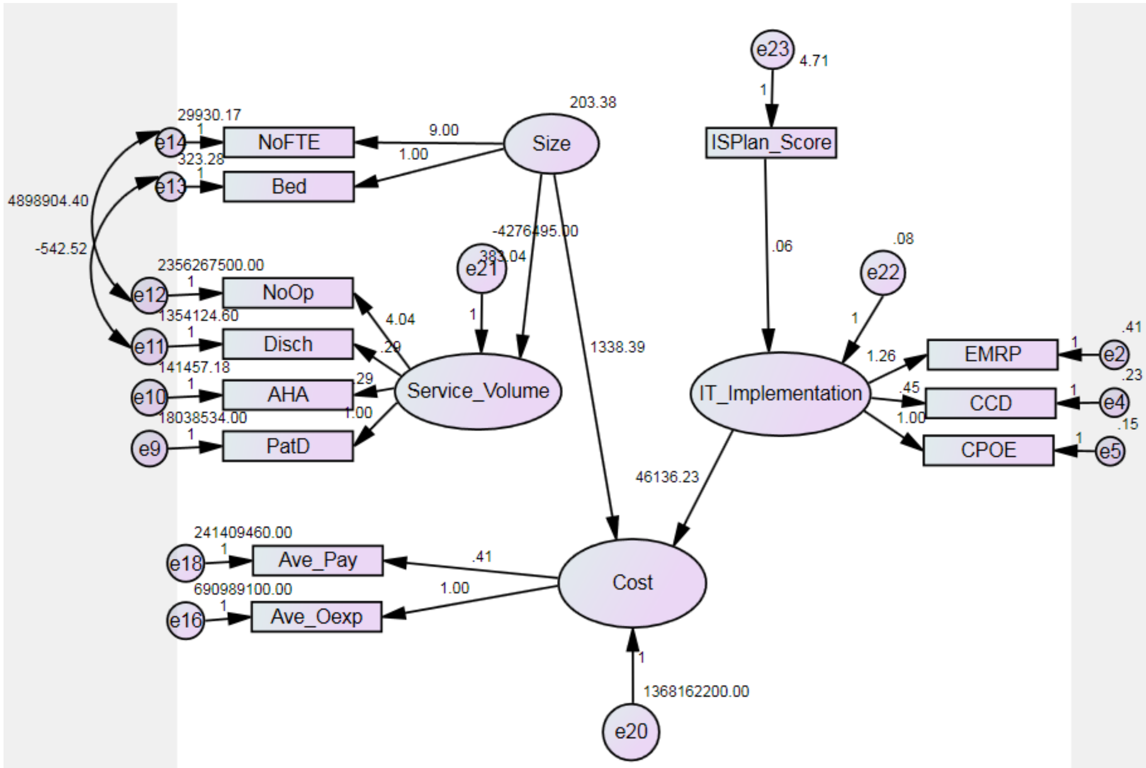

Figure 3.6 Result of the Adjusted Cost Model for Small Hospitals

As a result, the structural equation for the small hospitals is written as follows

$$\begin{bmatrix} Cost' \\ ServiceVolume' \\ ITImplementation' \end{bmatrix} = \begin{bmatrix} 0 & 0 & 46136.23 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} Cost' \\ ServiceVolume' \\ ITImplementation' \end{bmatrix}$$

$$+ \begin{bmatrix} 1338.389 & 0 \\ 383.04 & 0 \\ 0 & .06 \end{bmatrix} \begin{bmatrix} HSize' \\ ISPlan' \end{bmatrix} + \begin{bmatrix} \boldsymbol{\varepsilon}_{21} \\ \boldsymbol{\varepsilon}_{22} \\ \boldsymbol{\varepsilon}_{23} \end{bmatrix}$$

3.4.3 The Cost Model for Big Hospitals

The cost model for big hospitals tests the model fit with the dataset containing 384 big hospitals (Figure 3.7), the ones with more than 100 beds. The original complete model is overall acceptable and four paths are not significant, as shown in Table 3.14.

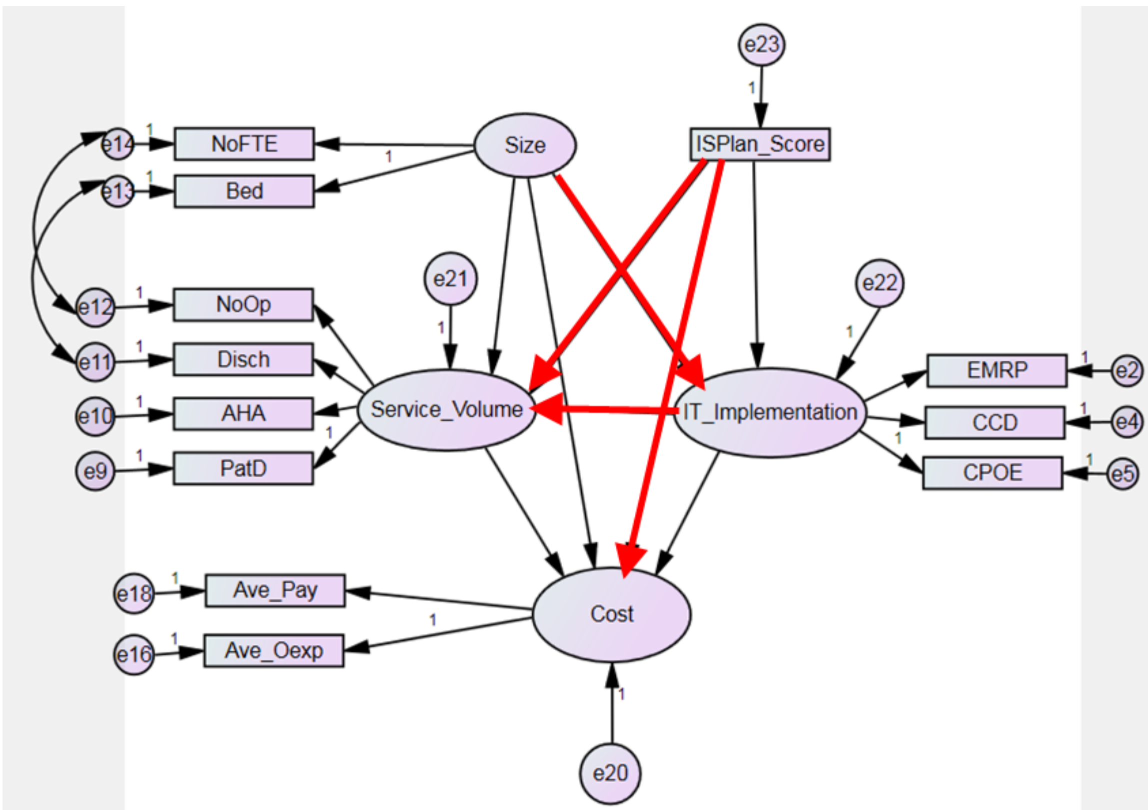

Figure 3.7 Insignificant paths in the Complete Cost Model for Big hospitals

			Estimate	S.E.	C.R.	P	Label
IT_Implementation	<---	ISPlan_Score	.019	.010	1.975	.048	
IT_Implementation	<---	Size	.000	.000	1.701	.089	
Service_Volume	<---	Size	270.375	9.522	28.394	***	
Service_Volume	<---	IT_Implementation	8.847	4867.900	.002	.999	
Service_Volume	<---	ISPlan_Score	-268.622	493.796	-.544	.586	
Cost	<---	IT_Implementation	42546.982	15978.845	2.663	.008	
Cost	<---	Size	-741.112	249.460	-2.971	.003	
Cost	<---	ISPlan_Score	-266.433	1559.590	-.171	.864	
Cost	<---	Service_Volume	2.693	.882	3.055	.002	
CPOE	<---	IT_Implementation	1.000				
PatD	<---	Service_Volume	1.000				
AHA	<---	Service_Volume	.200	.003	61.310	***	
Disch	<---	Service_Volume	.201	.003	64.436	***	
NoOp	<---	Service_Volume	2.977	.277	10.767	***	
Bed	<---	Size	1.000				
NoFTE	<---	Size	6.916	.267	25.932	***	
Ave_Oexp	<---	Cost	1.000				
Ave_Pay	<---	Cost	.377	.061	6.186	***	
EMRP	<---	IT_Implementation	1.791	.376	4.762	***	
CCD	<---	IT_Implementation	.751	.160	4.707	***	

Table 3.14 Paths of the Complete Cost Model for Big Hospitals

Similar to the adjusting process in section 3.4.1 and section 3.4.2, the insignificant paths were removed one by one from the one with largest P value until all the paths are significant (Figure 3.8). The same as the other two cost models, only H4 was accepted. That is, size interferes the relationship between service volume, IT implementation and costs. The bigger the size is, the less the cost spent. Comparing with the other two cost models, the path between IS plan and IT implementation disappears. It means that for big hospitals, IS planning has nothing to do with IT implementation status. There may be other factors (such as government policy, previous program) affecting the adoption of HIS/HIT systems.

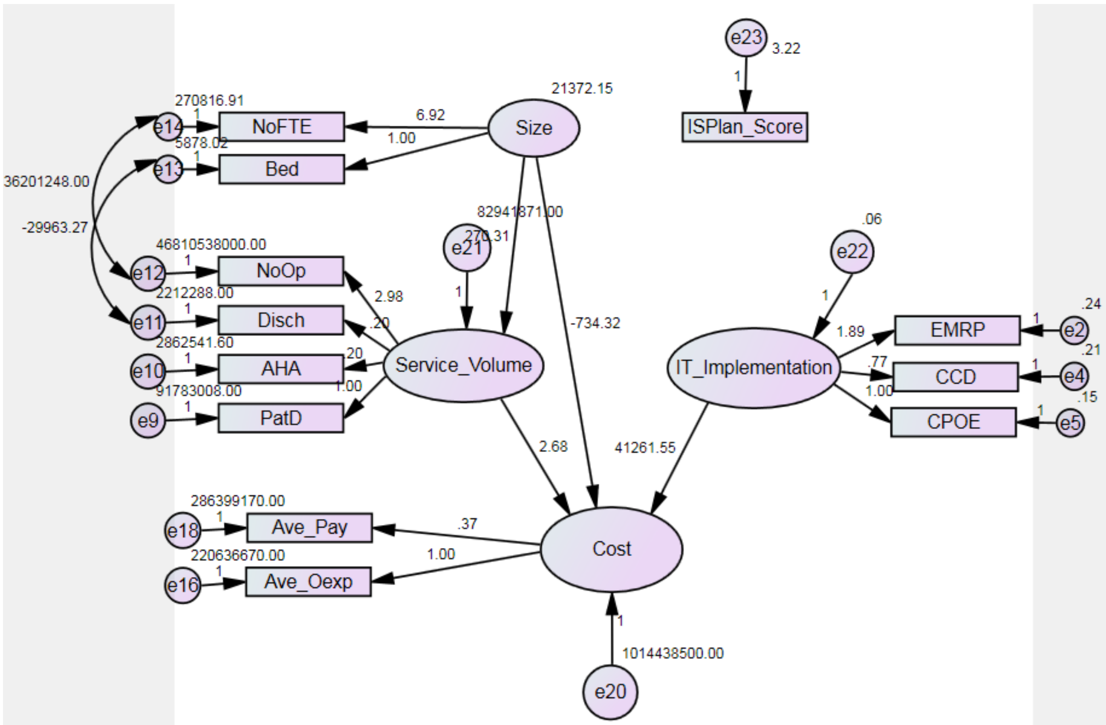

Figure 3.8 Result of the Adjusted Cost Model for Big Hospitals

As a result, the structural equation for the small hospitals is written as follows

$$\begin{bmatrix} Cost'' \\ ServiceVolume'' \\ ITImplementation'' \end{bmatrix} = \begin{bmatrix} 0 & 0 & 41261.554 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} Cost'' \\ ServiceVolume'' \\ ITImplementation'' \end{bmatrix}$$

$$+ \begin{bmatrix} -734.321 & 0 \\ 270.306 & 0 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} HSize'' \\ ISPlan'' \end{bmatrix} + \begin{bmatrix} \boldsymbol{\varepsilon_{31}} \\ \boldsymbol{\varepsilon_{32}} \\ \boldsymbol{\varepsilon_{33}} \end{bmatrix}$$

3.4.4 The Revenue Model for All Hospitals

Section 3.4.4 to 3.4.6 will repeat the processing steps for cost models in section 3.3.1 to 3.3.1. The complete model revenue model for all hospitals is constructed similarly. We take the patient revenue and operational revenue of hospitals divided by number of full time employees to represent the factor of revenue. In the complete revenue model with all 522 hospitals, the insignificant paths are highlighted in Figure 3.9 and Table 3.15.

