HEALTH INFORMATION TECHNOLOGY AND NURSE STAFF EFFICIENCY: AN EMPIRICAL TEST IN RESIDENTIAL CARE FACILITIES

by

JASON D. SMITH

Presented to the Faculty of the Graduate School of

The University of Texas at Arlington in Partial Fulfillment

of the Requirements

for the Degree of

MASTER OF ARTS IN URBAN AFFAIRS

THE UNIVERSITY OF TEXAS AT ARLINGTON

MAY 2012

DEDICATION

To Schmoopie

ACKNOWLEDGEMENTS

I would like to thank Dr. Darla Paulson for serving as my thesis advisor and for providing me with valuable research experience during my time at UT-Arlington. I would also like to thank Dr. Karabi Bezboruah for serving on my committee and providing me with early research experience as well. Thanks to Dr. David Coursey as well for serving on my committee. Finally, I should thank my family members, each of whom has been important to me and influential to me in some unique way.

ABSTRACT

HEALTH INFORMATION TECHNOLOGY AND NURSE STAFF EFFICIENCY: AN EMPIRICAL TEST IN RESIDENTIAL CARE FACILITIES

Jason D. Smith, M.A.

The University of Texas at Arlington, 2012

Supervising Professor: Darla Paulson

This study examines the effects of health information technology (IT) on nursing staff efficiency. Specifically, the impact of clinical health IT applications on nursing staff efficiency is considered, along with the impact of health information exchange on nursing staff efficiency in those facilities that utilize clinical IT. In an effort to elucidate these effects, I use data from the 2010 National Survey of Residential Care Facilities (NSRCF) to estimate six ordered logit models. The results indicate that clinical IT sophistication is positively associated with registered nurse (RN) HPPD. The effect on licensed practical nurses (LPN)/licensed vocational nurses (LVN) and personal care aides is not statistically significant. Further, the results indicate that information exchange sophistication is positively associated with LPN/LVN HPPD. The effect of information exchange capabilities on RNs and personal care aides is not significant. The findings in this newly-studied setting are contrary to those found in other care settings. Potential

reasons for this are discussed, along with limitations of the study and suggestions for future research.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF EQUATIONS

Equation Page

LIST OF ABBREVIATIONS

Abbreviation	Word or Phrase
ADE	Adverse Drug Event
ARRA	American Recovery and Reinvestment Act
BLUE	Best Linear Unbiased Estimators
CDC	Centers for Disease Control and Prevention
CDSS	Clinical Decision Support System
CAPI	Computer-Assisted Personal Interviewing Instrument
CPOE	Computerized Provider Order Entry
C.I	Confidence Interval
DSS	Decision Support System
EHR	Electronic Health Record
ERB	Ethics Review Board
HIS	Hospital Information System
HPPD	Hours Per Patient Day
IT	Information Technology
IOM	Institute of Medicine
ICU	Intensive Care Unit
LPN	Licensed Practical Nurse
LVN	Licensed Vocational Nurse
MRI	Magnetic Resonance Imaging
MLE	Maximum Likelihood Estimation
MSA	Metropolitan Statistical Area
NCHS	National Center for Health Statistics
NSRCF	National Survey of Residential Care Facilities

O.R...Odds Ratio

OLS..Ordinary Least Squares

PC...Personal Computer

PDA..Personal Digital Assistant

PACS..Picture Archiving and Communication System

RN...Registered Nurse

S.E...Standard Error

VIF...Variance Inflation Factor

VA..Veterans Administration

CHAPTER 1

INTRODUCTION

The committee believes IT must play a central role in the redesign of the health care system if a substantial improvement in health care quality is to be achieved during the coming decade.
National Research Council, 2001, p. 165

Recommendation 9: Congress, the executive branch, leaders of health care organizations, public and private purchasers, and health informatics associations and vendors should make a renewed national commitment to building an information infrastructure to support health care delivery, consumer health, quality measurement and improvement, public accountability, clinical and health services research, and clinical education. This commitment should lead to the elimination of most handwritten clinical data by the end of the decade.
National Research Council, 2001, p. 166

By computerizing health records, we can avoid dangerous medical mistakes, reduce costs, and improve care.
President George W. Bush, *State of the Union Address*, January 20, 2004

In 2001, the Institute of Medicine's (IOM) Committee on the Quality of Health Care in America released a major report on the state of the quality of healthcare provision in the United States. This sweeping report argued that the United States healthcare system was in need of a major overhaul. It argued that patients were not receiving the quality of care that they should have been receiving. Both doctors, other care providers, and patients were all reported to be frustrated with the current system of care delivery. Medical errors were still frequent and costs were still rising rapidly, despite advances in knowledge, new technology, and new drugs. In recognition of, and in response to these concerns, the authors of the report put forth a set of thirteen recommendations thought to be crucial to bringing the country's healthcare system into the 21st century. Among those was the recommendation that both public and private organizations make a major push towards the widespread adoption and use of health information technology, or health IT. The Committee boldly stated that handwritten clinical data should be eliminated by the end of the first decade of the 21st century. Among other things, The Committee argued that the various pieces of health IT would lead to fewer medical errors and more accurate diagnoses, less duplication, quicker and greater access to information. Ultimately, it was believed, health IT would be a central piece of a safer, more cost-effective, and more patient-centered national healthcare system (National Research Council, 2001).

Others across the country echoed the sentiments of the Committee on the Quality of Health Care in America and policy-makers began to respond. In his 2004 State of the Union Address, then President George W. Bush championed health IT, specifically electronic health records (EHRs), saying that computerized health records could reduce mistakes, cut down on costs, and ultimately improve quality of care (Bush, 2004). Later that year, the President would sign an executive order laying out a 10-year plan to ensure that most Americans would have an EHR within 10 years. Subsequent budgets put forth by the same President would have money set aside for health IT demonstration projects (HIMSS, n.d.). In 2009, as part of the American Recovery and Reinvestment Act (ARRA), $25.9 billion was set aside for health IT-related grants and contracts (HHS, 2012).

Aside from lofty rhetoric extolling the virtues of health IT and computerization in healthcare, has health IT really delivered on its promises? While the goal to eliminate handwritten clinical data by the end of the first decade of the new century has certainly not been met, some degree of progress has been made. As health IT has increasingly been adopted in a variety of settings, an increasing number of studies have been conducted on what impact health IT may have on healthcare organizations and facilities, along with quality of care. For the most part, these studies have had mixed results. For example, health IT applications have been shown to improve quality of care through fewer medication errors, greater adherence to guidelines, and enhanced clinical monitoring. Studies of organizational impacts are fewer in number and have been less rosy.

Absent from much of the discussion on what impacts health IT might have on the country's healthcare system and on individual organizations, is staffing efficiency. Although there has been a few studies conducted on the impact of health IT on staff efficiency, these studies have tended to focus on specific aspects of efficiency, such as documentation duplication and ease of information access. Additionally, they have focused primarily on physician efficiency and those that have focused on staff efficiency have focused primarily on registered nurses (RNs). Further, studies of information exchange capabilities within this domain have been virtually non-existent. This thesis attempts to add to our current understanding of what impact health IT has on staff efficiency. It looks at staffing efficiency at the organizational level and across different types of care givers, making use of a commonly used measure of efficiency, direct care hours per patient day (HPPD).

1.1 Research Question

Stated formally, the broader, working research question of this thesis can be written in the following manner: What impact (if any) does health IT have on staffing efficiency? Within this broad question, there are three smaller questions: What impact does health IT have on the efficiency of RNs?; What impact does health IT have on the efficiency of licensed practical nurses (LPNs) and licensed vocational nurses (LVNs)?; What impact does health IT have on the efficiency of personal care aides?

In an attempt to answer this research question, several hypotheses are stated based on previous literature and expectations. These hypotheses are tested using data collected on a sample of residential care facilities in the United States. It is difficult to provide a precise definition of residential care facilities as the definition varies widely by state and even within states. This variation in the definitions of residential care facilities is due primarily to a lack of national standards, relatively recent regulation at the state level, and a lack of agreement about what should constitute a residential care facility (Weiner et al., 2010). While it is difficult to define residential care facilities, included in this sample are residential care facilities, assisted living residences, board and care homes, congregate care homes, enriched housing programs, homes for the aged, personal care homes, and shared housing establishments that are licensed and regulated by a state, including Washington D.C. (Moss et al., 2011).

1.2 Organization of the Thesis

The organization of the rest of this thesis is as follows. In the second chapter, I begin by touching on some background issues. Here, I begin with some very basic definitions of technology, IT, and health IT. Second, I touch on some of the core functions of health IT. While there may be some disagreement on what the core functions of health IT are, discussed here are what I call the administrative, clinical, and exchange functions of health IT. The chapter then moves into a brief historical sketch of IT use in the healthcare industry, focusing primarily on the United States. Discussed here are some of the major public policies, technological developments, and trends in healthcare that have influenced IT use in this particular industry. After presenting a brief historical sketch of IT use in healthcare, the current state of health IT in the United States is discussed. Comparisons are made with other countries and across settings. Also discussed are some of the current health IT applications that are in use in a variety of settings. The discussion then moves to a review of the relevant literature. In this section of the chapter, I discuss some of the studies that have been conducted on the various impacts of health IT. This section of the chapter is divided into two parts: impacts on quality of care and organizational impacts. Each of these parts is further subdivided. Under impacts on quality of care, effects on medical errors, adherence to guidelines, and clinical monitoring are discussed. Under organizational impacts, effects on clinician satisfaction, costs, and efficiency are discussed. After reviewing the relevant literature, I identify some of the gaps and discuss the importance of better understanding health IT's impact on staffing efficiency. Finally, after reviewing the relevant literature and identifying some of the gaps in the literature, I make several hypotheses concerning the impact of health IT on staffing efficiency.

In chapter three of the thesis, I discuss the methodology used in the subsequent analyses. More specifically, I begin with a discussion of the data used to test the stated hypotheses. Here, I begin with a brief description of the data. I then discuss the sampling design and sampling frame of the survey, the scope of the survey, and the data collection procedures in more detail. After a discussion of the data, I move into a review of the concepts and variables used in the statistical analyses. This section of the chapter is divided into several subsections, one for each set of hypotheses. In each subsection, I discuss the dependent variable, focal predictor variables, and control variables used in the analysis, followed by a formal statement of each model. Finally, I discuss the procedure of analysis. In this portion of the chapter, the creation of the complex sample plan is discussed along with the final analytic sample sizes. Also discussed is the statistical method used in the analyses and some of the diagnostic checks. Finally, descriptive statistics are presented and discussed.

In chapter four, I discuss the results of the analyses. I begin with a I discussion of the results of each separate model in some detail. For each model, I focus primarily on the impact of the focal independent variables, both clinical and exchange information systems. The effects of other variables in the models are discussed briefly as well. After discussing the results of each model, some conclusions about the hypotheses and results are drawn and discussed.

Finally, in the fifth and final chapter of this thesis, I discuss the contribution of this study to the existing body of work on the impacts of health IT. After discussing the contribution of the study, I discuss the many limitations of the present study. Finally, directions and suggestions for future research on the subject are offered.

CHAPTER 2

BACKGROUND, REVIEW OF LITERATURE, AND HYPOTHESES

The organization of chapter two of this thesis is as follows. In the first section of the chapter, some background on health IT is provided. This background information helps set the stage for the literature review and later analyses. In this section, technology and information technology are defined using fairly general definitions. Next, health IT is defined. After that, the core functions of health IT, as I see them, are laid out for the reader. In the second section of the chapter a brief historical sketch of IT in healthcare is presented. This section is further divided into three sections: pre-1980's, 1980's onward, and the future. In the third section of the chapter, the current state of health IT in the United States and abroad is reviewed. In the fourth section, the health IT impacts literature is reviewed and summarized. Some gaps in this literature are pointed out. Finally, based on the literature review, gaps in the literature, and expectations, several hypotheses are made.

2.1. Defining Health IT

Technology describes both the tools and actions which direct a person's activities and decisions. These tools are grounded in scientific knowledge, practice, or ideology. Technology may be divided into "hard" and "soft" technology. Hard technology refers to machines and other tangible items. An example of a hard technology might be a desktop computer. Soft technology refers to guidelines, techniques, practices, or well-defined procedures. For example, an accountant may be expected to abide by a set of best practices or procedures (Schoech, 1999).

The term *information technology*, or IT, is most frequently used to describe a set of technologies that process information in electronic form. This has not always been the case though and information technologies can be non-electronic. Books and the typewriter are examples of older information technologies that are non-electronic. The computer is the basic building block of IT, but IT also includes telecommunications, networking, and other technologies used to collect, store, process, and disseminate data (Schoech, 199).

When applied to healthcare settings, the term *health information technology*, or health IT, is often used. Health IT most frequently describes a set of hard technologies that collect, store, process, and disseminate information, mostly in electronic form. These technologies are often used for both decision-making and knowledge sharing. These technologies may be applied in a broad variety of care settings, such as hospitals, physicians' offices, and nursing homes (National Research Council, 2011).

2.1.1 Core Functions of Health IT

Today, there exists widespread disagreement as to what exactly constitutes the core functions of health IT. Additionally, there seems to be little agreement as to what constitutes a *complete* functional system. While there is little agreement here, it is possible to identify three functions: the administrative function, the clinical function, and the exchange function. The three core functions are briefly discussed below.

2.1.1.1 Administrative Function

IT has historically supported administrative functions and it is in this function that health IT is the most mature and widely used, as it provides a more clear advantage over traditional manual systems. Early IT utilization in healthcare settings was primarily for administrative reasons and driven largely by financial concerns (Kissinger & Borchardt, 1996). Administrative functions performed by health information technologies includes both organizational administration and financial administration. Organizational administration might include programs designed to handle staffing and scheduling. Financial administration refers to programs that capture charges, handle billing and claims management, etc. Also included in this function are record information that is required by state and federal governments. The value of this function is measure by its ability to reduce overhead, capture revenue, and lead to financial stability (Kissinger & Borchardt, 1996).

2.1.1.2 Clinical Function

After an initial focus on utilizing IT for financial reasons, care providers began to focus more on making use of IT during the process of actual care provision. The clinical function of health IT refers to applications that are used during care provision. Applications under this function replace paper-based documentation, entry order, and patient information with electronic forms of the same. They also help with decision making. Included in this function are IT applications that store patient information, such as medication lists and allergies. Also included under this function are those applications that allow for electronic management of laboratory tests and other reports. Finally, decision support systems, such as computerized reminders, help with diagnoses, and medical interaction warnings are important applications of this function (Robert Wood Johnson Foundation, 2006).

2.1.2.3 Exchange Function

In recent years, a greater focus has been placed on developing ways to share and exchange information across networks and between networks. Although this function has received much focus as of recent years, the exchange function of IT in healthcare is probably the least developed of the core functions. Information exchange in healthcare settings refers to online communication between a healthcare team, between healthcare partners, and/or between care providers and patients. Tools of the exchange function may include email and web-based messaging, telemedicine, and home telemonitoring, among other things (Robert Wood Johnson Foundation, 2006). Ultimately, the value of this function is measured by its ability to increase knowledge and information sharing between two or more actors in the provision of care.

2.2 A Brief History of IT in Healthcare

The development and application of IT in the healthcare industry is very much linked to the needs and operating environment of the healthcare industry, the resources available to individual institutions, the availability and sophistication of computer technology, in addition to public policies. The early focus of IT applications was primarily on administrative tasks, although a few clinical applications were implemented in isolated areas and settings. In the early 1980's, the healthcare environment began to change, along with technology. A need was created for both administrative and clinical applications. Furthermore, technology became more sophisticated and more readily available, allowing for applications in a wider variety of settings. This need has continued into recent years, along with a more recent effort to develop applications for information sharing and exchange.

2.2.1 Pre 1980's

Some of the earliest applications of IT in the American healthcare industry were decision support systems (DSS). In the 1950s, Dr. Homer Warner, then of the University of Utah, began developing an expert system aimed at assisting in the diagnosis of congenital heart defects (Warner et al., 1961). Warner's program, Iliad, worked in the following manner: First, symptoms, signs, and laboratory results were entered into a computer. This data was then compared known conditions. Finally, a differential diagnosis was generated. The program allowed for an adjustment to reflect the prevalence of some condition in the population (Graber & VanScoy, 2003). Around this time, other programs aimed at assisting in the diagnosis of medical conditions were created as well. Examples of such systems include DxExplain, Internist-I, MYCIN, and QMR (Berner et al., 1994). These systems were not extensively used, as they were complex and required users to enter a wealth of data into the system. Consequently, few practitioners will willing to take the time to learn them and enter the data (Miller & Geissbuhler, 1999). These early systems were used primarily as teaching tools for nursing and medical students and were not widely used outside of these settings (Staggers et al., 2001).

Larger-scale use of IT in the healthcare industry began shortly after the passage of federal legislation supporting both Medicare and Medicaid. These amendments to the Social Security Act all but guaranteed that healthcare institutions would be reimbursed for providing care to a broad range of people (Kissinger & Borchardt, 1996). This cost-based reimbursement model led to the availability and assurance of a steady cash-flow. Ultimately, this led to a relatively stable healthcare environment. Because of the stable operating environment, providers began exploring ways to apply technology to address their healthcare needs. In this era, institutional survival was largely dependent on fee-for-service reimbursement, consequently, early health IT applications focused primarily on performing administrative functions. These applications were designed to focus on the financial needs of the organization and capture revenue (Staggers et al., 2001).

The development of hospital information systems (HIS) occurred shortly after Medicare and Medicaid legislation was enacted. HIS are large, computerized databases used to store a wealth of patient and administrative information (Staggers et al., 2001). One of the earliest and most complex of these systems, Technicon Medical Information Systems, began in 1965 at El Camino Hospital (Wiederhold & Perreault, 1990). This system combined administrative, clinical, and ancillary functions. Physician's orders could be communicated to other departments electronically, test and reports could be sent and received electronically, and nursing documentation could be performed on computers (Barrett et al., 1975). The HELP system at Latter-day Saints (LDS) hospital in Salt Lake City was another prominent, early HIS system. The system included automated lab reports, portions of patients' records in electronic form, and decision support. A similar system was built at the National Institutes of Health Clinical Center in Bethesda, Maryland (Kuperman, Gardner, & Pryor, 1991). Other early, notable HIS systems included the TMR system at Duke University Medical Center, the Regenstrief system at

Wishard Memorial Hospital in Indianapolis, and the Tri-Service Medical Information System (TRIMIS) at United States military hospitals worldwide (Barnett, 1984; GAO, 1992; McDonald et al., 1988).

At this point, other than a few notable exceptions, health IT systems performed primarily administrative functions. The prospective payment system did not require that providers be efficient. Furthermore, during this time, mainframe computers were prominent and few vendor-created applications existed. Thus, computer technology remained relatively expensive and few institutions possessed the in-house technical skills need to create new applications. Not surprisingly, early health IT systems were used primarily in large hospitals and academic medical centers where the capital and technical expertise required to implement such systems existed (Shortliffe, 2005).

2.2.2 1980's Onward

In 1983, Medicare switched from a retrospective, cost-based payment system to a prospective payment system. In a prospective payment system, a care provider receives a fixed payment to cover an episode of care during some period of time. The formulas for payment are complex, but the goal is to set the bundled, prospective payment on what it would cost an efficient provider to provide care. In this system, the efficient providers make money, while the inefficient providers lose money (Mayes & Berenson, 2006). More care settings were moved into this system and Medicaid and other insurers followed suit as well. These developments led to a shift in the focus of care from a physician orientation to a payer-focused orientation, emphasizing health promotion, disease prevention, and cost-effectiveness. The appropriateness of medical decisions were also emphasized. This major shift in the focus of care provision led to an increased need in a variety of care settings not only for administrative IT applications, but for clinical IT applications as well (Staggers et al., 2001). In addition, during this time, smaller, more affordable, and more powerful computers became increasingly available to a wide variety of organizations in a variety of care settings.

In addition to increasingly wide use of applications for administrative and clinical functions, one important development during this time was the greater development of the computerized patient record. Several major medical organizations pushed for the development of the computerized patient record as a way to fuse business and clinical goals and support the movement towards healthcare integration. A focus was also placed on tracking information across a lifespan (Dick & Steen, 1991). Computerized patient records were thought to have the potential to increase knowledge, bring about improvements in the quality of decision-making and ultimately, lead to better care and organizational outcomes. They were also believed to have the potential to bring about major cost-savings (Staggers, 2001).

2.2.3 The Future of Information Technology in Healthcare

When one looks at history, one can see how the model of healthcare delivery has influenced the technology involved in care provision. The future model of healthcare provision is uncertain, but healthcare costs are continuing to rise and the population is aging. Managed care has become the norm for the most part and the focus of care is on outcomes management, evidence-based practices, and care delivery across a variety of settings. The future of IT applications in healthcare settings will most likely continue to focus on the development of clinical applications, along with a new focus on information sharing and exchange in a wider variety of settings. A greater number of users and the internet will make this more of a reality (Staggers, 2001).

As a greater number of facilities and healthcare networks adopt different applications of health IT, especially computerized patient records, it is likely that an increased focus on information sharing between networks will take place. Advances in technology, the increasing availability of technology, and standardization will make information sharing possible (Jadad, 1999). In addition, care providers will be increasingly accepting of IT as a necessary, important, and routine part of care provision. As computers will continue to be ever more present in society, providers more open to using them. Increasing regulatory requirements may also mandate the use of information technology in all facilities (Staggers, 2001).

Of course, the sharing of information across networks leads to even more privacy issues than sharing within facilities or networks. The capability of those who are not authorized to view certain information may increase. Care providers may be tempted to access information as well. Thus, the future development and use of health information sharing and integration will largely be dependent on resolving difficult legal issues and complex issues of privacy and security (Christiansen, 1999).

Increasingly, the internet will be used as a tool to transform healthcare. This will likely increase the control of patients over care, redefine the roles of traditional care providers, and lead to a more patient-centered care model. New systems of record-keeping will allow for patients to enter data themselves and use data for decision-making. An example of this type of system is Kaiser Permanente's Web strategy (Cross, 2000). Patients will also have access to vast amounts of medical information. Clinicians and nurses will no longer be the only source of information, so they will need to transition from health experts to information brokers (Clark, 2000). Finally, provider-patient communications will also be transformed. The increasing use of email will allow patients to ask questions directly and quickly (Staggers, 2001).

2.3 Current State of Health IT in the United States

Accurate and updated statistics are somewhat hard to obtain, but the United States is generally thought to lag behind other countries in the adoption of the different applications that comprise health IT. A somewhat outdated 2002 Harris Interactive report showed that general practitioners' use of electronic technology in the United States lagged behind European countries, in particular Sweden, the Netherlands, and Denmark (Harris Interactive, 2002). Particularly striking is the percentage at which the general practitioners in the United States lag behind those in other countries in the use of electronic medical records. See Table 2.1 below for 2002 estimates of general practitioners' use of electronic technology in selected countries.

Table 2.1 General Practitioners' Use of Electronic Technology in Selected Countries

	Use Computer in Practice	Use PDA in Practice	Use Internet or GP Network	Use Electronic Medical Records	Practice has a Website
Finland	100%	4%	100%	56%	63%
Netherlands	100%	31%	100%	88%	47%
Sweden	98%	3%	93%	90%	42%
Germany	95%	10%	53%	48%	26%
United Kingdom	95%	18%	87%	58%	27%
France	89%	11%	80%	6%	11%
Austria	82%	2%	64%	55%	18%
Ireland	72%	6%	48%	28%	6%
Spain	71%	17%	43%	9%	6%
Denmark	70%	1%	62%	62%	13%
Luxembourg	68%	0%	46%	30%	12%
Italy	66%	0%	38%	37%	6%
Belgium	66%	7%	51%	42%	9%
Greece	52%	3%	27%	17%	4%
Portugal	37%	3%	19%	5%	2%
European Union Average	80%	11%	61%	29%	13%
United States	94%	17%	79%	17%	39%

Source: Harris Interactive (2002)

Within the United States, adoption rates of the different technologies vary greatly by care setting. There is no definitive source for adoption rates, but national estimates from 2006 suggest that 24% of MD practices, 61% of IDNs, 55% of stand-alone hospitals, 8% of SNF/rehab hospitals, 6% of home health agencies, and 86% of laboratories utilized electronic results viewing. Furthermore, in 2006 20% of IDNs utilized inpatient EHRs, while only 1% of SNF/rehab hospitals utilized the same technology. Finally, in 2006, only 2% of home health agencies utilized electronic patient-doctor communication, while 26% of pharmacies did so (Poon et al., 2006). See Table 2.2 below for 2006 estimates of the adoption rates of several applications by selected care settings. Other studies echo these findings (see Ash, Gorman, & Hersh, 1998; and Ash et al., 2004).

Table 2.2 National Estimates of Health IT Adoption by Care Setting

Care Setting	Res. Viewing	Inp. EHR	Inp. CPOE	Amb. EHR	Amb. CPOE	E-Pres.	Claims	Eligibility	Patient-Doc. Commun.
MD Practices	24%	--	--	9%	5%	--	79%	11%	6%
IDNs	61%	20%	15%	13%	10%	--	90%	28%	8%
Stand-Alone Hospitals	55%	12%	9%	7%	6%	--	85%	19%	4%
Home Health Agencies	6%	--	--	5%	--	--	73%	16%	2%
Labs.	86%	--	--	--	--	--	90%	47%	6%
Pharms.	--	--	--	--	--	5%	93%	76%	26%
Payors	--	--	--	--	--	--	94%	86%	--

Source: Poon et al. (2006)

2.3.1 Some Common Current Applications of Health Information Technology

Today, there exists a wide variety of health information technology applications. Each application can, I believe, be fit under one of the three core functions of health IT, although not always neatly. These applications are discussed in some detail below. Before discussing them, it is important to note that the applications featured below are only a few *examples* of common applications. This list is only a small slice of the available current applications and is in no way exhaustive. It should also be noted that the types of applications and the adoption of rates of these applications vary widely by care setting. Furthermore, the exact specification of each application (and ultimately, the system) will depend on a number of factors. For instance, it may depend on whether or not the application(s) was developed in-house or purchased from a commercial IT vendor, such as Eclipsys or MEDITECH. Finally, the development of these applications and their different uses are still evolving and will continue to evolve for years to come.

2.3.1.1 Administrative Applications

2.3.1.1.1 Billing and Reimbursement Management

Like many of the other administrative applications, electronic billing management is widely used. This particular application can be considered a part of the financial administrative function of health IT. Electronic billing management is the process by which a care provider electronically submits a claim or bill to an insurance company or other payer in response to the provision of some medical service. Often, after a service is provided, a provider will enter a terminology code that describes the level of service provided. The provider will also enter a diagnosis code. After this information is entered, the claim is submitted electronically. After sending this information, the provider will receive information from the payer regarding what and how much will be paid (Tech Target, 2012a).

2.3.1.1.2 General Ledger

General ledger applications are those that electronically support the tracking and reporting of a healthcare provider's financial accounts and statements of business. This particular application can be considered a part of the financial administrative function of health IT (MedPac, 2004).

2.3.1.1.3 Cost Accounting System

A cost accounting system in healthcare inventories the different costs involved in providing care. It is designed to lower costs and improve managerial decision-making. Cost accounting systems are relatively new in the healthcare industry. With the movement away from a reimbursement-based system to a prospective payment system, electronic cost accounting systems have become increasingly common. Like the electronic general ledger and electronic billing management, this specific application can be considered a part of the financial administrative function of health information technology (Toso, 2012).

2.3.1.1.4 Personnel and Payroll Management

Electronic personnel and payroll management is an important application that can be considered to be a part of both the financial and organizational administrative function. Electronic personnel management refers to the digital handling of issues, such as scheduling and other employee information. Payroll management refers to electronically handling issues, such as paychecks and benefits (MedPac, 2004).

2.3.1.1.5 Electronic Materials Management System

Electronic materials management systems track and manage inventory for a variety of care settings. Similar to personnel and payroll management, this application may be considered a part of both the financial and organizational administrative function of IT. Inventory tracking may include things, such as medical supplies, drugs, and other important materials. When inventory reaches a certain pre-defined level, the system will send an alert or automatically order the needed materials. This can lead to more effective utilization of resources and less waste. This application is similar to other resource planning systems used outside of the healthcare industry (MedPac, 2004).

2.3.1.2 Clinical Applications

2.3.1.2.1 Computerized Provider Order Entry (CPOE)

Computerized provider order entry, also sometimes referred to as computerized physician order entry, or simply CPOE, refers to an electronic medication and ordering fulfillment system. In this information system, clinicians directly (electronically) enter medication orders in to a computer system. The order is then transmitted to a pharmacy. This sort of system is designed with the intention of ensuring standardized, legible, and complete medication orders. More advanced CPOE systems allow for clinicians to place electronic orders for additional necessities, such as lab results and radiology test results. They may also be paired with a clinical decision support system (CDSS) (AHRQ, 2012).

2.3.1.2.2 Electronic Health Record (EHR)

Electronic health records, or EHRs, are probably the most widely-known and discussed application, though, like many other applications, there is no precise definition. In short, EHRs can be thought of as a systematic collection the health information of a patient or a larger population. They may include a range of data such as demographic information, medical history, allergies, billing information, personal statistics, and more (Gunter & Terry, 2005). A more sophisticated EHR will typically contain a larger amount and greater variety of data. They have evolved over time from a sort of in-house electronic file cabinet to a dynamic record that (ideally) can be shared. In addition, more sophisticated EHRs are often integrated with CDSS and CPOE systems, among other applications (MedPac, 2004).