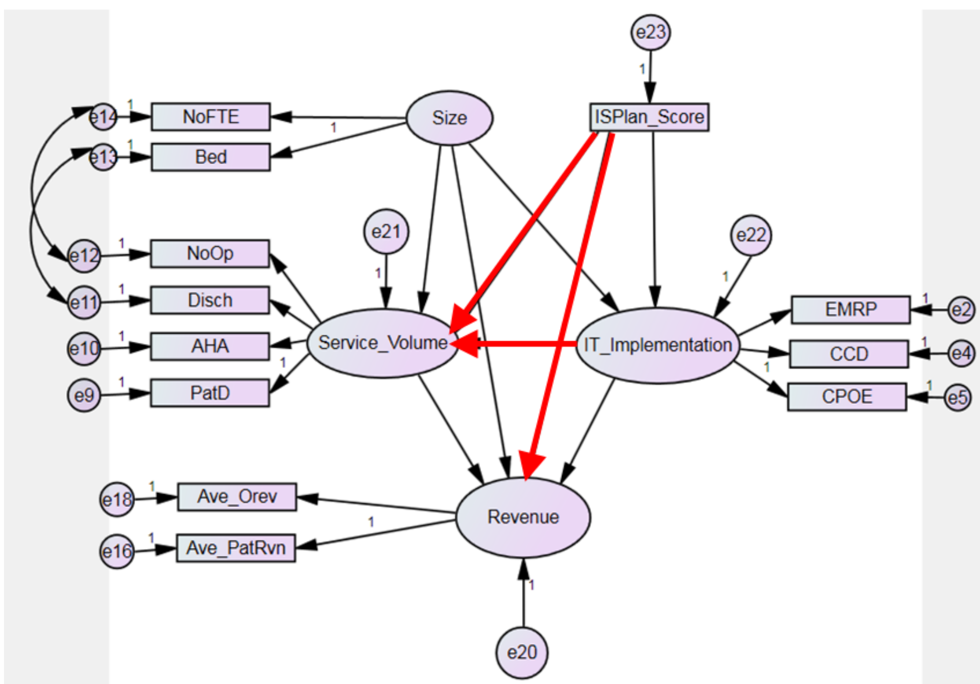

Figure 3.9 Insignificant Paths in the Complete Revenue Model for All hospitals

			Estimate	S.E.	C.R.	P	Label
IT_Implementation	<---	ISPlan_Score	.033	.009	3.737	***	
IT_Implementation	<---	Size	.000	.000	2.535	.011	
Service_Volume	<---	Size	251.033	6.204	40.462	***	
Service_Volume	<---	ISPlan_Score	-197.416	352.145	-.561	.575	
Service_Volume	<---	IT_Implementation	485.925	3349.550	.145	.885	
Revenue	<---	IT_Implementation	44524.232	16560.288	2.689	.007	
Revenue	<---	Size	-1158.005	332.220	-3.486	***	
Revenue	<---	Service_Volume	4.653	1.282	3.629	***	
Revenue	<---	ISPlan_Score	1912.691	1675.960	1.141	.254	
CPOE	<---	IT_Implementation	1.000				
PatD	<---	Service_Volume	1.000				
AHA	<---	Service_Volume	.204	.002	82.149	***	
Disch	<---	Service_Volume	.203	.002	83.538	***	
NoOp	<---	Service_Volume	3.059	.203	15.037	***	
Bed	<---	Size	1.000				
NoFTE	<---	Size	6.376	.176	36.289	***	
Ave_PatRvn	<---	Revenue	1.000				
Ave_Orev	<---	Revenue	.923	.038	24.190	***	
EMRP	<---	IT_Implementation	1.427	.248	5.752	***	
CCD	<---	IT_Implementation	.653	.125	5.219	***	

Table 3.15 Paths of the Complete Revenue Model for All Hospitals

After the insignificant paths being removed, the adjusted revenue model for all hospitals is shown in Figure 3.10. The path distribution and their pattern of all hospitals are quite similar in the revenue model and the cost model. However, cost and revenue are two opposite indicators of performance: lower cost and higher revenue mean better performance, and higher cost and lower revenue mean worse performance. As a result, H1 is rejected as the path between IT implementation and service volume is insignificant. We accept H2 and H3 because both service volume and IT implementation are significantly positively related with revenue. H4 is still accepted based on the fact that size is a significant moderator. Unlike in the cost model, the factor of size is now harmful to the performance that bigger size will reduces the revenue. Finally, H5 is rejected as IS plan is not directly related with revenue.

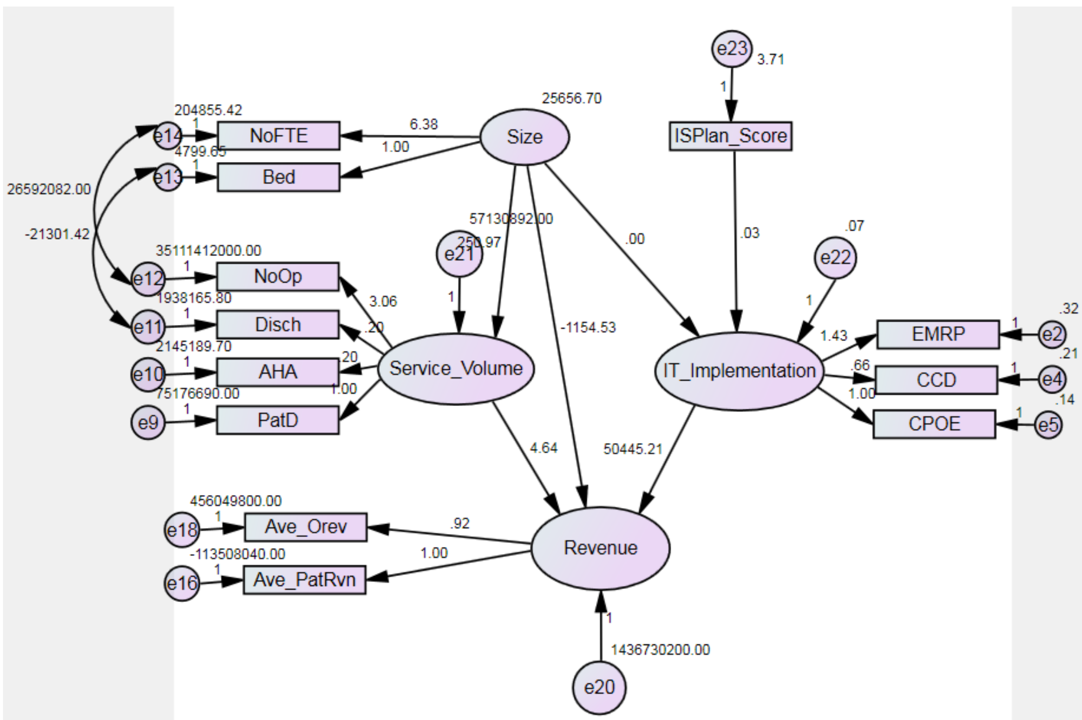

Figure 3.10 Result of the Adjusted Revenue Model for All Hospitals

The structural equation is written as follows:

$$\begin{bmatrix} Revenue \\ ServiceVolume \\ ITImplementation \end{bmatrix} = \begin{bmatrix} 0 & 4.641 & 50445.21 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} Revenue \\ ServiceVolume \\ ITImplementation \end{bmatrix}$$

$$+ \begin{bmatrix} -1154.527 & 0 \\ 250.966 & 0 \\ 0 & .035 \end{bmatrix} \begin{bmatrix} HSize \\ ISPlan \end{bmatrix} + \begin{bmatrix} \boldsymbol{\varepsilon_{41}} \\ \boldsymbol{\varepsilon_{42}} \\ \boldsymbol{\varepsilon_{43}} \end{bmatrix}$$

3.4.5 The Revenue Model for Small Hospitals

The insignificant paths of original complete revenue model for 138 small hospitals are highlighted in Figure 3.11.

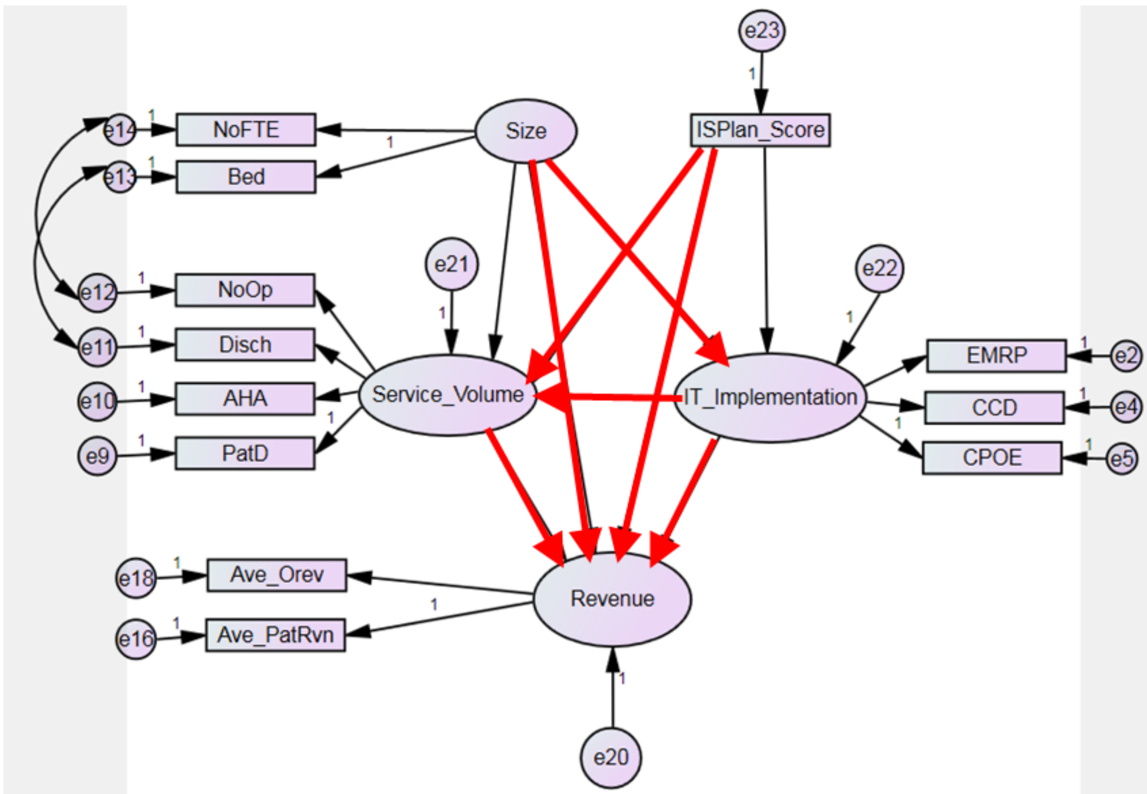

Figure 3.11 Insignificant Paths in the Complete Revenue Model for Small Hospitals

After the insignificant paths are removed, the adjusted revenue model for small hospitals are shown in Figure 3.12. Because sample size is relatively small (138), the adjusted revenue model is acceptable. According to Table 3.16, absolute fit is evidenced by the CMIN/DF of 1.036 being below the preferable cut-off of 3, and the SRMR of 0.0622 being below the suggested cut-off of 0.08, and the CFI of 0.998 being higher than the suggested cut-off of 0.95, and the RMSEA of 0.016 being below the suggested cut-off of 0.06. H3 and H4 are accepted, all others are rejected. For small hospitals, the growth in size and service volume are beneficial to increased revenue.