2.3.1.2.3 Clinical Decision Support System (CDSS)

A clinical decision support system, or CDSS, is an application that stores and analyzes data to be used in clinical decision-making. A CDSS is a spinoff of expert decision support systems commonly used in other industries, such as business. With a CDSS, clinicians will enter signs, symptoms, etc. into a computer. The computer will check and analyze the entered against a database. The outcome of this analysis will commonly be a diagnosis or recommendation. In addition, data mining may also be performed in an effort to predict future events, such as disease or drug interaction. Finally, decision support may also be provided in the form of computerized reminders. There are primarily two types of CDSS. The first type uses a knowledge database. This database is created beforehand and applies rules to patient data to produce an outcome to the end user. The second type of CDSS uses machine learning and intelligence to produce results for the end user (Tech Target, 2012b).

2.3.1.2.4 Mobile and Bedside Computing

Mobile and bedside computing is another important application of health information technology. Mobile and bedside computing refers to the use of electronic devise, such as personal digital assistants (PDAs), cellular phones, notebook personal computers (PCs), and other portable devices at the point of care, or at the bedside. Mobile computing has become increasingly popular in recent years as technology has allowed for smaller, cheaper, and lighter electronic devices. These devices are important to care providers, because it allows them to bring a wealth of information to the bedside. This was difficult in past years, as computers were too large and immobile (Arshad, Mascolo, & Mellor, n.d.). In addition, these applications can save care providers from making frequent trips if several applications are embedded into laptops or PDAs. In addition, mobile computing may also be thought of as a part of the infrastructure that supports and enables other applications to operate more effectively (MedPac, 2004).

2.3.1.2.5 Picture Archiving and Communication System (PACS)

An electronic picture archiving and communication system, or PACS, is a medical imaging application that stores diagnostic and radiological images from variety of sources (X-ray and magnetic resonance imaging, or MRI, for example). Images can also be transmitted electronically via a PACS. Ideally, the goal of the application is to provide economical and convenient storage and transmission of medical images in one place. This eliminates the need to manually file, retrieve, and transmit important images (Choplin, Boehme, & Maynard, 1992). Often times, a PACS may be integrated into a mobile computing system and/or health records (MedPac, 2004).

2.3.1.2.6 Automated Dispensing Machine

An automated dispensing machine is fairly straightforward. This technology distributes doses of medication in an automated manner (MedPac, 2004). Typically, they also track medication use. Most systems require user IDs and passwords, which allows for nurses to access the system, allows for tracking of patients to whom drugs are administered, and allows for detailed usage data, which can be used to improve administrative functions. The introduction of an automated dispensing machine usually has several goals: fewer medication errors, greater staffing efficiency, improved inventory tracking and billing functions, and less medical waste (Fung & Leung, 2009).

2.3.1.3 Exchange Applications

Exchange applications are those applications which allow for electronic healthcare-related information sharing between a healthcare team, between healthcare partners, and/or between care providers and patients. For instance, with exchange capabilities, a long-term care facility might be able to communicate with a pharmacy, patients' physicians, or a corporate office. Specific applications include those which are familiar to many patients and care providers, such as email and web-based messaging. Other, less familiar applications include telemedicine, which allows for the provision of care at a distance. For example, a physician may meet with a rural patient via video chat. Finally, simple use of the internet may allow for public health reporting and information exchange between care providers (Robert Wood Johnson Foundation, 2006).

2.4 Evaluation of the Impacts of Health IT

The existing literature on the impacts of health IT can be divided up into two lines of research: impacts on quality of care and organizational impacts. The questions asked in quality of care studies are obvious: how might health IT impact quality of care? What is it about health IT applications that can improve or degrade quality of care. Organizational impact studies ask questions concerning how health IT adoption and use affects job satisfaction, time utilization, costs, etc. Before reviewing both of these types of studies, it should be noted that the lines between the two types of studies are not neat. For instance, improved drug dosing may lead to improved quality of care, but it may also lead to decreased costs through decreases in length of stay, medication usage, and potential malpractice suits.

Finally, others might divide up the literature differently. This is only one of the possible ways of going about this.

2.4.1 Impact on Quality of Care

The existing literature on the impact of health IT on quality of care suggests that these technologies can have a positive impact. Health IT may work as a mediator on quality of care primarily through the reduction of medical errors, adherence to accepted guidelines, and enhanced clinical monitoring. These relationships are discussed further in the proceeding section, but they can be displayed graphically in the manner displayed in Figure 2.1 below.

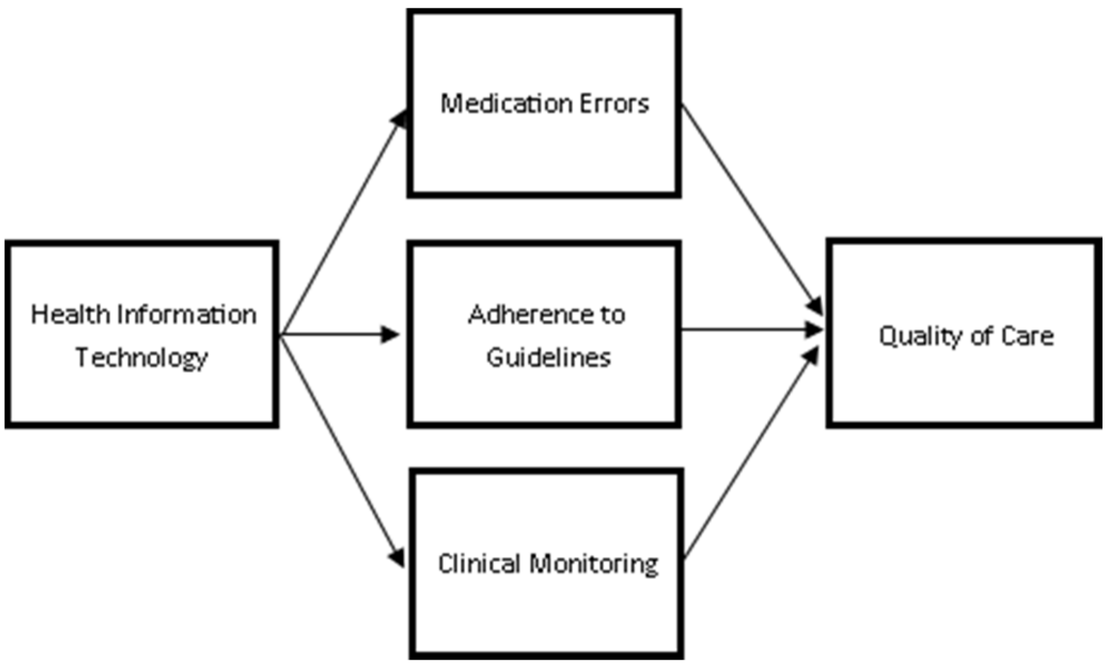

Figure 2.1 Relationship Between Health IT, Moderating Variables, and Quality of Care

2.4.1.1 Medication Errors

Studies suggest that health IT may improve quality of care by reducing the frequency of medical errors. First health IT systems may improve medication dosing. In studies conducted so far, improvements in dosing ranged anywhere from 12% - 21%. For example, Chertow et al. (2001) examined the effect of a computerized drug dosing algorithm to determine the effect on medication prescribing. They found that the program led to a 21% increase in appropriate medication orders. As a side note, they also found a 4.5% reduction in length of stay, which may also lead to reduced costs. Mullet et al. (2001) conducted a pre-post study in a pediatric unit in an effort to better understand the impact of computerized guidelines on antibiotic use and appropriateness. They found that the computerized guidelines led to a 32% relative decrease in the number of days that the drugs were prescribed outside the recommended range. They also found a 59% relative decrease in a composite measure of need for pharmacist interventions for incorrect dosing. Finally, they found a 6.3% absolute increase in proportion of patients receiving antibiotics. Finally, Evans et al. (1999) designed a pre-post study to examine the effect of computerized monitoring of antibiotic doses on appropriateness of dosing and rates of dosing. They found a 6% relative decrease in patients receiving excessive antibiotic doses, a 12% relative decrease in number of doses prescribed, and a 13% relative decrease in costs.

In addition to improvements in dosing, health IT may improve quality of care by reducing adverse drug events (ADEs). In the same pre-post study described earlier, Evans et al. (1999) found that computerized monitoring of antibiotic dosing led to a .6% relative decrease in antibiotic-related ADEs. From 1992-1995, Evans et al. (1998) conducted a study of computerized alerts on antibiotic usage. In terms of ADEs, Evans et al. found that, compared with the pre-intervention period, reductions were seen in antibiotic-associated ADEs, days of excess dosing, mismatches between infection susceptibility and antibiotic, and ordered drugs for which a patient was allergic. Reductions were also seen in antibiotic costs, length of stay, and total hospital costs. Bates et al. (1998) found similar results when they did a time-series study of CPOE on rates of medication errors and preventable ADEs. They found a 55% relative risk reduction in non-intercepted, serious medication errors. In addition, they found decreases for all levels of medication error severity. They concluded that health IT can certainly have a positive impact on reducing medication errors and ADEs. Bates et al. (1999a) came to similar conclusions after conducting another time-series study in which the impact of CPOE with decision support on rates of non-missed dose errors and serious medication error rates. They found an 86% relative reduction in non-intercepted, serious medication errors, an 82% relative reduction in non-missed dose errors, and reductions in all error types.

While most of the research on the impact of health IT on medication errors is quite sanguine, one major study suggests that it may actually lead to increased medication errors in some situations. In this study, Koppel et al. (2005) designed a mixed-methods study to examine the impact of CPOE in facilitating medication prescribing errors. They found that CPOE increased 22 types of medication error risks. They attributed these risks to two factors: fragmentation of data and flaws in human-machine interface. These findings suggest that the design of the application, interoperability, and exchange capabilities are potentially very important. Interestingly, the CPOE system evaluated in this case was a commercially available system sold by Eclipsys Corp.

2.4.1.2 Adherence to Guidelines

In addition to improving quality of care through the reduction of medical errors, studies suggest that health IT may have a mediating effect on quality of care by increasing adherence to accepted guidelines. The literature suggests that this may actually be the *primary* means through which health IT can lead to improvements in quality of care. As such, a large number of studies have been conducted on the impact of health information technology on adherence to guidelines (Chaudhry et al., 2006). In addition, a large number of these types of studies exist, because their usual focal application, DSS, is one of the oldest and most mature health IT applications. Most of these studies involve the examination of a DSS linked with some other application or applications. The most frequent of these studies examine the impact of DSS linked with EHRs. Some of the earliest such studies were conducted by McDonald. In the first study, McDonald (1976a) conducted a randomized controlled trial to determine the impact of computerized reminders on physician adherence to protocol-based care for diabetes[1]. McDonald saw a 15% increase in adherence to protocols. In a broader, but similar second study, McDonald (1976b) found similar results. McDonald found that the DSS linked with EHRs

[1] Protocol-based care is in itself a type of technology, soft technology. It is a set of industry-accepted standards and guidelines for diagnoses and recommendations for care. While they are generally accepted standards and guidelines and their use is encouraged, a care provider may choose work based off of knowledge or even habit.

led to a 29% absolute increase in adherence to protocols. In a third early study, McDonald et al. (1980) found that computerized reminders with and without literature citations increased adherence to protocols (19% absolute increase). In a fourth early study, McDonald et al. (1984) again examined the impact of computerized reminders on protocol-based care. In this clinical controlled trial in an outpatient setting, McDonald et al. found a 15-20% increase in adherence to protocol-based care, with very large increases seen in preventive care. In addition to the early McDonald-led studies, many other studies have found similar results when examining the impact of DSS linked with EHRs on adherence to accepted guidelines. Dexter et al. (2004), Dexter et al. (1998), Khoury (1998), Ornstein et al. (1995), Garr et al. (1993), Safran et al. (1995), Schriger et al. (1997), Litzelman et al. (1993), Canon and Allen (2000), Chin and Wallace (1999), Evans et al. (1994), Tierney et al. (1986), and Demakis et al. (2000) are examples of such studies. Interestingly, Demakis et al. found that the effect of computerized reminders decreased over time. Another study, Abookire et al. (2000) also found that attention to alerts decreased over time (although this study looked at a DSS linked with CPOE). In addition, attention to alerts decreased as the number of alerts increased. Some other studies, Overhage et al. (1996) and Rollman et al. (2002) found no statistically effect of computerized reminders on adherence.

While most adherence studies examine a DSS linked with EHRs as the primary intervention, others examine a DSS linked to CPOE. In one of these studies, Overhage et al. (1997) conducted a randomized controlled trial to examine the impact of point-of-care computerized reminders on adherence to guidelines. They reported a 25% absolute increase in adherence to guidelines. In other studies of this nature, Kucher et al. (2005) and Teich et al. (2000) also saw increases in adherence to protocol-based procedures.

Finally, other studies have looked at the impact of a stand-alone DSS on adherence to guidelines. These studies have, for the most part, come to the same conclusions as the previously mentioned studies: health information technologies, in particular DSS, have the potential to improve quality of care through increased adherence to guidelines and protocols. One of these studies, McDonald et al. (1992), conducted a randomized controlled trial to study the impact of computerized reminders on the need for the influenza vaccination. McDonald et al. reported an increase of 12-18% in influenza vaccination rates. In another randomized controlled trial, Rossi and Every (1997) found that a stand-alone DSS had led to an 11.3% absolute increase in appropriate hypertension treatment. In 1994, Wilson et al. (1995) analyzed data collected during a pre-post study of the effect of computerized guidelines for the prevention and treatment of pressure ulcers on treatment adherence. They found a 5% absolute decrease in ulcer development. Finally, Larsen et al. (1987) conducted another pre-post study to determine the effect of computerized guidelines on the appropriateness of antibiotic use. They reported several positive findings. First, they reported that the computer program suggested the correct antibiotic in 94% of cases, a 17% absolute increase. They also saw a 27% relative decrease in time to appropriate treatment after culture results. Further, they reported a 21% relative decrease in antibiotic cost, along with faster ordering time. Importantly, they found that physicians would recommend the program to other physicians and that 85% of users said the program improved antibiotic selection.

2.4.1.3 Clinical Monitoring

Finally, the literature suggests that health IT may have a mediating effect on quality of care by improving clinical monitoring. Quicker and better interventions may be designed. This can be done through the aggregation of data and large-scale screening, two things that are quite difficult to do with paper-based information (Chaudhry et al., 2006; Kerr et al., 2002). For example, in one study researchers scanned over 90,000 hospital admissions to look at the frequency of ADEs (Classen et al., 1997). In another study, Evans et al. (1992) used EHRs to identify ADEs, examine causes, and develop interventions to decrease ADEs. These interventions then led to increased ADE recognition and fewer ADEs. Evans et al. (1993) again used EHRs to determine that ADEs cause an increase in length of hospital stay and a subsequent increase ($1,939) in charges. Health IT has also been used to help identify infectious disease outbreaks. One study found that a county-based results reporting system led to a 29% absolute increase in identification of cases of shigellosis during an outbreak. This same study found a decrease in identification time (Overhage, Suico, & McDonald, 2001a). Another study found a 14% absolute increase in identification of hospital-caused infections and a decrease in identification time as well (Evans et al., 1986).

While health IT may improve clinical monitoring, there is some reason for caution when using it to do so. A few studies suggests that the validity of such results IT-based monitoring efforts may be compromised, if not downright incorrect. For instance, one of these studies found that high rates of false-positive results were found when automated algorithms were used (Kramer et al., 2002). Another study found that automated searches from computerized registries underestimated completion of quality-of-care processes when compared against the same task done manually (Kerr et al., 2002). The results of these two studies suggest that, at the least, caution should be used when using health IT for clinical monitoring purposes.

2.4.2 Impact on Organizations

2.4.2.1 Clinician Satisfaction

Clinician, or user, satisfaction is important to consider when evaluating the impact of health IT on healthcare organizations. Clinician satisfaction has important implications for the adoption, initial use, and repeated use of health information technologies. If users are unsatisfied with some technology, they may use it less or not use it all. Studies conducted on the impact of health information technology on user satisfaction are somewhat rare and user satisfaction has largely taken a backseat to quality of care-based studies. What studies do exist though, suggest that acceptance and user satisfaction increase over time. It is likely that, like any uptake of technology, familiarity with the system must increase. In addition, other kinks must be worked out. In one of these studies, Krall (1995) studied the impact of a commercially available EHR system on workflow and subsequently, attitudes about the EHRs. Lee et al.

(1996) found that user satisfaction with an order entry system was good. Krall found that, after initial frustration, physician satisfaction increased over time. Also, Lee et al. (1996) found that user satisfaction with an order entry system was good. Furthermore, Kilgore et al. (1998) compared two different intensive care unit (ICU) information systems with CPOE. They studied the systems' impact on work patterns. They found that staff satisfaction was higher with one system, because of the ease of use of the interface and greater support of existing workflow. This finding corroborates other studies that suggest that the design of the application is quite important. This study, and others (see Igbaria, Livari, & Maragahh, 1995 and Lee et al., 1996), suggest that the design and development of health information technology systems has much to do with end-user satisfaction.

In addition, it is important to consider and better understand how users *feel* about the improvements (or lack of) being brought on by a new technology. Perception may influence satisfaction and subsequent use (Lee et al., 1996). The research here suggests that users do perceive that health IT can lead to better outcomes. This is important. For example, Evans et al. (1994) conducted a randomized controlled trial and found that DSS linked with EHRs not only improved quality of care, but that 88% of physicians would recommend the program to other physicians[2]. Additionally, they found that 85% of physicians said that the program improved antibiotic selection and 81% of physicians said that they though that use of the technology intervention improved care. Pizziferri et al. (2005) found similar results. They found that physicians felt EHRs had improved quality, access, and communication. On the other hand, they found that it had negatively affected their workload. Finally, Overhage et al. (2001b) found that an order entry system positively affected physicians' perception of the care they provided, among other things. See Figure 2.2 for a graphical representation of the relationship between health IT and clinician satisfaction.

[2] Importantly, this might be one of the potential means through which health IT applications are diffused.

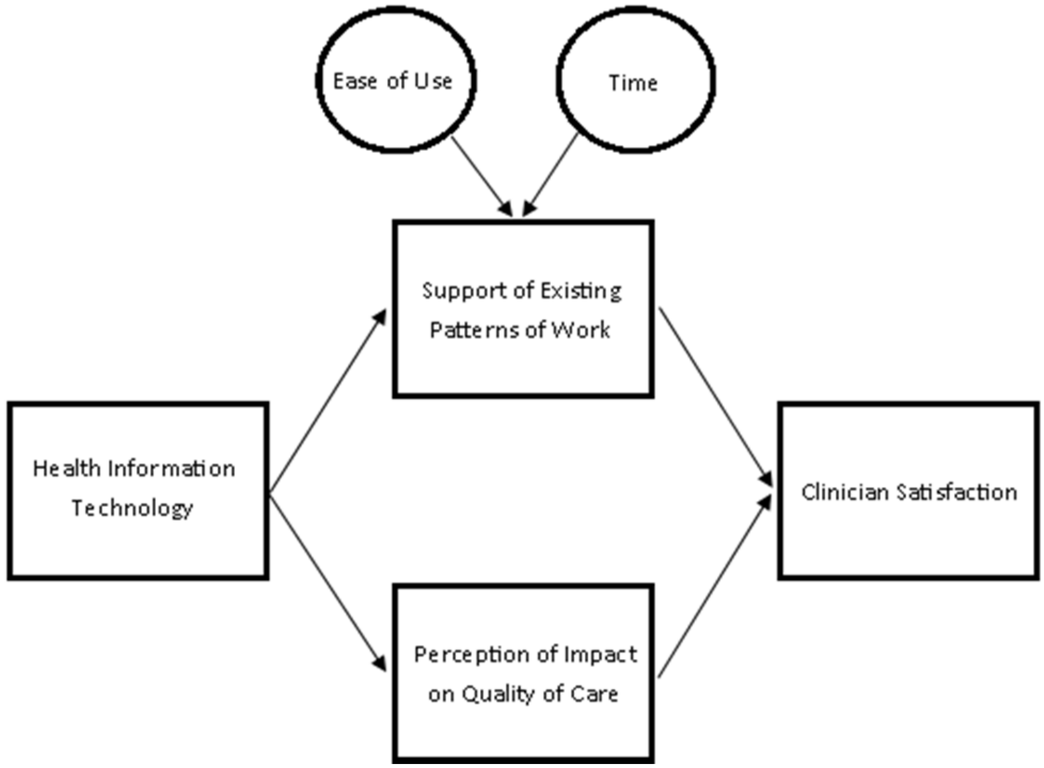

Figure 2.2 Relationship Between Health IT and Clinician Satisfaction

2.4.2.2 Costs

Research on the monetary costs associated with health information is quite limited. Most of the studies concerning the costs associated with health information technology are related to the utilization of care (See section 2.4.2.2.2 for a run-down of these studies). Two studies have found reductions in storage costs, although these studies are quite old, limiting their current use to researchers, policy-makers, and practitioners (See McDonald, 1976 and Wilson et al., 1982). Although they are old, it's easy to imagine even less storage space required today. Reductions in storage costs were due to decreased use of paper and smaller computers. Another study reported yearly maintenance costs of $700,000 (Teich et al., 2000). One study, Khoury (1998), reported that adherence to guidelines led to an estimated yearly savings of $2,470,000, although initial implementation costs were not included in the estimates. In another study conducted by Khoury, the long-term costs and benefits of EHR implementation at Kaiser Permanente were studied (Khoury, 1997). Khoury reported the estimated cost of development at $10 million. Total ongoing expenses were estimated at $1.1 million per year with expected savings of $3.7 million per year. The greatest savings reductions were expected to come from the reduction of medical record room staff. Further, this system was projected to pay for itself after 13 years.

2.4.2.2 Efficiency

The literature concerning the impact of health information technology on efficiency is relatively small and typically falls into one of two categories: utilization of time and utilization of care (Chaudhry, 2006).

2.4.2.2.1 Utilization of Time

In terms of the impact of health IT on time utilization, studies suggest that the effect is mixed. On one hand, studies suggest that time spent at the computer may increase, taking time away from patients. For instance, a 1993 study conducted at the Regenstreif Institute in Indianapolis found that the implementation of a physician inpatient order entry system on microcomputer workstations led to more time spent at the computer by physicians (Tierney et al., 1993). Another study conducted several years later in an outpatient setting at the Regenstrief Institute showed similar results. In this case, physicians continued to use paper despite having an order entry system. This led to duplication of tasks. In this same case, physician time per clinic visit increased 6.2% (Overhage et al., 2001b). In addition, another study, conducted in an outpatient setting at Brigham and Women’s Hospital in Boston, showed that physician use of EHRs led to a 0.5 minute decrease in clinic visit time (Pizziferri et al., 2005). Further, Mekhijian et al. (1988) found a 64% relative decrease in medication turnaround time, 43% relative decrease in completion time for radiology procedures, and a decrease in reporting time for lab results when they studied the impact of CPOE linked with EHRs. Cordero et al. (2004) also reported that health IT, in particular CPOE linked with a DSS, reduced turnaround time for medication and reduced radiology response time. They also reported that nurse leaders received 16 hours of training, nurses and clerical staff received 8 hours of training, and physicians received 2-4 hours of training.

On the other hand, several studies have shown small decreases in nursing documentation time. For example, Pierpont and Thilgen (1995) conducted a pre-post time-motion study of electronic health records in an ICU at a Veterans Administration (VA) hospital. The found a slight decrease (7%) in charting time and a slight (3%) decrease in data-gathering time. No change was seen in time spent in patients' rooms. Wong et al. (1998) found similar results when they conducted another pre-post time-motion study at a VA hospital. They again looked at the impact of EHRs on nurses' time utilization in an ICU. They found a slight decrease (10.9%) in documentation time. Unlike Pierpont and Thilgen (1995), they found an increase (8.8%) in time spent on direct patient care. Finally, Kuperman et al. (1999) studied how computerized alerts sent via pager would affect physician response time to deliver treatment. They found a slight decrease in mean time until treatment. While studies concerning utilization of time are mixed, importantly, and perhaps not surprisingly, studies have suggested that the time needed to operate many health IT applications decreases the longer care providers have used the applications. Krall (1995) described this phenomenon. The author found that physicians took about 30 days to return to baseline productivity levels after implementation of a commercially available electronic health records system. As of recently, no long-term evaluations of this phenomenon have been conducted (Chaudhry, 2006). See image 2.3 for a graphical display of the relationship between health IT and utilization of time.

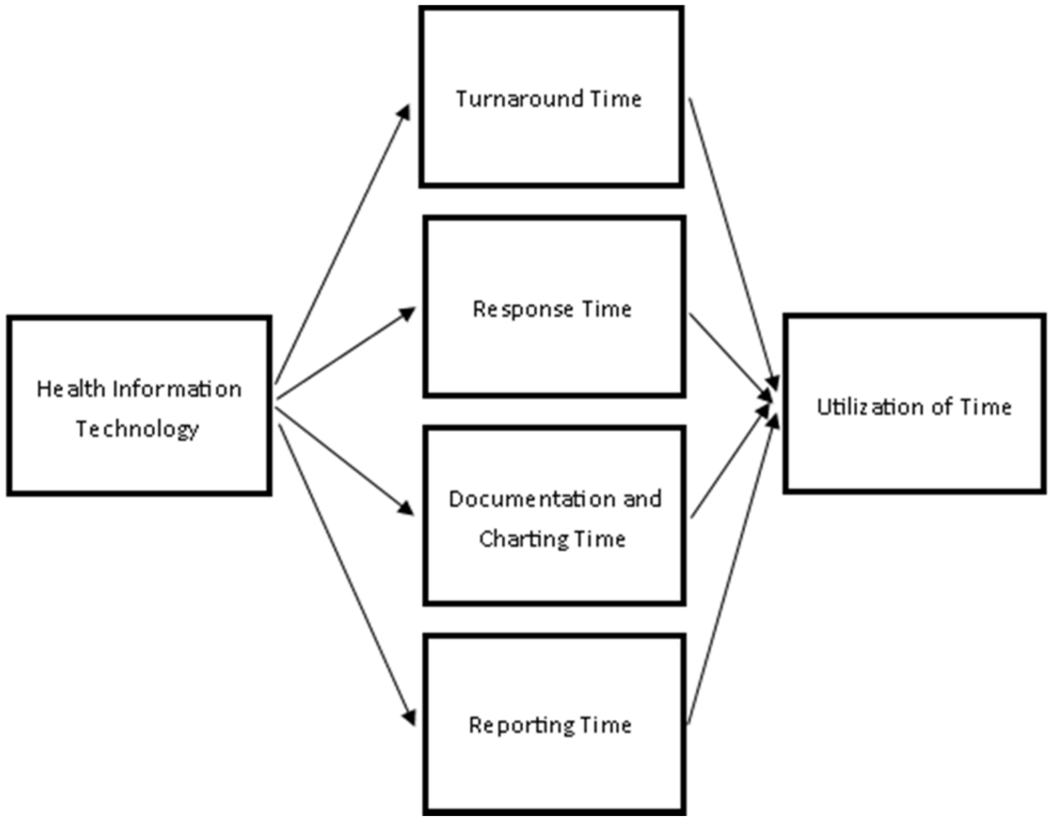

Figure 2.3 Relationship Between Health IT and Utilization of Time

2.4.2.2.2 Utilization of Care

A majority of the studies conducted concerning efficiency fall under the category of utilization of care. Studies suggest that this seems to be the primary area in which an efficiency benefit is provided with the adoption of health information technologies. In addition, the majority of these studies have been conducted on order entry systems and EHRs. Many studies show a decreased utilization of care. Tierney et al. (1988) conducted a study to determine the effect of a computer program that generated and displayed pretest probabilities for diagnostic tests with the utilization of care as an outcome variable. They found an 8.8% decrease in diagnostic test costs per visit. Tierney et al. (1987) designed a pre-post study to examine the impact of a computer program that would display previous test results as physicians order new results. In the old system, physicians would not see previous results displayed electronically. They found an 8.5% decrease in the number of test results ordered per visit. Tierney et al. (1990) conducted another study to examine the effect of information on tests costs on the utilization of care. They found that when physicians were given a graphical display of test costs, the number of diagnostic tests ordered decreased substantially (14.3%). They also found a 12.9% decrease in diagnostic test costs per visit. Again, Tierney et al. (1993) conducted a randomized controlled trial at the Regenstreif Institute in an effort to better understand the impact of CPOE on costs and utilization of health care. They found a reduction in total costs per admission, a decrease in test costs, and a decrease in length of stay. In addition, they found an increase in time spent ordering tests. In another study conducted at the Regenstrief Institute, Wilson et al. (1982) designed a randomized controlled trial study in which the impact of EHRs on the utilization of care. Specifically, they examined how computer-generated patient record summaries influenced care utilization. They found a decrease in tests ordered. Chen et al. (2003) found similar results when they conducted a pre-post study at Brigham and Women's Hospital. They found that computerized reminders on rates of inappropriate daily testing led to a 27% decrease in redundant laboratory tests. In another study at Brigham and Women's Hospital, Bates et al. (1999b) conducted a randomized controlled trial to determine the effect of computerized reminders on utilization of care. They found a 24% reduction in redundant tests. This delivered an estimated cost savings of $35,000 per year. Finally, Shojania et al. (1998) conducted another randomized controlled trial at Brigham and Women's Hospital and found that a point-of-care guidelines system on antibiotic use reduced antibiotic orders (32%). Additionally, Sanders and Miller (2001) found a 5% relative decrease in neuroradiology computed tomography (CT) and MRI diagnostic testing after a DSS and CPOE intervention. Finally, Chin and Wallace (1999) found that a commercially available EHR system linked with a DSS led to a 20% decrease in chest radiographs ordered and a 2.3% absolute decrease in prescribing of a depressant.