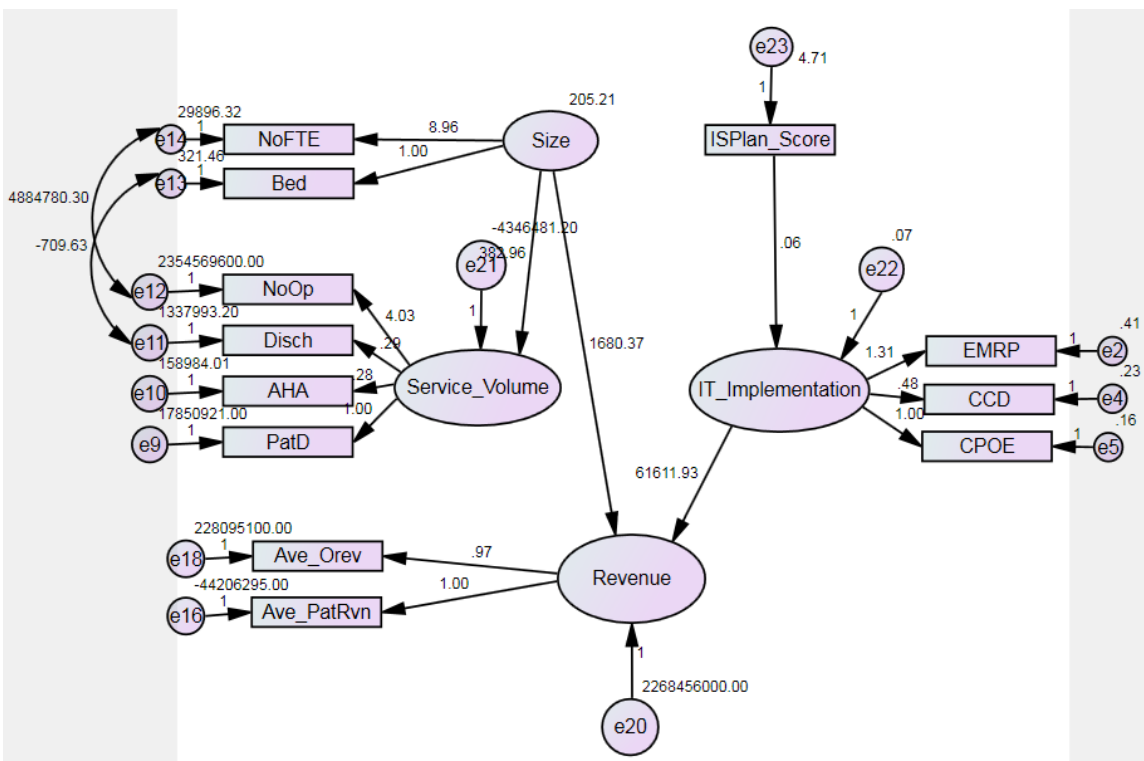

Figure 3.12 Result of the Adjusted Revenue Model for Small hospitals

Default model
Standardized RMR = .0622

Model	NPAR	CMIN	DF	P	CMIN/DF
Default model	29	50.763	49	.404	1.036
Saturated model	78	.000	0		
Independence model	12	974.014	66	.000	14.758

Model	NFI Delta1	RFI rho1	IFI Delta2	TLI rho2	CFI
Default model	.948	.930	.998	.997	.998
Saturated model	1.000		1.000		1.000
Independence model	.000	.000	.000	.000	.000

Model	RMSEA	LO 90	HI 90	PCLOSE
Default model	.016	.000	.058	.885
Independence model	.317	.299	.335	.000

Table 3.16 Model Fit of Adjust Avenue Model for Small Hospitals

The structural equation is written as follows:

$$\begin{bmatrix} Revenue' \\ ServiceVolume' \\ ITImplementation' \end{bmatrix} = \begin{bmatrix} 0 & 0 & 61611.925 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} Revenue' \\ ServiceVolume' \\ ITImplementation' \end{bmatrix}$$

$$+ \begin{bmatrix} 1680.373 & 0 \\ 382.964 & 0 \\ 0 & .061 \end{bmatrix} \begin{bmatrix} HSize' \\ ISPlan' \end{bmatrix} + \begin{bmatrix} \boldsymbol{\varepsilon_{51}} \\ \boldsymbol{\varepsilon_{52}} \\ \boldsymbol{\varepsilon_{3}} \end{bmatrix}$$

3.4.6 The Revenue Model for Big Hospitals

The insignificant paths of original complete revenue model for 384 big hospitals are highlighted in Figure 3.13.

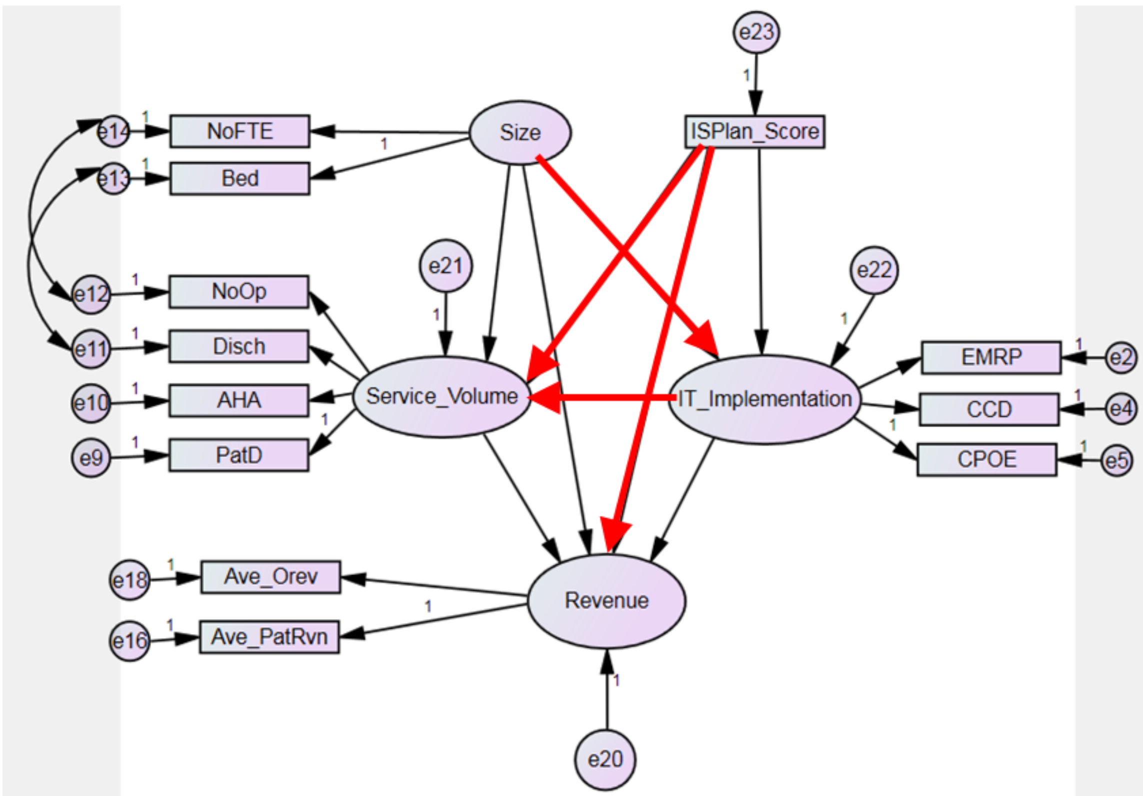

Figure 3.13 Insignificant Paths in the Complete Revenue Model for Big Hospitals

After the insignificant paths were removed, the adjusted revenue model for big hospitals are shown in Figure 3.14. The adjusted revenue model is accepTable and all paths left are significant. H1 and H5 are still rejected. H2, H3 and H4 are accepted while size negatively interferes the revenue instead of positively.

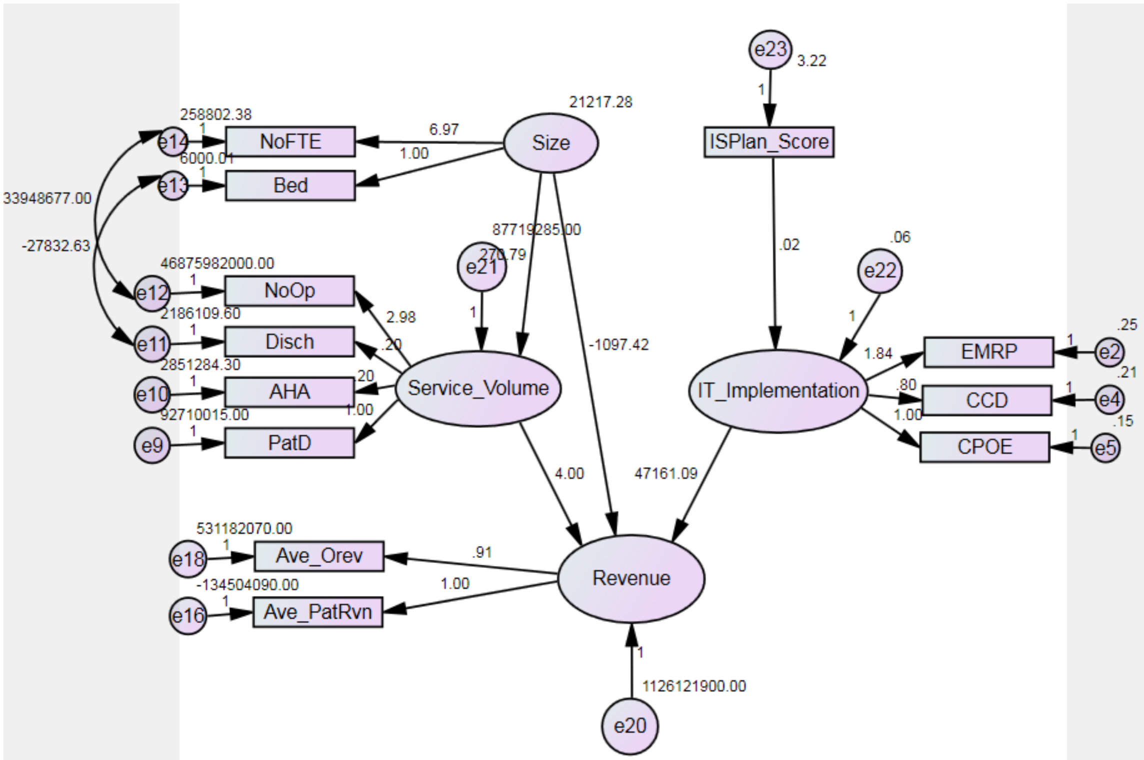

Figure 3.14 Result of the Adjusted Revenue Model for Big hospitals

The structural equation is written as follows:

$$\begin{bmatrix} Revenue'' \\ ServiceVolume'' \\ ITImplementation'' \end{bmatrix} = \begin{bmatrix} 0 & 4.002 & 47161.088 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} Revenue'' \\ ServiceVolume'' \\ ITImplementation'' \end{bmatrix}$$

$$+ \begin{bmatrix} -1097.424 & 0 \\ 270.794 & 0 \\ 0 & .019 \end{bmatrix} \begin{bmatrix} HSize'' \\ ISPlan'' \end{bmatrix} + \begin{bmatrix} \boldsymbol{\varepsilon_{61}} \\ \boldsymbol{\varepsilon_{62}} \\ \boldsymbol{\varepsilon_{63}} \end{bmatrix}$$

3.5 Discussion

The model fit statistics of complete model and adjusted model for all the six scenarios are summarized in Table 3.17 and Table 3.18. They are all overall acceptable.

Model fit statistics	Indicator Cut-Off	Cost All Hospital	Cost Small Hospital	Cost Big Hospital	Revenue All Hospital	Revenue Small Hospital	Revenue Big Hospital
CMIN/Df	< 3	2.033	1.096	1.704	2.143	1.036	1.716
SRMR	<.08	.0379	.0617	.0297	.0383	.0587	.0305
CFI	>.95	.992	0993	.991	.992	.998	.0992
RMSEA	<.05	.045	.026	.043	.047	.016	.043

Table 3.17 Model Fit Statistics of Complete Models

Model fit statistics	Indicator Cut-Off	Cost All Hospital	Cost Small Hospital	Cost Big Hospital	Revenue All Hospital	Revenue Small Hospital	Revenue Big Hospital
CMIN/Df	< 3	1.909	1.083	1.693	2.037	1.036	1.648
SRMR	<.08	.0369	.0638	.0438	.0375	.0622	.0412
CFI	>.95	.992	.993	.990	.992	.0998	.0992
RMSEA	<.05	.042	.025	.043	.045	.016	.041

Table 3.18 Model Fit Statistics of Adjusted Models

We summarize the testing results of five hypotheses of all six situations in Table 3.19. H1 is rejected in all situations, meaning that the level of IT implementation has not yet produced significant effect on service volume yet. H5 is also rejected in all settings, revealing that setting IS plans won't impact the influence of service volume or IT implementation to the financial performance. Size is influential in all situations based on the fact that H4 is accepted in all cases. This is consistent with many previous studies that size is an important influential factor. H3 is rejected in all cost models. The increase in IT implementation level leads to increasing costs, indicating worse performance. But higher IT implementation brings higher revenue for all hospitals. Similarly, H2 is also rejected in all cost models. The increase in service volume leads to increasing costs, indicating worse performance. However, higher service volume brings higher revenue for big hospitals (in the big hospital model and all hospital model), but no influence for small ones.

	H1	H2	H3	H4	H5
Cost / All	×	×	×	√	×
Cost / Small	×	×	×	√	×
Cost / Big	×	×	×	√	×
Revenue / All	×	√	√	√	×
Revenue / Small	×	×	√	√	×
Revenue / Big	×	√	√	√	×

Table 3.19 Results of 5 Hypotheses for 6 Situations

The path load parameters indicate the significance of each path, as well as how the factors are related. We also summarize the parameters of size, IS plan, service volume and IT implementation to cost (to the left) and revenue (to the right) in all three sample groups: all hospitals, small hospitals, and big hospitals. By looking at the value of the parameters, we can compare the influence of a same factor across models, as shown in Table 3.20. IS plan has no direct effect to both cost and revenue in all models. IT implementation increases more revenue than cost thus is beneficial to financial performance in all situations. We will discuss the influence of size and service volume separately in the following sections, as they have different effects in different models.

Cost (C) / Revenue (R)	Size		IS Plan		Service Volume		IT Implementation	
	C	R	C	R	C	R	C	R
All	-767.22	-1154.527	N/A	N/A	3.09	4.641	40660.908	50445.21
Big	-734.321	-1097.424	N/A	N/A	2.68	4.002	41261.554	47161.088
Small	1338.389	1680.373	N/A	N/A	N/A	N/A	46136.23	61611.925

Table 3.20 Influential Factors to Cost and Revenue

3.5.1 The Influence of Size

In all and big hospital models, size reduces the cost as well as the revenue. The decreasing impact of size to revenue is more intense than to cost. Thus expanding in size is harmful to performance in big hospitals rather than beneficial. To the contrary, size increases both the cost and revenue in small hospitals. The increase in revenue is more pronounced than in cost, therefore small hospitals gain benefits in terms of financial performance when size grows. We may conclude that the factor of size amplifies either the harmful or beneficial effect to financial performance.

It is also found that size is positively related with service volume in all scenarios, based on the natural fact that bigger hospital is, there are more physicians and beds to serve more patients, better facilities and equipment to deal with more complex cases. The path load from size to IT implementation is only significant in the model with all hospitals, but the parameter is 0, as shown in Table 3.21. It indicates that size has no effect on IT implementation level. Thus, in terms of HIS/HIT system quality in general, there may not be a big difference between big and small hospitals. The difference is the result after they apply the system within the organization.

Cost Model (CM) / Revenue Model(RM)	Service Volume		IT Implementation	
	CM	RM	CM	RM
All	250.604	250.966	+0	+0
Big	270.306	270.794	N/A	N/A
Small	383.04	382.964	N/A	N/A

Table 3.21 Parameters of Size to Service Volume and IT Implementation

3.5.2 The Influence of an IS Plan

Unlike size, IS plan is not directly related to cost or revenue in all six models. For big hospitals, the relationship between IS plan and IT implementation is not significant with a P value equal to 0.052. In other models, there is significant relationship between IS plan and IT implementation with P values lower than 0.05. It indicates that whether a hospital has set up a plan may impact the IT implementation result to a certain extent. Big hospital may have implemented IT in its system according to federal regulations for a long time, and small hospitals simply adopt HIS/HIT systems to maintain legitimacy. Therefore IS plan is not an important determinant to the implementation result.

3.6 Conclusion

Small hospitals gain benefits in financial performance when their size grows. The net average revenue (revenue deducted by cost) caused by increasing size is positive in the small hospital model. The negative affect of size to performance emerges when the hospital become larger. When the hospital size grows to certain level, the competitive advantage of economies of scale disappears. For small hospitals, the growth of size means more patients, more sources, more income and therefore better performance. But when a small hospital grows to a certain level, many issues arise. For the big hospitals, the positive effect to financial performance caused by size (cost decrease) is completely off-set by the direct negative influence (revenue decrease). The service volume brings positive affects only to big hospitals due to economies of scale; but at the same time, big hospitals bear negative influence from size: it implies that there must be some costs arising from the institution expansion. According to information transparency theory, when the size of an organization grows, the agency costs increase. The institutional growth decreases the information transparency levels within the organization, and at the same time adds some other costs such as policy reinforce costs, regulation costs, training costs, technical stuff costs, and maintenance costs, etc. As a result, big hospitals need to implement IT better in order to maintain good financial performance. HIS/HIT reduces communication costs and agency costs resulting from the divergence increase as the organization becomes larger (Gurbaxani & Whang, 1991). The expansion of a hospital may bring incentives to implement IT to reduce information transparency level and transaction cost.

Organization size is a function of technology, managerial decisions, outside pressure, and even luck (Oi & Idson, 1999). Big organizations tend to be more standardized in terms of their management, regulations, operations and performance. On the contrary, small hospitals are distributed less concentrated. Smaller organizations have more flexible regulations and less standardized operations, which leads to more variability in their performance. Figure 3.15 represents the plot of financial performance versus size of the hospitals. The financial performance is denoted by the value of yearly patient revenue divided by number of full-time employees, which is also the profitability of a hospital; the size of a hospital is represented by number of beds. It shows that the hospital's financial performance or profitability tends to converge when the size grows.

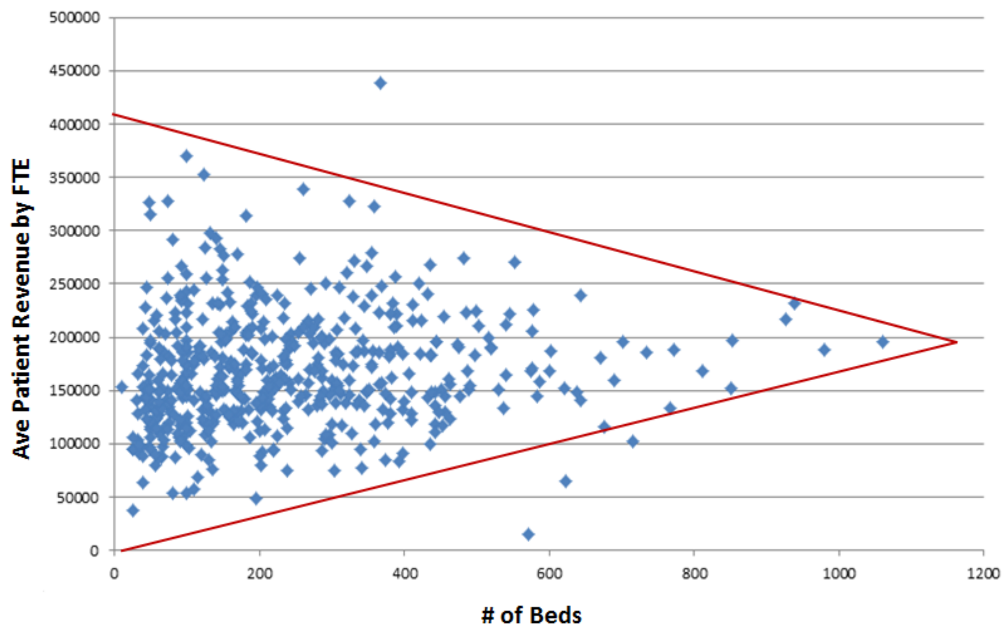

Figure 3.15 Plot of Hospital Size versus Performance

Institutional theory emphasizes the effect of institutional environment. It states that institutional environment can significantly influence the development of formal structures or the adoption of new structures in an organization, often more greatly than other outside pressures, such as market pressure (Tolbert & Zucker, 1983). Our findings show that although both small and big hospitals benefit from the implementation of HIS/HIT, the effects of size posing on them are opposite. According to institutional theory, the early-adopting firms would legitimize the innovative structures which improve their organizational performance. Big (also early adopter) hospitals adopt the new technologies and policies to improve efficiency, while small (also later adopter) ones may just follow to maintain legitimacy. Big hospitals are at the frontier of technological innovation. Big hospitals usually receive more government support and have more incentive to reinforce the implementation of new systems such as CPOE/CDSS/CCD than the small ones. Our findings are consistent with Rowan's case study in California public schools that adoption of innovative structures is slow and tentative when the institutional environment is contentious and unfocused, and that larger organization are more likely to add structured units (which help to retain new technologies, systems. once adopted) than smaller ones (Rowan, 1982). Hospitals are organization that are highly dependent on the institutional environment, and that rely on professionals extensively, thus the institutional pressures are higher than other business companies to adopt new structures (Powell & DiMaggio, 2012). The organizations adopt new structures more quickly when coercive pressures are high (such as state mandates), while the adoption rate is much slower and lower when the coercive pressures are low (Tolbert & Zucker, 1983). As a result, the adoption pattern and profitability mechanism in big and small hospitals are different.

CHAPTER 4

EXAMPLE OF EVMS

4.1 Background Information of EVMS

The Eastern Virginia Medical School (EVMS) clinic is located on South Hampton Avenue, Norfolk Virginia. The physicians specialize in family and internal medicine, obstetrics, medical and surgical specialties as well as radiation oncology, laboratory and pathology services, with the mission “to provide patient-centered quality healthcare to the patients that we serve”. In order to reach the goal, the medical group has been working very hard to deliver care that is safe, efficient, cost-effective and timely. In order to explore the current situation of EVMS Ghent Family Medicine, we conduct a data analysis, to identify the discrepancy between patient demand and provider supply, to see whether the capacity management in such an outpatient family machine has brought a good outcome.

The datasets from EVMS were mainly drawn from scheduling record spreadsheet provided by the hospital. Some data came from our interview with the doctors, such as the general workloads of doctors and residents. The dataset consists of the doctor schedule and patient records during the time period of July 2012 to December 2012. There are 131 days, for both morning and afternoon schedule. In our analysis, we take the average of the doctor and patient number for the morning and afternoon as the data points. Some of our results are as follows.

4.2 Statistical Findings

Figure 4.1 shows a linear relationship between the number of doctors and the number of patient. According to Figure 1, each doctor takes care of about 6 to 7 patients in 4 hours (half a day) on average.

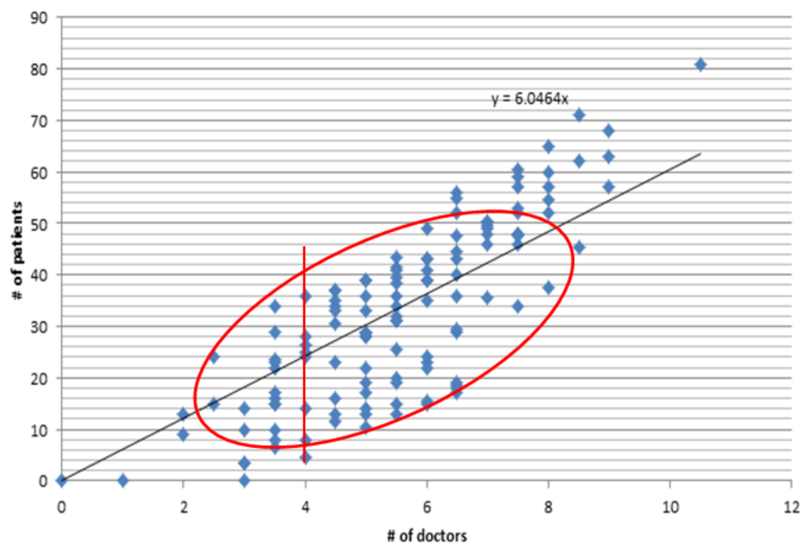

Figure 4.1 Relationship between Number of Doctors and Number of Patients (force s=0)

Four doctors will see 36 patients in half a day (max.). However, our previous interview indicates that the work load for a doctor is 20 minutes per patient, 24 patients per day. Some doctors say that 2 patients per hour is good, while 3 patients per hour is a bit too much. Therefore, the actual work load is far less than what it is supposed to be. There is room for improvement.