While a majority of studies have found a benefit in terms of utilization of care, several studies have found no statistically significant difference. For instance, Steele et al. (1989) conducted a randomized controlled trial at a VA hospital. Specifically, they looked at the impact of computer-generated paper-based feedback of medication costs versus in-person pharmacist-based counseling on costs. They found no statistically significant difference in costs between the two groups. In another study, Bates et al. (1997) found that a point-of-care display of tests costs system provided no statistically significant difference in utilization of care over a system without test cost information. Garrido et al. (2005) drew similar conclusions after analyzing the data obtained from their retrospective time-series study. Finally, Baird et al. (1984) found no statistically significant difference in refill rates after a DSS and electronic prescribing intervention in an outpatient setting.

2.4.3 Conclusions on Impacts Literature

In sum, a fairly large literature on the various impacts of health IT exists. Most of these studies are randomized controlled trials conducted in the care setting of large academic hospitals. Further, most of these studies have focused relatively heavily on the impact of a few popular clinical technologies such as order entry systems, EHR systems, and DSS that have been developed in-house. Their success varies somewhat, but these studies suggest that there is decent evidence to support claims that health information technologies may improve quality of care. This may work through the avenues of greater adherence to guidelines, fewer medication errors, and enhanced clinical monitoring. The greatest support for quality improvement claims is derived through greater adherence to guidelines and protocol-based care. In particular, DSSs seem to offer a great benefit in this arena.

While there is sufficient evidence to support claims that health information technologies may improve quality of care, the evidence concerning the organizational impacts of health IT is more mixed. These studies have largely taken a backseat to studies concerning impacts on quality of care. Although relatively few in number, organizational impact studies suggest that, after an initial period of disruption, users are generally pleased with the information systems under study. Importantly, studies show that users *feel* like their care is improved. Additionally, there is not a lot of information on the monetary costs and benefits of health information technology, although slight cost savings have been seen due to changes in care utilization. Finally, utilization of time and staffing efficiency studies are few in number and are mixed. Results suggest that the effect might be greater on nurses than on physicians (Poissant et al., 2005). Significantly, studies also suggest that the implementation, development, and design of the systems should be important considerations as they will have an impact on satisfaction and efficiency.

There exists plenty of gaps in the impacts literature. First, studies need to be conducted in a wider range of care settings. Additionally, research should broaden its focus in terms of the technologies evaluated. Health information exchange could be evaluated more here. Further, research should look deeper into evaluating commercially-available technologies, instead of in-house technologies. Research should also examine the organizational impacts (especially costs) of health information technology adoption in further detail. The research lens should be focused not only on outcomes, but also on what influences those outcomes. More research also needs to be conducted on the impact of health IT on staff efficiency, in particular nursing staff efficiency. Further, research should look at the impact of health information technology on the various *types* (RN, LVN/LPN, aides) of nurses as well. The rest of this study attempts to address two of the aforementioned gaps: the nursing staff efficiency and information exchange gaps. Further, because it addresses these questions in a new setting, the context gap is partially addressed as well.

2.5 Rationale for Study

While there is quite a bit of research on the impact of health information technology on quality of care, there is comparatively little research on organizational impacts. In particular, very little is known about staff efficiency. What is known about staff efficiency impacts is primarily concerned with physicians. Unfortunately, the nature of work for physicians and nurses is fundamentally different (Poissant et al., 2005). Additionally, the research on staffing efficiency that *is* concerned with nurses typically looks at RNs. Again, like the contrast between physicians and nurses, the nature of work for the different types of nurses is quite different.

A better understanding of the impact of health information technology on nursing staff efficiency (at all levels) is important for a couple of reasons. First, we know that there is possibly a link between direct hours per patient day (HPPD) and quality of care. In a seminal article, Needleman et al. (2002) found that a higher proportion of RN direct care HPPD was associated with shorter stays, fewer urinary tract infections, and lower rates of pneumonia among other things. Other studies have found similar results (see Hartz et al., 1989; Kovner & Gergen, 1998; and Manheim et al., 1992 for some examples). Health IT applications may allow settings to provide the same quality of care, but in a more efficient manner. This could lead to reduced labor costs, and reduced healthcare costs in general. Increased staff efficiency may also free up more time for face-to-face care. Further, a better understanding of the relationship between health IT and efficiency may help managers better allocate scarce resources. For instance, managers may be better able to judge whether the addition of health IT is worth the initial costs. Finally, a better understanding of health IT and efficiency may help policy-makers better allocate public resources. For instance, grant money and incentives may be direct or re-direct on the basis of actual evidence.

Virtually nothing is known about the impact of exchange information systems on nursing staff efficiency. What we do know about the impact of health information technology on nursing staff efficiency is concerned with clinical applications. It is quite conceivable that information exchange applications may influence the efficiency of nursing staff.

2.6 Hypotheses

Several hypotheses regarding the impact of clinical information systems can be made. In short, it is expected that facilities with more sophisticated clinical information systems will exhibit greater nursing staff efficiency than those facilities with less sophisticated clinical information systems. These hypotheses can be stated in the following manner:

H_1: Residential care facilities with more sophisticated clinical information systems will be more likely to exhibit greater RN staffing efficiency than residential care facilities with less sophisticated clinical information systems.

H_3: Residential care facilities with more sophisticated clinical information systems will be more likely to exhibit greater LPN/LVN staffing efficiency than residential care facilities with less sophisticated clinical information systems.

H_5: Residential care facilities with more sophisticated clinical information systems will be more likely to exhibit greater personal care aide staffing efficiency than residential care facilities with less sophisticated clinical information systems.

Existing literature suggests that, in many cases, physicians may not realize efficiency gains from use of clinical health IT (see Overhage et al., 2001b and Tierney et al., 1993). While they are very few in number, the literature suggests that nurse labor efficiency gains may be made through increased use of clinical health IT though. This may be due to some of the basic differences between the tasks performed by the different care givers. Much of nursing consists of documentation and charting, whereas this is not so much the case with physician work. From previous studies, we know that clinical health IT applications may reduce charting and documentation time for nurses (Pierpont & Thilgen, 1995; Wong et al., 1998). For example, if nurses have the ability to document care given and write in their nurses' notes electronically, the need to write them in manually is eliminated. Ultimately, this saves time. Further, having resident demographics, medical provider information, service plans, and other information in electronic form may eliminate the need to search through files of paper information (Pierpont & Thilgen, 1995). Finally clinical IT may increase nurse efficiency through decreases in medication turnaround time, completion of lab procedures, and decreases in reporting time (Cordero et al., 2004; Mekhijian et al., 1988). While studies that have focused on these areas have been conducted on physicians, this is an area where there is some task overlap between the care givers.

Some hypotheses regarding the impact of exchange information capabilities on nurse efficiency can be made as well. It is expected that, in those facilities with clinical IT applications, facilities with more sophisticated information exchange capabilities will exhibit greater nursing staff efficiency than those facilities with less sophisticated exchange information systems. Stated another way, it is expected that those facilities with more sophisticated exchange capabilities will exhibit fewer HPPD for each type of nurse. More formally, theses hypotheses may be stated in the following manner:

H_2: Residential care facilities with more sophisticated exchange information systems will be more likely to exhibit greater RN staffing efficiency than residential care facilities with less sophisticated exchange information systems.

H_4: Residential care facilities with more sophisticated exchange information systems will be more likely to exhibit greater LPN/LVN staffing efficiency than residential care facilities with less sophisticated exchange information systems.

H_6: Residential care facilities with more sophisticated exchange information systems will be more likely to exhibit greater personal care aide staffing efficiency than residential care facilities with less sophisticated exchange information systems.

Information exchange could lead to increased nursing staff labor efficiency. For instance, the ability to electronically send and receive patient information to and from a resident's physician may save time by eliminating the need to call, mail, and travel to the physician to deliver the information. In another related example, the ability to electronically transmit information to and from a pharmacists may eliminate the necessity to travel and perform other time-consuming tasks. It may also eliminate the need for special staff to perform these tasks.

CHAPTER 3

METHOD

In order to test the aforementioned hypotheses, this study uses data from the 2010 National Survey of Residential Care Facilities (NSRCF). More specifically, this study utilizes residential care facility-level data from the first-stage of the 2010 NSRCF. Using this data, six separate ordered logit models are specified and estimated. Models 1 and 2 tests hypotheses 1 and 2 and examine the impact of clinical and exchange health information systems on the efficiency of RNs. RNs are nurses that have received a degree from an approved nursing program at a college or university and have successfully passed a licensing exam. These programs take from two to five years to complete. Additionally, they work in a variety of care settings and perform a variety of tasks, such as administering medication, giving shots, and documenting care (Shi, 2007).

Models 3 and 4 test hypotheses 3 and 4 and examine the impact of clinical and exchange health information systems on the efficiency of LVNs and LPNs. LVNs and LPNs are nurses that have completed a state-approved practical nursing or vocational nursing program that typically lasts approximately one year (Shi, 2007). Like RNs, they work in a variety of care settings. For the most part, hey perform tasks that are similar to RNs, but focus more on basic nursing activities, such as monitoring vital signs, observing patients, and assisting with bathing and feeding. In many cases, LPNs and LVNs cannot treat or diagnose most conditions and cannot administer fluids or prescription medications like RNs can (Buchbinder & Buchbinder, 2007).

Finally, Models 5 and 6 tests hypotheses 5 and 6 and examine the impact of clinical and exchange health information systems on the efficiency of personal care aides. Personal care aides are unlicensed patient attendants that work under the supervision of licensed nurses and physicians. They are frequently employed by residential care facilities and assist with activities, such as bell calls, changing bedding, and providing assistance with meals, changing clothes, etc. They are often trained on the job, instead of in the classroom, and are required to pass a competency examination (Buchbinder & Buchbinder, 2007).

The organization of chapter three of this thesis is as follows. First, the data used to conduct subsequent statistical analyses is discussed. Here, a brief description of the data is provided, followed by a more detailed description of the sampling design and sampling frame, the scope of the survey, and data collection procedures. After discussing the data used, the concepts and variables used in the statistical models are discussed. Here, the concepts and variables used to represent those concepts are discussed for each of the six models. While each model is similar in many ways, it is best to fully discuss each. Finally, the procedure of analysis for the six models is discussed. This final section covers the creation of the complex samples plan, a brief discussion of the statistical method used, and some of the diagnostic checks performed.

3.1 Data

3.1.1 Description of the Data

The 2010 NSRCF is a recent two-stage probability sample survey designed with the specific aim of collecting a wealth of data on residential care service providers in the United States. The survey, conducted by interviewers and a branch of the Centers for Disease Control and Prevention (CDC), collected a multitude of information, including data on organizational characteristics, staff characteristics, and information on the clients that these facilities serve. 2,302 facilities participated in the 2010 NSRCF along with over 8,000 residents of those facilities.

3.1.2 Sampling Design and Sampling Frame

The 2010 NSRCF utilized a stratified probability design. The sample was selected in two stages. The first stage of sample selection was carried out by the National Center for Health Statistics (NCHS) at the CDC. This stage involved the selection of residential care facilities from the sampling frame. The sampling frame was created from lists of licensed care providers obtained from the 50 states and Washington, D.C. The final sampling frame of 39,635 represented the universe of residential care facilities providing service in the United States. Within the sampling frame, facilities were stratified primarily by size, defined as the number of licensed beds, and census region. Within this primary strata, residential care facilities were sorted according to metropolitan statistical area (MSA) status and operating state. A total of 3,605 facilities were randomly sampled with the probability of selection proportional to facility size.

The second stage of sample selection consisted of the collection of resident data. This stage of sample selection occurred in-person and at the selected facilities. This stage was completed by interviewers. Residents were randomly selected from a census list provided by the facility. A maximum of six residents were selected at each facility. The selected residents only included those defined as current residents, or those residents who were on the facility rolls as of midnight on the day before the interview took place (Moss et al., 2011).

3.1.3 Scope of the Survey

As stated earlier, a total of 3,605 residential care facilities were randomly selected to participate in the 2010 NSRCF. Only state-licensed facilities were eligible to be selected for participation. More specifically, only those facilities that served an adult population, had at least one current resident, had four or more licensed residential care beds, provided room, board, and at least two meals a day, featured around-the-clock supervision, included help with personal care or health-related services were eligible to be selected. Residential care facilities that exclusively served the mentally ill, mentally disabled, or both were deemed ineligible to participate in the survey (Moss et al., 2011). In the end, 2,969, or 82 percent, of the 3,605 facilities in the sample were deemed to be in the scope of the survey and eligible to participate. Of those facilities deemed to be within the scope of the study, 2,302 agreed to participate. This resulted in an unweighted facility-level response rate of 79 percent and a weighted facility-level response rate of 81 percent (Moss et al., 2011).

3.1.4 Data Collection Procedures

Data collection for the 2010 NSRCF took place between March 2010 and November 2010. This data collection effort consisted of both facility recruitment for the study and in-person interviewing. During the recruitment phase of data collection, selected facility directors were mailed a folder that contained a variety of materials, such as a letter from the director of the survey, an Ethics Review Board (ERB) approval letter, confidentiality information, etc. After sending the aforementioned packages, recruiters followed up with facility directors via telephone in an attempt to address any questions or concerns, obtain a commitment to participate in the survey, administer the screening questionnaire, and set up a time and date to administer the in-person questionnaires. After scheduling an in-person interview, directors received additional information regarding the interview via postal mail (Moss et al., 2011).

The in-person interviewing phase of data collection consisted of trained interviewers administering the survey using a computer-assisted personal interviewing (CAPI) instrument. The CAPI consisted of three separate modules. The first module was comprised of the facility-level questionnaire. This module was completed with the director of the facility, or another person designated by the as the survey-taker by the director. Among other things, the facility-level questionnaire included questions concerning facility characteristics, such as the number beds, chain status, ownership, and services provided. The second CAPI module consisted of the resident selection questionnaire used to identify three to six residents to take the subsequent resident questionnaire. The third module, administered to the selected residents, consisted of the resident questionnaire. The resident questionnaire was completed with the facility director or other caretaker. Among other things, this questionnaire consisted of questions concerning the residents' demographics, services received, and health condition. No residents were directly interviewed (Moss et al., 2011). While the 2010 NSRCF contains a multitude of data collected during the two stages, this study only utilizes facility-level data collected during the first stage of the survey. Thus, the second stage of the survey will not be discussed in any more detail.