From Table 4.1 we can see that Tuesdays and Wednesdays are easy days, while Mondays, Thursdays and Fridays are busy days, especially on

Mondays. Moreover, the standard deviation associated with patients is much higher than that of doctors every day, especially on Mondays. Then here comes the question: does the current schedule respond to the high demand on Mondays?

	Average # of Doctors	STD DEV of Doctors	Average # of Patients	STD DEV of Patients	# of pts per doc
Monday	7.4	1.3	51.3	13.0	7
Tuesday	6.1	1.3	33	13.0	5.5
Wednesday	4.6	1.4	12.5	5.2	2.7
Thursday	5.1	1.3	33.7	11.8	6.6
Friday	4.8	1.64	32.6	15.3	6.8

Table 4.1 Number of Patients and Doctors Each Day (half day based, holiday excluded)

Similar pattern is also found when we do monthly demand analysis (Table 4.2): November has the highest standard deviation associated with patient as well as the doctors. The assumption is that it is because of the seasonal factors: November is the month of Thanksgiving and it is very closed to Christmas break. People tend to travel, have parties, reunion and engage in more risky behavior in terms of health issues. Thus it has the highest variation in demand.

	Average # of Doctors	STD DEV of Doctors	Average # of Patients	STD DEV of Patients	# of pts per doc
July	5.2	1.9	31.1	16.4	6.0
August	5.0	1.1	29.6	13.3	5.9
September	6.6	1.4	38.5	17.0	5.8
October	5.3	1.6	27.5	16.9	5.2
November	6.0	2.4	38.7	21.8	6.5
December	5.1	1.9	29.2	16.7	5.7

Table 4.2 Number of Patients and Doctors Each Month (half day based, holiday excluded)

4.3 Gap between Patient Demand and Doctor Schedule

Figure 4.2 shows the changes in the patient numbers and doctor numbers in half a year. We can see that the service time provided by physicians is level and stable, while the demand for service from patients is sporadic and lumpy. Figure 4.2 suggests that sometimes there were too many service hours, and at other times there appeared to be insufficient service resource that might lead to long waiting time and unhappy patients. Delays in obtaining service lead to patient dissatisfaction, higher cost, and adverse consequences. Similarly, comparing with the actual number of patients seem by the doctors each day which is sporadic and lumpy in Figure 4.3, the line for expected number of patients appears more level and stable. It indicates that the current patient schedule doesn’t fit the intended workload capability of doctors.

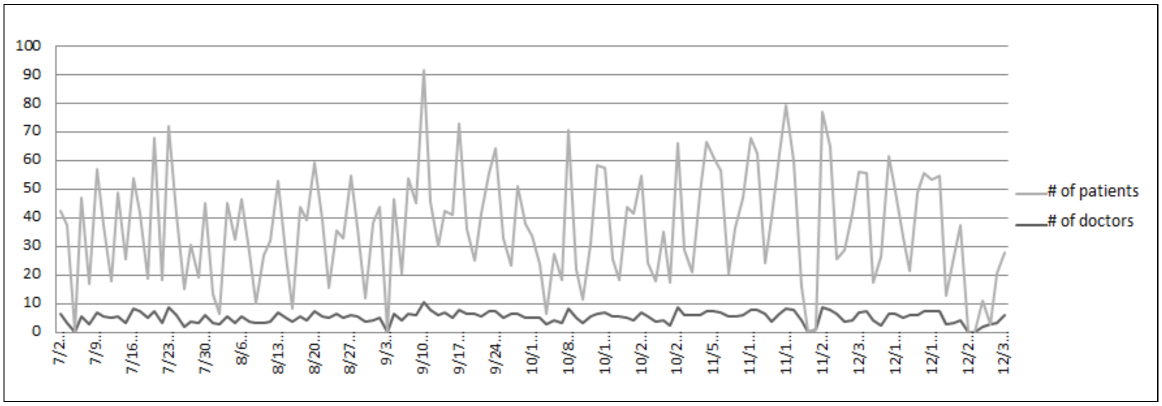

Figure 4.2 Number of Patients and Doctors of the Time Period

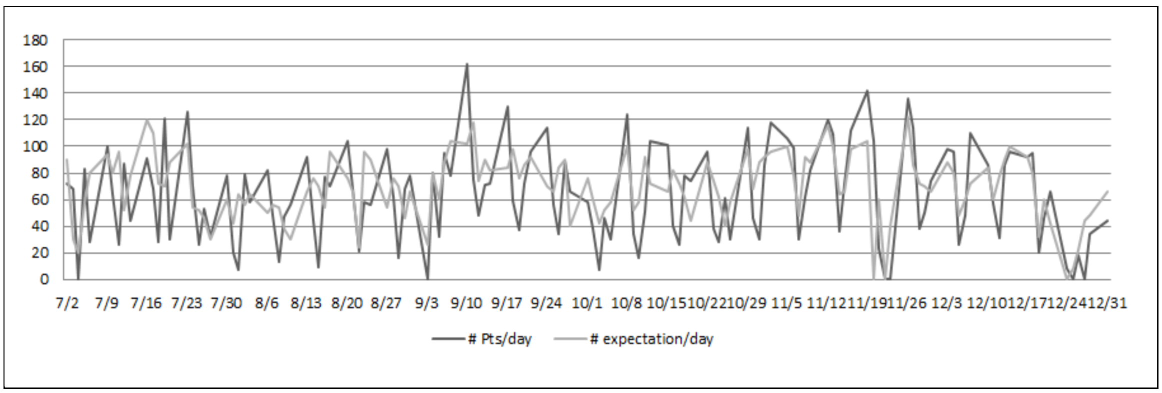

Figure 4.3 The Actual Number of Patients Seen Each Day versus the Expected Number of Patients Seen Each Day

Finally we face such a question: are we able to determine a consistent demand pattern that matches the level supply of providers? What we find is that the pattern of the patient demand and the service provider is not consistent. As shown in Figure 4.4, the shape of the demand and service curve can be triangle, negative slope, and concave. Other than these standard shapes, there are some other shapes as shown in Figure 4.4(d). In other words, the variability of patient demand and the service seems to be significant.

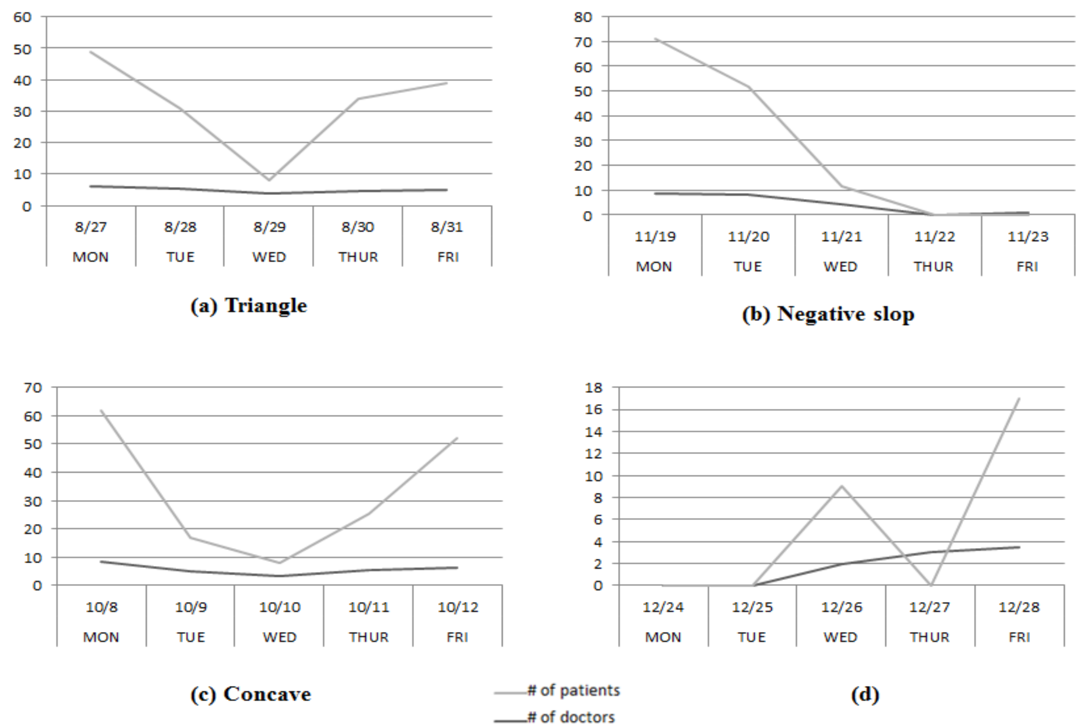

Figure 4.4 The Pattern of Patient Demand and Service Provider by Weeks

Such variability may come from patients and the service providers. From the perspective of patients, the variability comes from: 1) different patient types, such as new patients, follow-up patients, return patients, etc.; 2) different schedule types, such as by appointments, late show, no show, overbooking, walk-in patients, urgent patients, emergencies, patients who want the same doctor, etc.; and 3) different service times, such as the diagnosis by annual physical, for new patients, for follow-ups, for patients who want to have all health issues done in one visit, etc. From the perspective of the service providers, the variability may come from: 1) the difference in provider's schedule, e.g., the doctor schedule is made quarterly, 3~4 months in advance, while the medical aid schedule is made a day before the service; 2) variability in service time, that the standard (20 minutes per patient) does not apply to all doctors and there is at least a 5% chance the doctors will run their appointment late. Our findings highlight the mismatch between the patient demand and the schedule of service provider.

Our goal is to reduce the bottleneck of the services, reduce the waiting time of the patients and improve patients' satisfaction towards the services. Some lean service operations can take place to reach the goal, such as better scheduling, understanding patient's needs and their tolerance span, and matching patient's demand with providers' supply. For example, parents with young children will be scheduled early in the morning or late in the afternoon, so the parents don't need to take time off during the day; retired senior citizens (who don't mind waiting a little longer than the scheduled time) can be scheduled in the middle of the day. The physician schedule, nurse schedule and patient schedule need to be integrated, and the patient information also need to be integrated with staff schedule. Such categorizing work will be processed by decision support module, as described in Chapter 5.

CHAPTER 5

INTEGRATED INFORMATION SYSTEM DESIGN

5.1 Enterprise information system and information integration

Mandl & Kohane (2012) summaried four generic components of EHR: secure private storage, communications, documentation tools and other tools (Mandl & Kohane, 2012). These four components are shown in Table 5.1:

Generic Components for EHRS	
Private Storage	Local database Cloud database
Communications	Among providers Between providers and patients
Documentation tools	Text-processing Spell checking interaction Data Base (Oracle, SQL, Hadoop…)
Other tools	Loading Graphing Mapping Analyzing data Searching

Table 5.1 Components of EHRs

In recent years, cloud storage has become a popular solution for distributed big data (Deng, Petkovic, Nalin, & Baroni, 2011; Poulymenopoulou, Malamateniou, & Vassilacopoulos, 2012; Rolim et al., 2010).The cloud database has significant benefits in terms of cost, security, accessibility, collaboration and sharing, etc. To simplify our design, we choose local database (MySql) for storage purpose, because our research focuses on a decision support module for smart scheduling at current stage. The local database can be further moved to a cloud server and more components will be included. Figure 5.1 shows a web-based browser-server system for health care data management (L. Li et al., 2008).