3.2. Concepts and Variables

3.2.1 Dependent Variables

The first concept is RN staff efficiency. This is the dependent variable for all six of the models. In models1 and 2, RN staff efficiency is the dependent variable. As a measure of RN staff efficiency, the dependent variable in models 1 and 2 is RN direct care HPPD. Direct Care HPPD is a practitioner-accepted measure of efficiency for nurses (Dunham-Taylor & Pnczuk, 2006). It is calculated in the following manner using data from several questions:

$$RN\ HPPD = \frac{\frac{RN\ Number\ of\ hours\ worked\ in\ last\ week}{7}}{Number\ of\ residents}$$

Equation 3.1 Calculation of RN HPPD

Direct care HPPD refers to the hands-on care that nurses provide to patients throughout the day. The dependent variable in models 1and 2 is measured at the facility-level and is the respondent's answer to how many RN direct care HPPD their facility exhibited at the time of the survey. In an effort to protect respondents' identities, answers were organized into groups. Thus, the dependent variable is measured at the ordinal level and contains five categories. It was originally coded in the following manner: 1=0 HPPD, 2=0.1-0.25 HPPD, 3=0.26-0.50 HPPD, 4=more than 0.5 HPPD, and -8=don't know. This coding was kept for the analysis. A facility response of -8 was treated as missing during the analysis.

The same measure of efficiency was used in models3, 4, 5, and 6. In the case of models 3 and 4, LPN/LVN HPPD was used. The measure is calculated in the following manner:

$$LPN/LVN\ HPPD = \frac{\frac{LPN/LVN\ Number\ of\ hours\ worked\ in\ last\ week}{7}}{Number\ of\ residents}$$

Equation 3.2 Calculation of LPN/LVN HPPD

The dependent variable for models 3 and 4 is again ordinal and contains five categories. As originally coded, they were as follows: 1=0 HPPD, 2=0.1-0.25 HPPD, 3=0.26-0.5 HPPD, 4=more than 0.5, and -8=don't know. The original coding was kept for the analysis. A facility response of -8 was treated as missing. In the case of models 5 and 6, personal care aide HPPD was used as the dependent variable. Like the others, it is calculated in the following manner:

$$Aide\ HPPD = \frac{\frac{Aide\ Number\ of\ hours\ worked\ in\ last\ week}{7}}{Number\ of\ residents}$$

Equation 3.3 Calculation of Aide HPPD

Again, the variable is measured at the ordinal level and contains five categories. As originally coded, they were: 1=0-0.9 HPPD, 2=1.0-1.9 HPPD, 3=2.0-2.9 HPPD, 4=3 or more HPPD, and -8=don't know. The original coding scheme was kept for the analysis. Finally, a facility response of -8 was treated as missing during the analysis.

3.2.2 Independent Variables

3.2.2.1 Clinical IT Sophistication

The focal predictive variable in models 1, 3, and 5 is a facility's level of sophistication in clinical information systems. To measure clinical IT sophistication, a simple, unidimensional additive index was created. The index is composed of 17 individual items. Each of the items asks whether or not the facility has a specific computerized capability. For example, one clinical computerized capability might be reminders for guidelines. For each individual item, a response of yes was coded as a 1, while a response of no was coded as a 0. Additionally, responses that were not ascertained or facilities that did not know whether they had the computerized capabilities were coded a -9 and -8 respectively. These response were rare (1 response of -8 for each item and 1 response of -9 for each item, except for the question about electronic health records). These responses were treated as missing for reliability tests and later analyses. See the table below for the wording and coding of each individual item.

Table 3.1 Individual Items Composing Clinical IT Sophistication Index

Wording	Coding Scheme
Does the facility computerized capabilities have resident demographics?	0=No 1=Yes -8=Don't know -9=Not ascertained
Does the facility computerized capabilities have medical provider information?	0=No 1=Yes -8=Don't know -9=Not ascertained
Does the facility computerized capabilities have functional assessments?	0=No 1=Yes -8=Don't know -9=Not ascertained
Does the facility computerized capabilities have individual service plans?	0=No 1=Yes -8=Don't know -9=Not ascertained
Does the facility computerized capabilities have clinical notes, such as medical history and daily progress notes?	0=No 1=Yes -8=Don't know -9=Not ascertained
Does the facility computerized capabilities have patient problems list?	0=No 1=Yes -8=Don't know -9=Not ascertained
Does the facility computerized capabilities have medication administration?	0=No 1=Yes -8=Don't know -9=Not ascertained
Does the facility computerized capabilities have maintaining list of resident's medications?	0=No 1=Yes -8=Don't know -9=Not ascertained
Does the facility computerized capabilities have maintaining active medication allergy list?	0=No 1=Yes -8=Don't know -9=Not ascertained
Does the facility computerized capabilities have orders for prescriptions?	0=No 1=Yes -8=Don't know -9=Not ascertained
Does the facility computerized capabilities have warnings of drug interactions or contraindications?	0=No 1=Yes -8=Don't know -9=Not ascertained

Table 3.1 - continued

Does the facility computerized capabilities have orders for tests?	0=No 1=Yes -8=Don't know -9=Not ascertained
Does the facility computerized capabilities have viewing laboratory/imaging results?	0=No 1=Yes -8=Don't know -9=Not ascertained
Does the facility computerized capabilities have reminders for guideline based interventions or screening tests?	0=No 1=Yes -8=Don't know -9=Not ascertained
Does the facility computerized capabilities have discharge and transfer summaries?	0=No 1=Yes -8=Don't know -9=Not ascertained
Does the facility computerized capabilities have public health reporting?	0=No 1=Yes -8=Don't know -9=Not ascertained
Other than for accounting or billing purposes, dos this facility use electronic health records?	0=No 1=Yes -9=Not ascertained

Responses for each item were summed to create a score for each facility. The highest possible score is a 17, while the lowest possible score is a zero. In other words, the more sophisticated a facility's clinical IT system, the higher it will score on the clinical IT sophistication index. Reliability for the clinical IT sophistication index was deemed excellent (Cronbach's Alpha = .926).

3.2.2.2 Exchange IT Sophistication

The focal predictive variable in models 2,4, and 6 is a facility's level of sophistication in exchange information systems. To measure exchange information system sophistication, another simple, unidimensional additive index was created. This index is composed of eight individual items. Each of the items asks whether or not the facility's computerized system supported some type of electronic information exchange with another entity, such as a pharmacy or hospital. Originally, if the facilities had any of the computerized capabilities listed above, they were asked the set of questions on exchange capabilities. Further, facilities that did not have any of the above capabilities were originally coded as a -1, because they skipped the set of questions on exchange capabilities. In creating the exchange IT sophistication index, facilities that skipped the set of questions concerning exchange capabilities were recoded as a 0, or no, because they did not have the exchange capabilities. Responses of -8 and -9 to the individual items were few, but were treated as missing during the creation of the final score, reliability tests, and later analyses. See the table below for individual item wording and coding schemes.

Table 3.2 Individual Items Composing Exchange IT Sophistication Index

Wording	Coding Scheme
Does this facility’s computerized system support electronic health information exchange with physicians?	0=No 1=Yes -8=Don’t know -9=Not ascertained
Does this facility’s computerized system support electronic health information exchange with nursing home?	0=No 1=Yes -8=Don’t know -9=Not ascertained
Does this facility’s computerized system support electronic health information exchange with hospital?	0=No 1=Yes -8=Don’t know -9=Not ascertained
Does this facility’s computerized system support electronic health information exchange with pharmacy?	0=No 1=Yes -8=Don’t know -9=Not ascertained
Does this facility’s computerized system support electronic health information exchange with laboratory/tests?	0=No 1=Yes -8=Don’t know -9=Not ascertained
Does this facility’s computerized system support electronic health information exchange with other health or long term care provider?	0=No 1=Yes -8=Don’t know -9=Not ascertained
Does this facility’s computerized system support electronic health information exchange with resident’s personal health record?	0=No 1=Yes -8=Don’t know -9=Not ascertained
Does the facility’s computerized system support electronic health information exchange with public health reporting?	0=No 1=Yes -8=Don’t know -9=Not ascertained

Responses to each item were summed to create a score for each facility. The highest possible score was is an eight, while the lowest possible score is a zero. Reliability for the exchange IT sophistication index was deemed excellent (Cronbach's Alpha = .903)

It should be noted that these measures are far from perfect. The indices are simple, perhaps even *too* simple. Neither index takes into account interoperability between applications. Additionally, a facility's level of exchange IT sophistication is not only limited by its computerized capabilities, but it is also limited by the computerized capabilities of those outside of the facility, such as physicians and hospitals. While far from perfect, this approach is somewhat similar to the approach used by Davis, Brannon, and Whitman (2009), although they looked at administrative and clinical information systems, instead of clinical and exchange information systems.

3.2.3 Control Variables

Several control variables were included. Each of the control variables are the same in each of the models (although descriptives and estimates may be somewhat different because of slight differences in the number of missing cases). Selected were variables that have been shown or thought to influence staffing and efficiency in healthcare settings. In a perfect model, many more control variables would be included, but those included here are limited to those that were collected by the survey administrators. This is a limitation that is discussed later.

3.2.3.1 Organizational Characteristics

Facility size has been shown to influence direct care HPPD. Specifically, facility size has been shown to have a negative relationship with staffing. Larger facilities are not required by law to have proportionate staffing and may actually achieve economies of scale (Cohen & Spector, 1996; Harrington, Swan, & Carrillo, 2007). In the analysis, facility size is defined as the number of beds reported. The original coding scheme was as follows: 1=Small (4-10 beds); 2=Medium (11-25 beds); 3=Large (26-100 beds); and 4= Extra Large (100+ beds). This coding scheme was altered so that dummy variables were created for medium, large, and extra large facilities. Small facilities served as the reference category.

Chain-owned facilities have been found to have lower costs, although this may not be due staffing (Cohen & Spector, 1990). Little additional research has been done on the influence of chain status, but regardless, the variable is included in the analysis as a possible confounding variable. In this analysis, chain status is defined as the respondent's answer to the question: "Is this facility owned by a chain, group, or multi-facility system?". The variable was originally coded 1=Yes; 2=No. This coding scheme was altered so that 1=Yes and 0=No.

Type of ownership is another variable that has been shown to have an influence on direct care HPPD. Compared with private, for profit facilities, nonprofit and public facilities have been shown have higher direct care HPPD (Aaronson et al., 1994; Cohen & Dubay, 1990; Cohen & Spector, 1996; Harrington et al., 1998; Harrington et al., 2000; McGregor et al., 2005). Here, ownership status is defined as the respondent's answer to the question: "What is the type of ownership of this facility?". Respondents were given three options: private for profit, private nonprofit, or state, county, or local government. Responses to this question were then collapsed into two categories by the survey administrators: 1=private, for profit; and 2=private nonprofit or state/county/local government. This scheme was recoded where 0=private, for profit and 1=private nonprofit or state/county/local government.

3.2.3.2 Participation in Medicaid Program

Participation in Medicaid places staffing level requirements on facilities and may influence direct care HPPD (Munroe, 1990). In addition, Medicaid patients may constrain nursing homes by providing low reimbursement rates in addition to frequently having greater, or more intense, care needs (Nyman, 1988). In the survey, respondents were asked the following question: "Is this residential facility certified or registered to participate in Medicaid?". Respondents' answers were originally coded 1=yes; 2=no; and -8=don't know. Responses were recoded 1=yes; 0=no; and -8=don’t know. Cases with a coding of -8 were treated as missing during the analysis.

3.2.3.3 Participation of Volunteers and Contract Workers in Care Provision

Participation of volunteers in the provision of care may influence direct care HPPD. For instance, if a volunteer performs basic care duties, nurses may be allowed more direct care time with patients. Or on the other hand, if a facility frequently relies on volunteers to provide care, they may be able to staff nurses at a lower level. In the survey, respondents were asked whether or not the facility had used any volunteers to help the facility’s residents or staff in *any* way in the past 7 days or last work week. Respondents were originally coded 1=yes and 2=no. This scheme was recoded so that 1=yes and 0=no.

Additionally, participation of contract workers may influence staffing levels. Contract workers are thought to be beneficial as they are considered to be more flexible and cheaper. They can be brought in at times of increased need and dismissed soon after (Bourbonniere et al., 2006). The use of contract workers may indicate potential volatility or variance in the dependent variable, HPPD. Respondents were asked whether or not their facility used contract workers to provide direct care to residents. Responses to this question were originally coded as 1=yes and 2=no. For analysis, responses were recoded as 1=yes and 0=no.

3.2.3.4 Service of Persons with Developmental Disabilities or Those with Severe Mental Illness

Another factor which might influence a facility’s direct care HPPD is whether or not the facility serves any residents with developmental disabilities, such as mental retardation, autism, and Downs syndrome. Additionally, whether or not the facility serves residents with severe illnesses, such as schizophrenia or psychosis, may further influence direct care HPPD. Residents with developmental disabilities and mental illness are likely to require more direct care. Facilities were asked whether or not they served any persons with developmental disabilities or those with severe mental illness. They were asked to exclude Alzheimer’s disease or other dementias. Responses were originally coded 1=yes; 2=no; and -8=don't know. These responses were recoded so that 1=Yes; 0=No; and -8=don't know. Responses of -8 were treated as missing during the analysis.

3.2.3.5 Admissions and Discharge Policies

Both a facility's admissions and discharge policies could conceivably influence direct care HPPD. If a facility has more strict admissions policies, it will admit fewer residents that require more intense care. Conversely, if a facility has less strict admissions policies, it will admit a wider variety of residents, including those who require more intense care. A facility's discharge policies work much in the same way. A facility with strict discharge policies will discharge residents who have conditions that require more intensive care, such as behavior issues or incontinence of urine. A facility with less strict discharge policies will allow residents with such issues to continue living in their facility, regardless of the impact on the amount of care required.

In order to capture the nature of a facility's admission policies, a unidimensional additive index was created. This index was created to measure the strictness of a facility's admissions policies. This index is composed of ten individual items that are worded in the same manner. For each individual item, a response of yes was coded as a 0, as this indicated a less strict admission policy. Additionally, if a facility had no specific admission policy for an item and made decisions based on a case by case basis, the facility response was coded as a 1. This indicated a level of moderate strictness, as they both do and don't admit resident sometimes. Further, if the facility did not admit residents for a specific item, they were coded a 2. This indicated a more strict admission policy for the item. Finally, on some items a response was not ascertained or the facility refused to answer the questions. Responses of this type were rare (1 or 2 facilities for each item, the same facility). These responses were treated as missing for reliability tests and subsequent analyses. See the table below for wording and coding of each individual item.