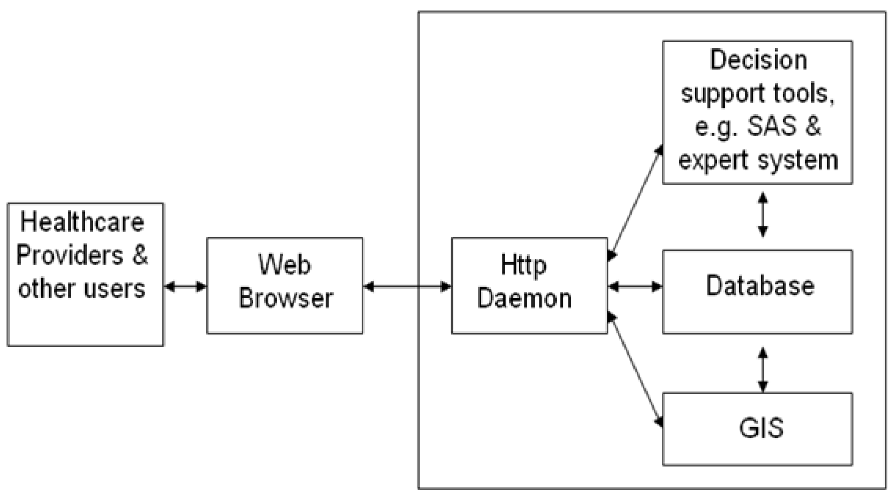

Figure 5.1 A Web-based Healthcare System by Li (L. Li et al., 2008).

Based on these systems, we completed and designed an integrated system with decision support module (Figure 5.2). The ER diagram of the proposed integrated information system in the following shows the data flow along the system. There are two layers in the system: application service layer and the data processing and information integration layer.

The system consists of a Web-based interface that allows users to create and edit categories similar to managing directories in the Microsoft File Explorer. Simply by clicking and dragging documents into different categories, users can classify (or re-classify) patient records. All the patient documents are stored in a MySQL database. For automatic classification, we use a support vector machine method (Chang & Lin, 2011) utilizing users' manual classification as training input. The patients in a same category group will have the higher priority to be scheduled the same way. Each of the patient records or data points contain multiple factors such as arrival time/depart time, total waiting time, service time, gender, age, zip codes, occupation, illness type, etc. Our goal is to classify the upcoming patients in a smart way so that the same type of patients are grouped together, therefore assisting the service provider to make scheduling decisions in an efficient way.

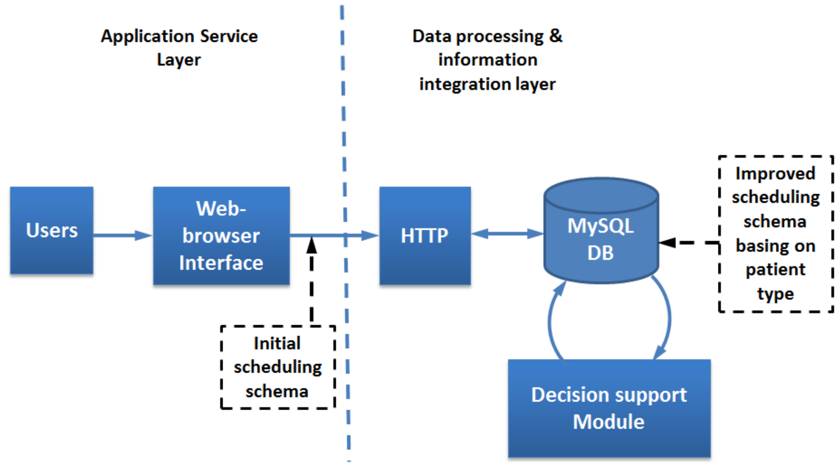

Figure 5.2 The Healthcare System with Decision Support Module

Compared with traditional healthcare data management system, the proposed system has the following advantages:

a) It allows the system administrator to collaboratively build and maintain a smart scheduling schema—facet classification schema from the initial scheduling schema provided by the users or hospital practitioners. This function is achieved by a Joomla system based on MySQL database. At the beginning, a small group of hospital practitioners is asked to build a scheduling facet classification schema for a sample patient data, for example: the busy time group, the flexible time group, and the easy time group. Then it allows a large group of hospital practitioners to collaboratively edit the scheduling schema through the support of deleting, adding and renaming facets and categories and manually classifying the patient record by dragging and dropping them into categories.

b) It is able to systematically enrich the existing facet scheduling schema with the help of human interaction. This function is achieved by utilizing the patient metadata pool and a statistical co-occurrence model. Under the co-occurrence model, we can identify a parent-child relationship between categories X and Y if all documents associated with Y are also associated with X. With this assumption, if most or all of the documents associated with a category belong to another category at the same time, the first category is highly possible to be a subcategory of the second category. This is the key insight of the co-occurrence model, because the system can then automatically find all possible parent-child relationship. After all, the administrator or user has the privilege to make final decision whether or not to implement such parent-child relationship.

c) It is able to automatically classify the incoming patient data into user-managed facet scheduling schema, and makes the evolution of the facet schema possible. This function is achieved by using a support vector machine learning algorithm to automatically locate the new coming datasets in suitable facets and categories. For each category, the algorithm checks whether or not the documents belong. It should be noted that the main classification approach relies on collaborative classification schema generated by the hospital practitioner group. If we ask the practitioner group from different hospitals to build a schema, the classification schema is different thus the way how the new coming patients would be scheduled can be different. The automated classification to the new patient datasets is used as a recommendation provided to users. The final decision whether the recommendation is accepted or not is still made by the system administrators or users. Nevertheless, the automated approach is used for initial classification when new documents are brought into the collection.

d) The system also helps the hospital practitioners manage interruptions (Ash et al., 2004), and remind them if current patient has been put under the other categories, whether they would like to continue the following activities.

Because of the existence of redundant or wrongly placed categories created by the multitude of users in the collaborative classification system, a WordNet-based algorithm (G. A. Miller, 1995) is adopted into (a) and (b) to calculate the similarity among words and categories, and to notify users or system administrator of such schema errors. For more details about the faceted classification system, please refer to a series of studies of our NSF-founded project (Fu, Maly, Wu, & Zubair, 2009; J. Li, 2010; Maly, Wu, & Mohammad Zubair, 2009; H. Wu, Zubair, & Maly, 2006, 2007).

5.2 Appointment Schedule Design Based on Patient Type.

Employing the data mining methods in healthcare systems is not new. Duan et al. designed a data mining algorithm using nursing diagnosis data to create a recommender system as a part of a healthcare information system

(Duan, Street, & Xu, 2011). Li & King (1999) proposed a representative staff planning model to analysis the cost and benefits of staff task flexibility (L. L. X. Li & King, 1999). In their model, two different types of demand were classified: regular demand, which is demand from patients who have made the appointment; and irregular demand, which is demand from walk-in patients. In other words, different types of patient needs to be treated differently.

A number of classification methods can be found in the literature, which distinguish between learning methods and non-learning methods. The basic non-learning methods are quite limited, such as categorizing the documents based on word matching between records using category names and content/metadata. For instance, a record with "java" will match both the apple category as a coffee, and programming language. A variety of statistical learning methods have performed better than non-learning methods to classify the metadata (Maly, Wu, Zubair, & Antonov, 2009). These methods include nearest neighbor classifiers, regression models, Bayesian probabilistic classifiers, inductive rule learning algorithms, neural networks, online learning approaches, example-based approaches, decision trees, genetic programming techniques, and many hybrid methods, and support vector machines (SVM). There are some studies comparing the advantages and disadvantages of different classification techniques (Mahinovs, Tiwari, Roy, & Baxter, 2007; Sebastiani, 2002). In the field of HIS/HIT, Duan et al. used random selection and greedy selection as their evaluation mechanisms for classification (Duan et al., 2011). The problem of adopting their algorithm in our research is not only an efficiency issue when the number of nodes increases dramatically (Y. Wang et al., 2010), but also the predefined classification categories (such as: risk for infection, pain acute, anxiety, high risk for injury, etc.) they used to provide recommendations. In their case, if the definition was not accurate, the classification of patients would be problematic. Moreover, the predefined terms such as “high risk for injury” may refer to different scenario in different hospitals according to time, health professional group, and location. As a result, a uniform classification method cannot be appropriately applied to all situations.

The method Duan et al developed was non-learning. Among the variety of statistical learning methods, statistical Naïve Bayesian classifier is the simplest and the most widely used non-learning method. Due to its simplicity, it is also the single most researched classifier appeared in almost all articles on the text classification related topics. The Naïve Bayes classifier assumes that features of the input data vector are statistically independent. It estimates the posterior probability $\mathrm{P(C_i|d)}$ of category C_i given document d via Bayes’ rule:

$$\mathrm{P(C_i|d)} = \frac{\mathrm{P(d|C_i)\,P(C_i)}}{\mathrm{P(d)}}$$

$P(\mathrm{d})$ is equal to 1 as it is the given patient document to be classified. $P(\mathrm{C_i})$ can be estimated using the number of documents in category *Ci* divided by the total number of documents in the collection. $P(d|C_i)$ can be estimated by the following equation:

$$\mathrm{P(d|C_i)} = \prod\nolimits_{\mathrm{t \in d}} \mathrm{P(t|C_i)}$$

Here *t* represents one of the feature vector components (terms) in document d, such as time/depart time, total waiting time, service time, gender, age, zip codes, occupation, illness type, etc. $P(t|C_i)$ can be estimated in terms of the frequency of occurrence of term t appearing in category *Ci* as follows:

$$P(t|C_i) = \frac{n(C_i, t) + \lambda}{n(C_i) + \lambda|V|}$$

Here $n(C_i, t)$ is the number of occurrences of term t in documents that have been assigned into category Ci , $n(C_i)$ is the total number of occurrences of terms in documents in category Ci with $n(C_i) = \sum_t n(C_i, t)$, |V| is the number of distinct terms in all of the documents, λ is a constant and ≥ 0. The latter two coefficients are to ensure $P(t|C_i)$ to be non-zero. After estimating the probability of each category given a document, the document is finally assigned to the category with the highest probability (Agrawal & Srikant, 2001). The main reason that we don't adopt statistical Naïve Bayesian classifier is its assumption of independence among different vectors. In our case, such assumption cannot be satisfied: a patient's factors such as region, age, type, income, staying time are very likely to be related. For example, older people are more likely to have heart attack and more likely to be a returned patient instead of new patient. As a result, we need to consider other classification tools to construct the algorithm.

Currently one of the most widely adopted classifiers is the Support Vector Machines (SVM). As early as 1963, Vapnik and Lerner introduced the Generalized Portrait algorithm (Vapnik, 1963), which was implemented by SVM by Cortes and Vapnik in 1995 to solve the two-class pattern recognition problems

(Cortes & Vapnik, 1995). SVM is based on the Structural Risk Minimization principle and it is a supervised learning method. Given a set of training sets, each having been defined as belong to one of two classes, an SVM training algorithm predicts whether a new document will be classified into one class or the other. A support vector machine constructs a hyper-plane or set of hyper-planes in a high dimensional space. Such space is used for classification purpose, regression or other tasks. The goal is to achieve the largest distance to the nearest training data points of any class, called functional margin. In general, the larger the margin is, the lower the generalization error of the classifier will be. The hyper-plane is written as

$$\mathrm{W} \cdot \mathrm{X} - \mathrm{b} = 0$$

The vector X is an arbitrary data point to be classified, and the vector W and the constant b are learned from a training set of linearly separable data. Let $\mathrm{D} = \{(\mathrm{X_i}, \mathrm{c_i}) | \mathrm{X_i} \in \mathrm{R^p}, \mathrm{c_i} \in \{-1,1\}\}_{\mathrm{i}=1}^{\mathrm{n}}$ denotes the training set of n data points, where $\mathrm{c_i} \in \{-1,1\}$ is the classification for $\mathrm{X_i}$, 1 indicating $\mathrm{X_i}$ in the given class and -1 indicating not in the given class. If the training data are linear separable, we can draw the two hyperplanes of the margin in a way that there are no points between them and then try to maximize their distance. In this case, the SVM problem is to find W and b to minimize the vector 2-norm ||W|| subject to the following constraints:

$$\mathrm{W} \cdot \mathrm{X_i} - \mathrm{b} \geq 1 \text{ for } \forall \mathrm{i} \text{ with } \mathrm{c_i} = 1$$

$$\mathrm{W} \cdot \mathrm{X_i} - \mathrm{b} \leq -1 \text{ for } \forall \mathrm{i} \text{ with } \mathrm{c_i} = -1$$

The SVM problem can be solved using quadratic programming techniques (Vapnik, 2000; Yang & Liu, 1999). The algorithms for solving linearly separable cases can be extended for solving linearly non-separable cases by introducing soft margin hyper-planes. Another approach is to map the original data vectors to a higher dimensional space where the new features contain interaction terms of the original features, and the data points in the new space become linearly separable (Vapnik, 2000; Yang & Liu, 1999).