Table 3.3 Individual Items Composing Admissions Policy Strictness Index

Wording	Coding Scheme
In terms of this facility's admission policy, do you admit a resident who is unable to leave the facility in an emergency without help?	0=Yes 1=No specific policy 2=No -9=Not ascertained
In terms of this facility's admission policy, do you admit a resident who has moderate to severe cognitive impairment, that is, the resident does not know who they are?	0=Yes 1=No specific policy 2=No -9=Not ascertained
In terms of this facility's admission policy, do you admit a resident who exhibits problem behavior such as wandering, temper outbursts, or combative behavior to other residents?	0=Yes 1=No specific policy 2=No -9=Not ascertained
In terms of this facility's admission policy, do you admit a resident who needs skilled nursing care on a regular basis?	0=Yes 1=No specific policy 2=No -9=Not ascertained
In terms of this facility's admission policy, do you admit a resident who needs daily monitoring for a health condition like assistance taking insulin or monitoring blood sugar?	0=Yes 1=No specific policy 2=No -9=Not ascertained
In terms of this facility's admission policy, do you admit a resident who is regularly incontinent of urine?	0=Yes 1=No specific policy 2=No -9=Not ascertained
In terms of this facility's admission policy, do you admit a resident who is regularly incontinent of feces?	0=Yes 1=No specific policy 2=No -7=Refusal -9=Not ascertained
In terms of this facility's admission policy, do you admit a resident who needs two people to help them get in and out of bed or needs a hoyer lift to get in and out of bed?	0=Yes 1=No specific policy 2=No -9=Not ascertained
In terms of this facility's admission policy, do you admit a resident who has a history of drug or alcohol abuse?	0=Yes 1=No specific policy 2=No -8=Don't know -9=Not ascertained
In terms of this facility's admission policy, do you admit a resident who requires end of life care?	0=Yes 1=No specific policy 2=No -9=Not ascertained

Responses for each item were summed. The highest possible score on the admissions policy strictness index is a 20, while the lowest possible score is a 0. Higher scores indicate that a facility's admissions policies are more strict, while lower scores indicate less strict admissions policies. Reliability was deemed acceptable (Cronbach's alpha = .754).

To capture the nature of a facility's discharge policies, another unidimensional additive index was created. This index was created to measure the strictness of a facility's discharge policies. This index, like the admissions index, is composed of ten individual items. The coding for this index is the opposite of the admissions strictness index though. A facility response of yes was coded as a 2, as this indicated a more strict discharge policy. Like the admissions index, if a facility had no specific policy for an item, it was coded as a 1. If the facility responded with no for a specific item, the response was coded as a 0, indicating a less strict discharge policy. Again, on some items a response was not ascertained or the facility refused to answer the question. Responses of this type were again rare (1 or 2 facilities for each item, the same facility). These responses were treated as missing for reliability tests and subsequent analyses. See the table below for wording and coding of each individual item.

Table 3.4 Individual Items Composing Discharge Policy Strictness Index

Wording	**Coding Scheme**
In terms of this facility's discharge policy, do you discharge a resident who is unable to leave the facility in an emergency without help?	0=No 1=No specific policy 2=Yes -9=Not ascertained
In terms of this facility's discharge policy, do you discharge a resident who has moderate to severe cognitive impairment, that is, the resident does not know who they are?	0=No 1=No specific policy 2=Yes -9=Not ascertained
In terms of this facility's discharge policy, do you discharge a resident who exhibits problem behavior such as wandering, temper outbursts, or combative behavior to other residents?	0=No 1=No specific policy 2=Yes -9=Not ascertained
In terms of this facility's discharge policy, do you discharge a resident who needs skilled nursing care on a regular basis?	0=No 1=No specific policy 2=Yes -9=Not ascertained
In terms of this facility's discharge policy, do you discharge a resident who needs daily monitoring for a health condition like assistance taking insulin or monitoring blood sugar?	0=No 1=No specific policy 2=Yes -9=Not ascertained

Table 3.4 - continued

In terms of this facility's discharge policy, do you discharge a resident who is regularly incontinent of urine?	0=No 1=No specific policy 2=Yes -9=Not ascertained
In terms of this facility's discharge policy, do you discharge a resident who is regularly incontinent of feces?	0=No 1=No specific policy 2=Yes -1=Legitimate skip -9=Not ascertained
In terms of this facility's discharge policy, do you discharge a resident who needs two people to help them get in and out of bed or needs a hoyer lift to get in and out of bed?	0=No 1=No specific policy 2=Yes -8=Don't know -9=Not ascertained
In terms of this facility's discharge policy, do you discharge a resident who has a history of drug or alcohol abuse?	0=No 1=No specific policy 2=Yes -1=Legitimate skip -8=Don't know -9=Not ascertained
In terms of this facility's discharge policy, do you discharge a resident who requires end of life care?	0=No 1=No specific policy 2=Yes -7=Refusal -9=Not ascertained

Responses for each item were summed to create a total score for each facility. The highest score possible on the discharge policy strictness index is 20, while the lowest possible is a 0. Interpretation of the index is the same as with the admissions policy index. Higher scores indicate more strict discharge policies, while lower scores indicate less strict discharge policies. Reliability was deemed acceptable (Cronbach's Alpha = .735).

3.3 Procedure of Analysis

3.3.1 Creation of Complex Sample Plan

As stated earlier, the data contained in the 2010 NSRCF was obtained through a complex sample. This complex sample included stratification, clustering, and oversampling. As such, a complex samples plan was created in SPSS in order to produce more accurate standard errors and more accurate estimates. The complex samples wizard in SPSS was used to create the complex sample plan. The facility-level public-use data file came with three important variables: PUFSTRATA, PUFPOFAC, and FACFNWT. For the first stage design variables, the variable PUFSTRATA was designated as the strata for the complex sample plan. Further, the variable FACFNWT was selected as the sample weight. For the estimation method, equal WOR (equal probability sampling without replacement) was selected. For the size of the design, population size was selected from the units drop-down menu. Further, the variable PUFPOPFAC was selected as the variable from which to read values. No other stages were added to the sample plan. This complex samples plan and SPSS was used in all subsequent analyses.

3.3.2 Final Analytic Sample Sizes

Listwise deletion was used to handle missing data in all of the models. Listwise deletion is a fairly basic method of handling missing data. In listwise deletion, if a case is missing a value on a single variable that is included in the analysis, the entire case is dropped from the analysis. This method of handling missing data can cause problems if the number of missing data is high (Allison, 2001). Fortunately, that is not the case here and, on the whole, the 2010 NSRCF has very little missing data. For models 1 and 2, use of listwise deletion resulted in 16 (0.7%) cases deemed as invalid. The final analytic sample for models 1 and 2 included 2,286 cases (although ordered logit was run on a subpopulation in model 2)[3]. For models 3 and 4, listwise deletion resulted in 17 (0.74) cases deemed as invalid for analysis. The final analytic sample for models 3 and 4 included 2,285 cases (again, ordered logit was run on a subpopulation in model 4)[4]. Finally, for models 5 and 6, use of listwise deletion resulted in 20 (.87%) cases deemed as invalid. The final analytic sample for models 5 and 6 included 2,282 cases (again, ordered logit was run on a subpopulation in model 6)[5].

[3] Model 2 n = 1,475
[4] Model 4 n = 1,474
[5] Model 6 n = 1,472

3.3.3 Ordered Logit

For traditional ordinary least squares (OLS) to yield best linear unbiased estimators (BLUE), a certain set of assumptions must be met. The consequences of violation of these assumptions varies by assumption. Some of these assumptions are easier to meet, or can be dealt with easily, while others are more difficult to meet. One difficult assumption to meet is the assumption that the dependent variable in the analysis needs to be interval-level. In situations where the dependent variable is not interval-level, it is recommended that maximum likelihood estimation (MLE) techniques, such as logit, be used instead. In this case, the dependent variable in each model has more than two outcomes that are discrete and clearly ordered. As each of the outcome variables in this study have more than two outcomes, are discrete, and are clearly ordered, ordered logit was selected as the appropriate method of analysis here (Borooah, 2002).

3.3.3.1 Cell-Count Check

A cell-count check was done by creating cross-tabulations of the categorical and response variables involved in each of the models. The cell-count check did not reveal any cause for concern.

3.3.3.2 Outliers

Tests for outliers revealed no significant data points. A majority of the variables in each model are categorical in nature. In addition, the four additive indices included in the different models can only run a certain range of values.

3.3.3.3 Multicollinearity

In an effort to check for any potential multicollinearity problems, six linear regression models were estimated with each of the dependent variables (although they are not important in this case) and the actual independent variables in the analyses. Variance inflation factor (VIF) scores and tolerance scores were checked for the variables in models 1, 3, and 5 along with the variables in models 2, 4, and 6. For weaker models, VIF scores over 2.5 are a cause for concern (Allison, 1999). For the independent variables in model 1, potential multicollinearity was detected between admissions policies (VIF = 4.537; tolerance = .220) and discharge policies (VIF = 4.508; tolerance = .222). Again, in model 3, potential multicollinearity issues were detected between admissions policies (VIF = 4.531; tolerance = .221) and discharge policies (VIF = 4.503; tolerance = .222). In model 5 as well, potential multicollinearity issues were detected between admissions policies (VIF = 4.537; tolerance = .220) and discharge policies.

In model 2, multicollinearity problems were detected between admissions policies (VIF = 4.861; tolerance = .206) and discharge policies (VIF = 4.829; tolerance = .207). The same issues were detected in models 4 (admissions policies VIF = 4.853 and tolerance = .206; discharge policies VIF = 4.820 and tolerance = .207) and 6 (admissions policies VIF = 4.863 and tolerance = .206; discharge policies VIF = 4.831 and tolerance = .207). Because of these multicollinearity issues, the variable measuring the strictness of discharge policies was dropped from all subsequent analyses.

3.3.3.4 Parallel Slopes Assumption

An important assumption of ordered logit models is that of parallel slopes. In other words, ordered logit assumes that the slope coefficients linking a variable to different outcomes will be the same across all outcomes. In order to test the validity of the parallel slopes assumption, a multinomial logit model can be fitted on the data (Borooah, 2002). However, the results from this test are only suggestive, as this is not strictly a likelihood-ratio test (Stata, 1999). Additionally, some argue that the statistical tests performed by software packages are too sensitive and have a tendency to reject the hypothesis that the sets of coefficients are the same (Harrell, 2001). The Wald F tests for models 1, 3, and 5 were 6.860 (22 df), 7.047 (22 df), and 17.633 (33 df) respectively. Additionally, Wald F tests for models 2, 4, and 6 were 3.156 (22 df), 2.015 (22 df), and 2.275 (33 df) respectively. The parallel slopes tests were marginal as the Wald F values were deemed to be only moderately large.

3.3.3.5 Final Models

The final models are represented in the functions below.

$$RNHPPD_i = \beta_1 + \beta_2(CLINICALIT_i) + \beta_3(ADMISSIONS_i) + \beta_4(VOL_i) + \beta_5(CONTRACT_i) + \beta_6(MEDICAID_i) + \beta_7(DISABIL_i) + \beta_8(OWN_i) + \beta_9(CHAIN_i) + \beta_{10}(FACMED_i) + \beta_{11}(FACLARGE_i) + \beta_{12}(FACXL_i) = Z_i + \varepsilon_i$$

Equation 3.4 Model 1

$$LPN/LVNHPPD_i = \beta_1 + \beta_2(CLINICALIT_i) + \beta_3(ADMISSIONS_i) + \beta_4(VOL_i) + \beta_5(CONTRACT_i) + \beta_6(MEDICAID_i) + \beta_7(DISABIL_i) + \beta_8(OWN_i) + \beta_9(CHAIN_i) + \beta_{10}(FACMED_i) + \beta_{11}(FACLARGE_i) + \beta_{12}(FACXL_i) = Z_i + \varepsilon_i$$

Equation 3.5 Model 2

$$AIDEHPPD_i = \beta_1 + \beta_2(CLINICALIT_i) + \beta_3(ADMISSIONS_i) + \beta_4(VOL_i) + \beta_5(CONTRACT_i) + \beta_6(MEDICAID_i) + \beta_7(DISABIL_i) + \beta_8(OWN_i) + \beta_9(CHAIN_i) + \beta_{10}(FACMED_i) + \beta_{11}(FACLARGE_i) + \beta_{12}(FACXL_i) = Z_i + \varepsilon_i$$

Equation 3.6 Model 3

Models 1, 3, and 5 may be represented in the above manner by equations 3.4, 3.5, and 3.6. Models 2, 4, and 6 may be represented in the manner below in equations 3.7, 3.8, and 3.9. In those facilities where the clinical IT score is greater than 0, direct care HPPD is thought to be explained by the set of variables below.

$$RNHPPD_i = \beta_1 + \beta_2(EXCHANGEIT_i) + \beta_3(ADMISSIONS_i) + \beta_4(VOL_i) + \beta_5(CONTRACT_i) + \beta_6(MEDICAID_i) + \beta_7(DISABIL_i) + \beta_8(OWN_i) + \beta_9(CHAIN_i) + \beta_{10}(FACMED_i) + \beta_{11}(FACLARGE_i) + \beta_{12}(FACXL_i) = Z_i + \varepsilon_i$$

Equation3.7 Model 4

$$
\begin{aligned}
LPN/LVNHPPD_i \\
&= \beta_1 + \beta_2(EXCHANGEIT_i) + \beta_3(ADMISSIONS_i) + \beta_4(VOL_i) + \beta_5(CONTRACT_i) \\
&+ \beta_6(MEDICAID_i) + \beta_7(DISABIL_i) + \beta_8(OWN_i) + \beta_9(CHAIN_i) + \beta_{10}(FACMED_i) \\
&+ \beta_{11}(FACLARGE_i) + \beta_{12}(FACXL_i) = Z_i + \varepsilon_i
\end{aligned}
$$

Equation 3.8 Model 5

$$
\begin{aligned}
AIDEHPPD_i = \beta_1 + \beta_2(EXCHANGEIT_i) + \beta_3(ADMISSIONS_i) + \beta_4(VOL_i) + \beta_5(CONTRACT_i) \\
+ \beta_6(MEDICAID_i) + \beta_7(DISABIL_i) + \beta_8(OWN_i) + \beta_9(CHAIN_i) + \beta_{10}(FACMED_i) \\
+ \beta_{11}(FACLARGE_i) + \beta_{12}(FACXL_i) = Z_i + \varepsilon_i
\end{aligned}
$$

Equation 3.9 Model 6

CHAPTER 4

DESCRIPTIVE STATISTICS, RESULTS, AND DISCUSSION

The chapter that proceeds is a presentation of descriptive statistics of the models, the results obtained from the models, and a discussion of those results. The organization of this chapter of this thesis is as follows. First, descriptive statistics for each of the models are presented and discussed. This section of the chapter is divided into two sections: descriptive statistics for the factors and descriptive statistics for the covariates. After presenting descriptive statistics for the models, the estimates yielded by each of the models are presented. Finally, a discussion of those estimates follows last.