5.3 Algorithm Description and Main Functions

There are two stages: merging for new global schema, and auto classification of new patient data. The first stage is to create new global classification schema according to the personal schemas of individual doctors. It is to learn the classification structure. The second stage is to classify a new patient data set into the global schema. It is to learn the classification method. These two stages can continuously follow each other.

5.3.1 Merging for New Global Schema

The overall algorithm design describing the subroutines and their dependency is shown as follows. Please refer to the appendix materials for more details on the algorithm.

```
-     findSimilar  ($type, $parentid_of_parent, $id_of_category/facet)
        └  match ($id1,$id2)
              └ similar ($id1, $id2)
                    └ countCats ($id)
                    └ getScore ($word1, $word2)


-     copycats ($old_parent_id, $new_parent_id)
       └copyItems ($old_item_id, $new_item_id)
```

Where:

findSimilar: returning the number of matched sub-categories under a parent.

$type = 'g' or 'p', where g is "global" and p means "parent";

match: whether two entries are matched or not

similar: counting the number of similar sub-categories under two entries

countCats: counting the number of sub-categories

getScore: giving the WordNet similarity score between two words.

Copycats: copying an entry and its sub-categories from local to global

copyItems: copying an item from local to global

The idea of merging facets means to evaluate all the personal schemas, picking up the most useful and widely used facets/category/items, involving the new contents to enrich/reconstruct the global schema. As shown in Table 5.2, there are two different types of facets during the process: global schema, and the personal schema:

Global	Personal
Good facet/category definition Useful for most users Optimized Wide coverage	Personal use May contain non-facet schemas Personal wording for facet/category/tag Narrow coverage

Table 5.2 Comparison between Global and Personal Schema

Figure 5.3 is an example for a global schema created by a small hospital practitioner group, and some personal schema created by some individual hospital practitioners. The goal of the algorithm is to generate a new better global schema from the existing old global schema and individual schemas. For example, in the following global schema, we have three facets: Patient type, Day to see, and Age. There are several categories under each facet. What we need to nore that the definition of each personal categories merely depends on the group of people who provide initial classification schema. The personal classification schemas are related with individual doctor's experience, background, and feelings. For instance, there is no such a year range how old is considered to be “young” or how old is classified as “old”. The system simply keep a record and “learns” the pattern how the individual user classify the sample patient data, as well as all perspectives of each dataset.

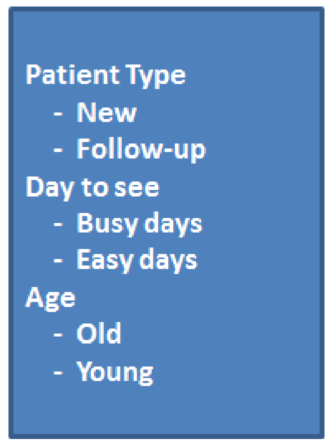

Figure 5.3 Example of a Global Schema

The global schema gives individual hospital practitioners an example how they can manage the patient datasets. Each user can create a personal schema under their account. Figure 5.4 is an example of three personal schemas:

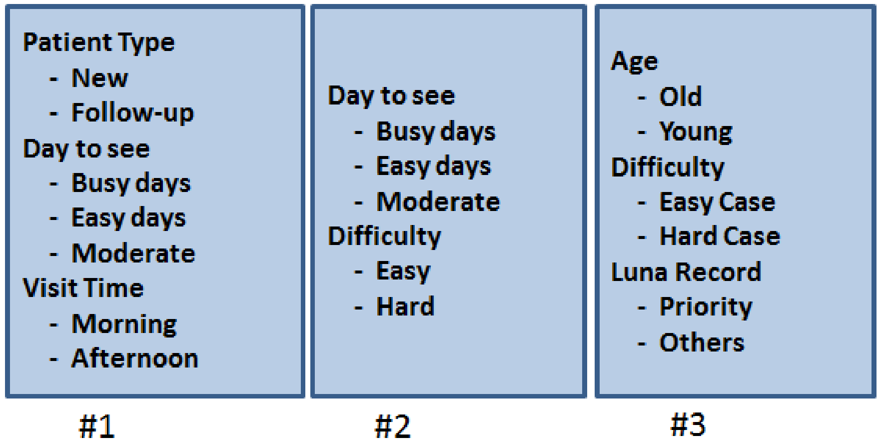

Figure 5.4 Example of a Personal Schema Set

Compared with global schema, the personal schemas look similar but focus more on individual use. The facet “Luna Record” is only for a personal record purpose and is the only one that kind in all facets among the personal schemas. Such kind of a personal facet is to be discarded when enriching the global schema. The facet of #2 user “difficulty” seems to be a useful one, as it has been notified by two out of three users: #3 user also creates a similar facet call “Difficulty”. So we will merge the facet “Difficulty” together with its categories and data sets to the new global schema. Moreover, under “Day to see” facet, two out of three create a new category call “Moderate”, indicating that the old global schema might have missed this important category. We will also add this category from the personal facets to the new global schema. The merging process for the example is illustrated in Figure 5.5:

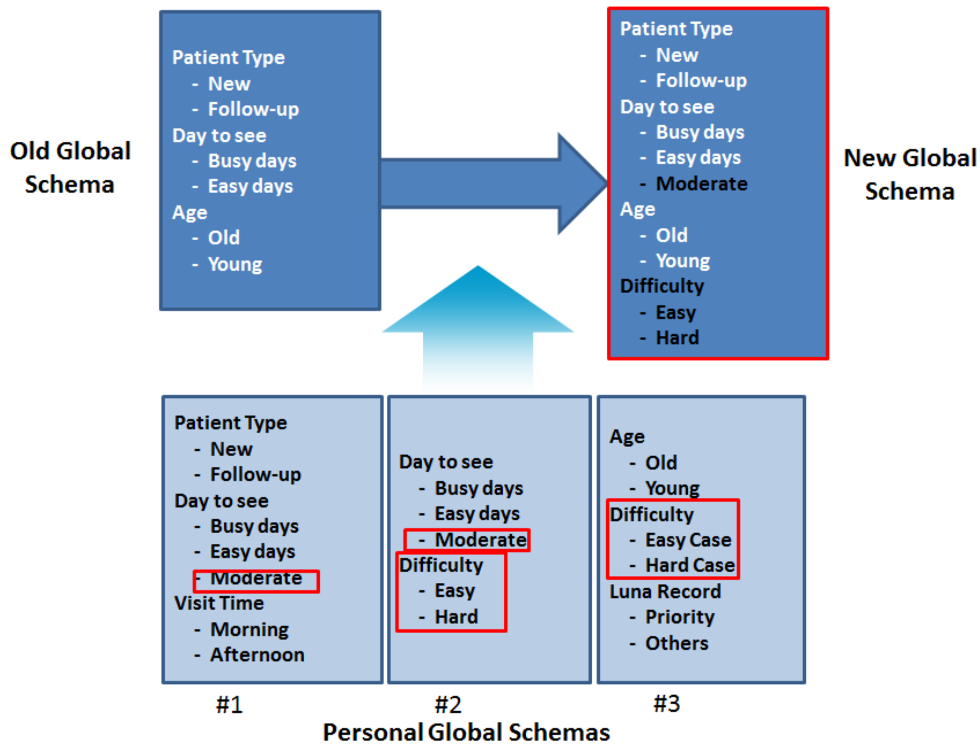

Figure 5.5 Merging Process from Old Global Schema to New Global Schema

The algorithm evaluates all the personal schemas, picking up the most useful and widely used facets/category/items, involving the new contents to enrich/reconstruct the global schema. A new facet is created only when a facet and its similar facets 1) are not existing in the global schema, and 2) are used in more than half of the personal schema. A new category under a global facet is created only when: 1) a category and its similar category are not existing in the global old facet, and 2) the personal facet containing the global new category is similar to the global old facet, and 3) more than half of the users who have the (similar) global facet have the new category under it. The term “Similar” means two entities are either Wordnet similar or structure similar.

5.3.2 Auto Classification of New Patient Data Set

After the new global schema is updated, a new patient dataset can be classified into the existing category by directly using SVM classifier (Ó Séaghdha, 2009), as illustrated in Figure 5.6. Three steps are involved for the improved classification:

Step 1: Achieving keyword space. Getting the related words of each facet.

Step 2: Keyword selection. Keeping the keywords whose distances are close enough to the keyword space.

Step 3: Classification with WordNet kernels.

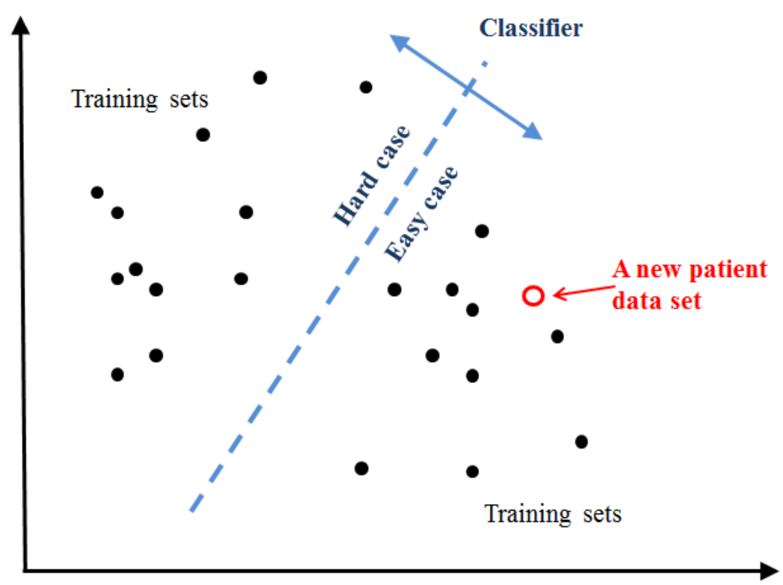

Figure 5.6 Classification of a New Patient Data

Step 1.

Redundant keywords are one of the most key factors causing false classification. The first step to exclude the unnecessary tags is to find out the possible related words of the facet. The semantic rhyming dictionary, which is an online tool developed by Doug Beeferman at Carnegie Mellon University, is adopted for this words selection aim (Fellbaum, 1998). It uses WordNet to help sort the output based on how near in meaning a word is to a certain target meaning. By step 1, a facet key word space can be created: $S=\{w_1,w_2,w_3\ldots\ldots w_n\}$, where w_1~w_n present the words included in the key word space. For example, the facet "family" has a key word space which contains 182 words in it.

Step 2.

This step is to select only the keywords that are close enough to the words in the keyword space. For example, "address" and "height" are irrelevant to determine whether a patient case is urgent or non-urgent. The distance between a pair of words can be measured by WordNet::Similarity, which is a Perl module that implements a variety of semantic similarity and relatedness measures based on information found in the lexical database WordNet (Fellbaum, 1998; G. A. Miller, 1995; Pedersen, Patwardhan, & Michelizzi, 2004) . Suppose t_i presents certain tag of the pictures; $w_j \in S$; Path_len(t_i, w_j)means the path length between two words. Then we define:

$$\begin{cases} \text{If Path\_len}(t_i, w_j)<3 \text{ (or score>.333), } t_i \text{ is kept in the dataset;} \\ \text{Otherwise, } t_i \text{ is excluded from the dataset} \end{cases}$$

By step 2, a new dataset with selected tags is created.

Step 3

Classification is performed in this step. In this step, libsvm algorithm with WordNet kernels, a widely used library for SVM, will be adopted(Chang & Lin, 2011) to classify the new patient dataset into a suitable category under each facet using the existing patients' datasets of each categories as training sets.

CHAPTER 6

SUMMARY AND FUTURE WORK

With the rapid development of technology, the increasing use of mobile digital devices, and efforts from the whole society, the HIS/HIT systems are moving towards a new era. IT is making health care systems safer, more intelligent, and more efficient. Let's look at the research questions at the very beginning: Do HIS/HIT systems influence different hospitals the same way? How to understand and explain the mechanism that HIS/HIT improves the performance of hospitals? Our research reinforces the positive effect of HIS/HIT to hospital performance. At the same time, it reveals that big hospitals implement HIS/HIT systems to overcome the issues such as transaction costs and communication cost, in order to increase their efficiency, and that smaller hospitals may be just followers to adopt HIS/HIT systems to maintain legitimacy. More importantly, we also reveal that the factor of hospital size is beneficial to financial performance for small hospitals, while harmful to big ones. This means that with hospital growth, the competitive advantage of economies of scale disappears because the information transparency level becomes lower and transaction costs become higher. For large hospitals, the positive effect caused by size is almost completely off-set by the direct negative influence of size. Big hospitals have the incentives and resources as well as the intuitional pressure to implement HIS/HIT systems to improve the performance.

The case study in EVMS highlights the mismatch between patient demand and service provider schedules. To solve this problem, we propose a decision support method to capture the classification patterns from the doctor, to establish a new global classification schema, and to classify the new patient cases into facet categories. Such a system provides valuable recommendations to health providers, helping them gain more transparent information from patients, and make better scheduling decisions to minimize gaps between patient demand and the provided services.

Despite the achievements of this research, there are still some limitations. Our study only assesses the financial perspective of the healthcare system performance. Of course the measurement criteria for performance must consists with an organization's objectives(Globerson, 1985). Ziebell states (Ziebell & DeCoster, 1991):

> *In profit organizations, performance criteria usually results in financial terms. Even though financial measures do not really measure all aspects of how well the organization satisfies the needs of its resource contributors, the measures of financial efficiency and profitability are fairly well accepted. However, profitability measures often are inappropriate, irrelevant and/or unavailable for voluntary NPOs (not-for-profit organizations)*

Although it has been proven that financial performance is a crucial component of performance measurement matrix for hospitals, we should still note that non-financial performance issues cannot be ignored. The complete 2014 HIMSS report contains data of 52598 hospitals. 2458 of them indicate their profit status. 93.7% (2302 divided by 2458) of them are not-for-profit. Despite the fact that we concentrate on only one aspect of the healthcare performance measurement, more efforts need to be done to explore the non-financial aspects of healthcare system performance. For example, SERVQUAL model, a measurement framework for service quality from the consumer perceptions (Parasuraman, Zeithaml, & Berry, 1988), can be adopted to evaluate and compare the quality of the healthcare services across different systems. The quality of clinic services based on information systems will be measured and compared from five dimensions: tangibles, reliability, responsiveness, assurance and empathy:

1) Tangibles: physical facilities, equipment and appearance of personnel;
2) Reliability: ability to perform the promised service reliable and accurately;
3) Responsiveness: willingness to help customers and provide prompt service;
4) Assurance: knowledge and courtesy of employees and their ability to inspire trust and confidence; and
5) Empathy: caring, individualized attention provided to customers;

Many studies have gained success in adopting the SERVQAUL model to evaluate the performance in health care research discipline. Babarkus and Mangold (1992) found that the SERVQUAL scales could be used to assess the gap between the patient perceptions and expectations, and that SERVQUAL was applicable as a standardized measurement scale to compare results in different industries (Babakus & Mangold, 1992). In particular, Lam (1977) checked a hospital service quality in Hong Kong and the result indicated that SERVQUAL was consistent and reliable as a measurement tool (Lam, 1997). Youssef et al (1995) examined at the service quality of NHS hospitals (Youssef, Nel, & Bovaird, 1995). Pakdil and Harwood evaluated the patient satisfaction for a preoperative assessment clinic with SERVQUAL (Pakdil & Harwood, 2005). And a recent study in 2010 compared the service quality between public and private hospitals using SERVQUAL (Yeşilada & Direktör, 2010).

Based on all these facts, we can say confidently that SERVQUAL is an appropriate and reliable tool as a measurement infrastructure for these proposed healthcare systems. For future studies, we can adopt the infrastructure by Babakus and Mangold as our measurement framework (Babakus & Mangold, 1992) to conduct a questionnaire survey to collect data from the patients. The framework is described in Table 6.1:

Tangibles
- P1: the clinic has up-to-date equipment
- P2: the clinic's physical facilities are visually appealing
- P3: the clinic's employees appear neat

Reliability
- P4: the clinic provides its services at the time it promises to do so
- P5: when patients have problems, the clinic's employees are sympathetic and reassuring
- P6: the clinic's is accurate in its billing

Responsiveness
- P7: the clinic's employees tell patients exactly when services will be performed
- P8: Patients receive prompt service from client's employees
- P9: the clinic's employees are always willing to help patients

Assurance:
- P10: patients feel safe in their interactions with clinic's employees
- P11: clinic's employees are knowledgeable
- P12: clinic's employees are polite
- P13: employees get adequate support from clinic to do their jobs well

Empathy
- P14: the clinic's employees give patients personal attention
- P15: the clinic have patients' best interests at heart

Table 6.1 SERVQUAL Framework

Further research should also check the outliers found in this research. There is convergence of hospital performance when their size grows. Although most hospitals are within the convergent group, a small number of significant outliers are beyond the range, as highlighted in Figure 6.1. Additional investigations could be performed to identify the distinctive characteristics of these outliers. Quantitative research combined with case study would provide deeper insights to the application of Institutional Theory in the field of healthcare systems.

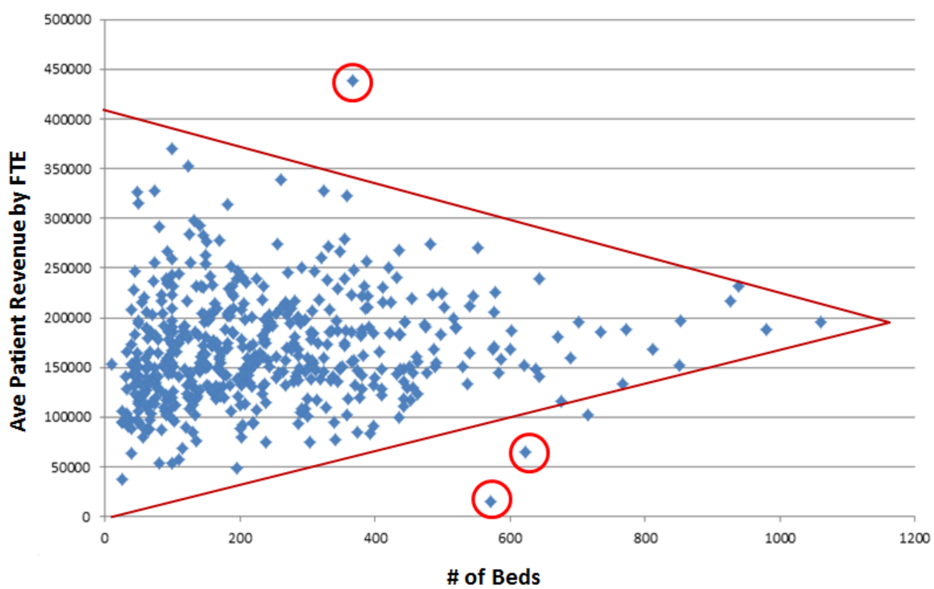

Figure 6.1 Existence of Outliers

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APPENDICES

Algorithm description of main functions:

Appendix 1 Main merging process

Appendix 1.1 Merging facets

```
for each facet pfacϵ{facets created by users}  {
# match pfac with each facet gfac ϵ {global facets pool}, get the number of
matched global facets
  $global_match_count = findSimilar('g', 0 , $id_of_pfac)

  if $global_match_count == 0 {
# match pfac with every pfac ϵ {facets created by users}, get the number of
matched local facets
$local_match_count = findSimilar('p', 0 , $id_of_pfac)

if $local_match_count/$total_number_of_local_facet > ration_threshold  {
          merging the facet to global;
     }
  }
}
```

Appendix 1.2 Merging categories

```
for each local facet pfac ϵ {facets created by users} {
  for each global facet gfac ϵ {global facets pool} {

     if match(id_of_pfac, id_of_gfac)==1 {
        for each local category lcatϵ{sub-categories of pfac} {

           #the category has no matched subcategory under gfac
           if findSimilar('g', categoryid_of_pfac,c)=0 {
               merging the category lcat under the facet gfac;
           }
        }
     }
   }
}
```

Appendix 2 Subroutines

Appendix 2.1 Subroutine to find the number of similar entries under a parent

```
sub findSimilar ($type,$parentid_of_parent,$id_of_category/facet){
  for each category gcatϵ{sub-categories of $parentid_of_parent}{
    #Match the local one with the global sub-categories;
    $matched = match($id_of_gcat, $id_of_category/facet)

    if two $matched ==1 {
       $count++;
    }
  }
  return $count;
}
```

Appendix 2.2 Subroutine to match two entries

```
sub match ($id1,$id2)   {
  check the match_result Table match_results
  if match record existed {
     return $matched;
  }

  if the $id1 and $id2 have the same name{
     $matched = 1;
  }
  else {
      $sim = getScore ($name_of_id1, $name_of_id2)
      if ($sim == 1) {
```

```
        $matched = 1;
      }
      else {
        # count the number of similar subcategories
        $subcount = similar(id1,id2);
        $global_subcats = countCats($id1);
        $local_subcats = countCats($id2);
        ratio = $subcount/($global_subcats*$local_subcats);

          if ($ratio > $ratio_threshold) {
            $matched = 1;
          }
          else {
            $matched = 0;
          }
       }
    }

  Insert the match_result Table;
  return $matched;
}
```

Appendix 2.3 Subroutine to count # of similar subcategories under 2 entries

If the entry $id1 has *p* sub-categories while entry $id2 has *q* ones, this function will return # of matched sub-terms in *p**q* pairs.

```
sub similar ($id1, $id2)  {
  for each categories cat1ϵ{sub-categories of id1} {
    for each categories cat2ϵ{sub-categories of id2} {
      if ($name_of_cat1 == $name_of_cat2) {
```

```
          $count++;
        }
        else {
          $sim = 0;
          $sim = getScore($name_of_cat1,$name_of_cat2);
          if ($sim > $sim_threshold) {
            $count++;
          }
        }
      }
    }
    return $count;
  }
```

```
Match (i,j)
For each entity i {
    Match (i,j)=0
    For each entity j {
        If WN-similarity of i and j is 1 {
                 Entity i and entity j are similar
           }
        Else If i and j are WN-similar {
                Count similar sub-entities {
                    For each sub-entity {
                           For each sub-entity {
                             If WN-similar then count++
                           }
                       }
                }
                Count sub-entities of j
```

```
                Count sub-entities of i
                Calculate ratio
                If ratio above threshold {
                    Entity i and entity j are similar.
                 }
            }
            If Entity i and entity j are similar {
              Match(i,j)=1
             }
     }
}

/* determine the merging of facet from personal schema to global one*/
Mark New(pf)=1
Count the number of total personal facets
For each personal facet pf {
     For each global facet gf {
          If Match(pf,gf)=1 {
               New(pf)=0
          }
     }
     If New(pf)=1{
          For each rest personal facet pfr {
                         If New(pfr)=1{
                              If match(pf,pfr)=1 then count++
                         }
                    }
            Calculate the ration=count/(total personal facet number)
            If ratio above threshold {
                  Copy the personal facet pf and its sub-category/items to global
            }
```

```
        }
}

/*determine the merging of category from personal schema to global one*/
For each global facet gf {
    Mark NewC(pc)=1
    For each personal facet pf {
        If Match(pf,gf)=1 {
            For each personal category pc under pf {
                  Count the number of personal category under pf
                  C_cat_all++
                  For each sub-categories gc under facet gf {
                     If Match(pc, gc)=1 {
                         NewC(pc)=0
                     }
                  }
            }
          }
     }
    If NewC(pc)=1
    For each rest personal category pcr {
          If New(pcr,gf)=1 {
              If match(pcr,pr)=1 then C_cat_match++
              }
    }
    Calculate the ration=C_cat_match/C_cat_all
         If ratio above threshold {
             Copy the personal cat pc and its sub-ones to global facet gf
         }
     }
}
```

VITA

Liuliu Fu studied Electronic Engineering between 2001 and 2005 in Tsinghua University of China. After receiving her Bachelor's degree at 2005, she worked as project manager in Beijing Huaqi Information Digital Technology Co., Ltd until 2007. Since 2008, she studied in Information Technology Department of Old Dominion University and received Ph.D. at 2015.

CONTACT INFORMATION

- **Name:** Liuliu Fu (Luna)
- **Address:** College of Business and Public Administration
  Old Dominion University, Norfolk, VA 23529, USA
- **Email :** luna.foe@gmail.com

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