4.1 Descriptive Statistics

4.1.1 Descriptive Statistics for Models 1 and 2

Table 4.1 Descriptive Statistics for Factors in Models 1 and 2

	Model 1			**Model 2**		
Variable	*Range*	*%*	*S.E.*	*Range*	*%*	*S.E.*
Dev. disability or mental illness	0-1	38.8	.011 (1.356)	0-1	38.8	.014 (1.242)
Medicaid	0-1	49.9	.012 (1.497)	0-1	49.4	.015 (1.249)
Medium-sized facility	0-1	15.9	.003 (.156)	0-1	17.3	.006 (.400)
Large-sized facility	0-1	27.8	.003 (.124)	0-1	37.1	.009 (.530)
Extra large-sized facility	0-1	6.7	.002 (.183)	0-1	10.2	.004 (.307)
Nonprofit or public ownership	0-1	17.6	.007 (.936)	0-1	23.0	.011 (.924)
Chain	0-1	37.7	.011 (1.248)	0-1	44.5	.014 (1.090)
Contract workers	0-1	16.4	.009 (1.553)	0-1	16.3	.011 (1.364)
Volunteer workers	0-1	33.5	.010 (1.167)	0-1	41.7	.014 (1.124)

Table 4.1 - continued

Notes. Data are weighted on known population parameters; Model 1 n = 2,286; Model 2 n = 1,475; Standard error presented with design effects in parentheses

Table 4.1 above displays descriptive statistics for the factors in model 1. In model 1, an estimated 38.8% of facilities served residents with developmental disabilities or severe mental illness. Further, 49.9% of the facilities in model 1 accepted Medicaid as a form of payment. In addition, 15.9% of facilities in the analytic sample were listed as medium-sized (11-25). Additionally, 27.8% of facilities in the analytic sample were listed as large-sized (26-100 beds), while 6.7% of facilities were listed as extra large-sized (over 100 beds). 17.6% of facilities in model 1 were private nonprofit or publicly-owned facilities, while 37.7% of facilities were listed as members of a chain. Further, 16.4% of facilities in model 1 used contract workers in direct care, while 33.5% of facilities took advantage of volunteer labor. Finally, design effects for each of the factors in the model 1 are low.

Table 4.1 above also displays descriptive statistics for the factors in model 2. In the case of model 2, 1,475 facilities were included in the analytic sample, because they had at least one clinical IT application. Design effects are low again in model 2. In model 2, 38.8% of the sample reported that they served residents with developmental disabilities or severe mental illness, while 49.4% of facilities reported that they accepted Medicaid payment from residents. Further, 17.3% of facilities were listed as medium-size, 37.1% of facilities were listed as large-sized, and 10.2% of facilities were listed as extra large-sized. 23.0% of facilities in model 2 were nonprofit or public-owned, while 44.5% were listed as belonging to a chain of residential care facilities. Finally, 16.3% of facilities in model 2 used contract workers, while 41.7% used volunteers to help.

Table 4.2 below displays descriptive statistics for the covariates in models 1 and 2. In model 1, the lowest score on the clinical IT sophistication index was a 0, while the highest score was a 17, making the range for the index 17. The estimated mean for this index was 3.81, meaning that, on average, residential care facilities in model 1 had 3.81 clinical IT applications.

The lowest score on the admissions strictness index was 0, while the highest score was a 20. The range for this index is 20. The estimated mean for this index is 7.94. In model 2, clinical IT sophistication was not considered, but exchange IT sophistication was. The range for the exchange IT sophistication index was 8, with a low score of 0 and a high score of 8. The estimated mean for this index is .70. On the admissions index in model 2, the range was 20, with a high score of 20 and a low score of 0. The estimated mean for this index is 7.96. Design effects were low in both models

Table 4.2 Descriptive Statistics for Covariates in Models 1 and 2

	Model 1				**Model 2**			
Variable	*Range*	*Est. Mean*	*Conf. Interval*	*S.E.*	*Range*	*Est. Mean*	*Conf. Interval*	*S.E.*
Clinical IT soph.	0-17	3.81	3.59/4.04	.114 (1.485)	-	-	-	-
Exchange IT soph.	-	-	-	-	0-8	.70	.59/.80	.054 (1.392)
Admissions strictness	0-20	7.94	7.73/8.15	.106 (1.295)	0-20	7.96	7.70/8.21	.129 (1.144)
Notes. Data are weighted on known population parameters; Model 1 n = 2,286; Model 2 n = 1,475; Confidence interval level = 95%; Standard error presented with design effects in parentheses								

4.1.2 Descriptive Statistics for Models 3 and 4

Table 4.3 Descriptive Statistics for Factors in Models 3 and 4

	Model 3			**Model 4**		
Variable	*Range*	*%*	*S.E.*	*Range*	*%*	*S.E.*
Dev. disability or mental illness	0-1	38.8	.011 (1.356)	0-1	38.8	.014 (1.243)
Medicaid	0-1	49.9	.012 (1.497)	0-1	49.5	.015 (1.249)
Medium-sized facility	0-1	15.9	.003 (.156)	0-1	17.3	.006 (.400)
Large-sized facility	0-1	27.8	.003 (.124)	0-1	37.1	.009 (.530)
Extra large-sized facility	0-1	6.7	.002 (.183)	0-1	10.2	.004 (.307)

Table 4.3 - continued

Nonprofit or public ownership	0-1	17.6	.007 (.936)	0-1	23.0	.011 (.924)
Chain	0-1	37.7	.011 (1.248)	0-1	44.4	.014 (1.090)
Contract workers	0-1	16.4	.009 (1.553)	0-1	16.3	.011 (1.364)
Volunteer workers	0-1	33.5	.010 (1.167)	0-1	41.7	.014 (1.124)
Notes. Data are weighted on known population parameters; Model 3 n = 2,285; Model 4 n = 1,474; Standard error presented with design effects in parentheses						

Table 4.3 above displays descriptive statistics for the factors in model 3. In model 3, an estimated 38.8% of facilities in the analytic sample served residents with developmental disabilities or severe mental illness. 49.9% of facilities in the analytic sample accepted Medicaid from residents. Further, 15.9% of facilities were described as medium-sized, 27.8% of facilities were described as large-sized, and 6.7% of facilities were described as extra large-sized. Additionally, 17.6% of facilities in model 3 were listed as public or nonprofit, 37.7% of facilities were listed as belonging to a chain, 16.4% of facilities utilized contract workers, and 33.5% of facilities used volunteers. Design effects are low in model 3.

Table 4.3 above also displays descriptive statistics for the factors in models 4. In the case of model 4, 1,474 facilities were included in the analytic sample, because they had at least one clinical IT application. Here, 38.8% of facilities were listed as serving those some residents with developmental disabilities or severe mental illness. Further, 49.5% of facilities in model 4 accepted Medicaid. 17.3% of facilities were reported to be medium-sized, 37.1% were reported to be large-sized, and 10.2% were reported to be extra large-sized. 23.0% of facilities were listed as nonprofit or public and 44.4% of facilities were listed as chain members. Finally, 16.3% of facilities used contract workers and 41.7% of facilities used volunteer workers. Design effects were low.

Table 4.4 below displays descriptive statistics for the covariates in models 3 and 4. For model 3, the range of the clinical IT sophistication index was 17, with a low score of 0 and a high score of 17. The estimate mean for the index is 3.81. For the admission strictness index in model 3, the range is 20. The low score is 0, while the high score is 20. The estimated mean for this index is 7.94. In model 4, the clinical IT sophistication was not considered. The range for the exchange IT sophistication index is 8. The low score is 0, while the high score is 8. The estimated mean is .70. The range for the admissions strictness index is 20, with a low score of 0 and a high score of 20. The estimated mean for the index is 7.96. Finally, design effects are low in the models.

Table 4.4 Descriptive Statistics for Covariates in Models 3 and 4

	Model 3				**Model 4**			
Variable	*Range*	*Est. Mean*	*Conf. Interval*	*S.E.*	*Range*	*Est. Mean*	*Conf. Interval*	*S.E.*
Clinical IT soph.	0-17	3.81	3.59/4.03	.115 (1.485)	-	-	-	-
Exchange IT soph.	-	-	-	-	0-8	.70	.59/.80	.054 (1.392)
Admissions strictness	0-20	7.94	7.73/8.15	.106 (1.295)	0-20	7.96	7.71/8.21	.129 (1.144)
Notes. Data are weighted on known population parameters; Model 3 n = 2,285; Model 4 n = 1,474; Confidence interval level = 95%; Standard error presented with design effects in parentheses								

4.1.3 Descriptive Statistics for Models 5 and 6

Table 4.5 below displays descriptive statistics for the factors in model 5. In model 5, 38.8% of residential care facilities reported that they served residents with developmental disabilities or severe mental illnesses. 49.9% of facilities reported that they accepted Medicaid. Additionally, 15.9% of facilities in the analytic sample reported as medium-sized, 27.8% reported as large-sized, and 6.7% reported as extra large-sized. Further, 17.6% of facilities were listed as public or nonprofit and 37.7% belonged to a chain. 16.4% of facilities made use of contract workers, while 33.5% of facilities made use of volunteer workers. Design effects were low for the variables.

Table 4.5 Descriptive Statistics for Factors in Models 5 and 6

	Model 5			Model 6		
Variable	*Range*	*%*	*S.E.*	*Range*	*%*	*S.E.*
Dev. disability or mental illness	0-1	38.8	.011 (1.356)	0-1	38.8	.014 (1.242)
Medicaid	0-1	49.9	.012 (1.497)	0-1	49.5	.015 (1.249)
Medium-sized facility	0-1	15.9	.003 (.156)	0-1	17.4	/006 (.400)
Large-sized facility	0-1	27.8	.003 (.124)	0-1	37.0	.009 (.529)
Extra large-sized facility	0-1	6.7	.002 (.183)	0-1	10.2	.004 (.305)
Nonprofit or public ownership	0-1	17.6	.007 (.936)	0-1	23.1	.011 (.924)
Chain	0-1	37.7	.011 (1.248)	0-1	44.4	.014 (1.090)
Contract workers	0-1	16.4	.009 (1.553)	0-1	16.3	.012 (1.366)
Volunteer workers	0-1	33.5	.010 (1.167)	0-1	41.7	.014 (1.124)
Notes. Data are weighted on known population parameters; Model 5 n = 2.282; Model 6 n = 1,472; Standard error presented with design effects in parentheses						

Table 4.5 above presents descriptive statistics for the factors in model 6 as well. Design effects are low for the factors in model 6. In model 6, 38.8% of facilities served those with developmental disabilities or mental illness and 49.5% of facilities accepted Medicaid as a form of payment. Further, 17.4% of facilities were reported to be medium-sized, while 37.0% of facilities were reported to be large-sized. 10.2% of facilities were reported to be extra large-sized. Additionally, 23.1% of those in model 6 were listed as nonprofit or public facilities and 44.4.% were listed as chain members. Finally, 16.3% used contract workers and 41.7% used volunteer workers.

Table 4.6 Descriptive Statistics for Covariates in Models 5 and 6

	Model 5				**Model 6**			
Variable	*Range*	*Est. Mean*	*Conf. Interval*	*S.E.*	*Range*	*Est. Mean*	*Conf. Interval*	*S.E.*
Clinical IT soph.	0-17	3.81	3.59/4.04	.115 (1.485)	-	-	-	-
Exchange IT soph.	-	-	-	-	0-8	.70	.59/.80	.054 (1.394)
Admissions strictness	0-20	7.94	7.73/8.15	.106 (1.294)	0-20	7.96	7.70/8.21	.129 (1.144)
Notes. Data are weighted on known population parameters; Model 5 n = 2.282; Model 6 n = 1,472; Confidence interval level = 95%; Standard error presented with design effects in parentheses								

Table 4.6 above displays descriptive statistics for the covariates in models 5 and 6. In model 5, the range for the clinical IT index is 17. The low score is 0 and the high score is 17. The estimated mean for the index is 3.81. Design effects are low. For the admissions strictness index, the range is 20, with a high score of 20 and a low score of 0. The estimated mean is 7.94. In model 6, the estimated mean for the exchange IT sophistication index is .70. The range for the index is 8, with a high score of 8 and a low score of 0. The range for the admission strictness index is 20. The low score is 0 and the high score is 20. The estimated mean for the index is .796. Design effects are low.

4.2 Results

4.2.1 Models 1 and 2

Table 4.7 below displays the estimated net effects of the factors and covariates in the models on a measure of RN staff efficiency, RN direct care HPPD. The results from model 1 suggest that the variables in the model do an acceptable job of explaining the variance in the dependent variable (Nagelkerke pseudo R^2 = .133). Additionally, the results from model 2 suggest that the model does an acceptable job of explaining RN direct care HPPD in those facilities with clinical IT applications (Nagelkerke pseudo R^2 = .096).

4.2.1.1 Impact of Clinical IT Sophistication on RN Direct Care HPPD

Consider that model 1 examined the impact of clinical IT sophistication on RN direct care HPPD, a measure of efficiency. It was hypothesized that, all else equal, residential care facilities with more sophisticated clinical IT systems would exhibit greater RN staffing efficiency than residential care facilities with less sophisticated clinical IT systems. In other words, it was expected that clinical IT sophistication would be negatively associated with RN direct care HPPD. The results from model do suggest that clinical IT sophistication is a significant predictor of RN direct care HPPD in residential care facilities ($p < .05$). While it does appear to be a significant predictor of the dependent variable, the effect is marginal. The effect moves in the opposite direction specified in hypothesis 1. Here, the degree of clinical IT sophistication is positively associated with higher RN direct care HPPD. More specifically, 1 additional clinical IT application is estimated to increase the odds of moving to the highest group of RN direct care HPPD by 1.027, or 2.7% (O.R. = 1.027; C.I. = 1.006/1.049).

4.2.1.2 Impact of Exchange IT Sophistication on RN Direct Care HPPD

Model 2 examined the impact of exchange IT sophistication on RN direct care HPPD. Recall that hypothesis 2 conjectured that, in those facilities with clinical IT applications, those with more sophisticated exchange capabilities would exhibit greater RN staffing efficiency than those facilities with less sophisticated exchange systems. In other words, like model 1, the primary independent variable in model 2 was expected to have a negative relationship with the dependent variable. The results from the model suggest that this is the case, although the effect is not statistically significant (O.R. = .974; C.I. = .907/1.047).

4.2.1.3 Other Findings

Several other interesting findings emerged from models 1 and 2. In model 1, in addition to the level of clinical IT sophistication, six other variables were found to be statistically significant predictors of RN direct care HPPD. Whether or not the facility accepts Medicaid as a form of payment was shown to be a significant predictor of the dependent variable ($p < .001$).

Somewhat unsurprisingly, the results indicate that acceptance of Medicaid is positively associated with the dependent variable (O.R. = 1.635; C.I. = 1.343/1.991). This finding is not too surprising, as participation in Medicare and Medicaid requires meeting certain staffing requirements. This finding is also in agreement with the literature (see Munroe, 1990 and Nyman, 1988). Another variable, admissions policy strictness, was also statistically significant ($p < .001$). In this case, admissions policy strictness was negatively associated with the dependent variable. In other words, facilities with stricter admissions policies generally had fewer RN direct care HPPD. A one unit increase in admissions policy strictness is estimated to decrease the odds of moving from the low to high category of the dependent variable by .955, or 4.5% (OR = .955). Additionally, ownership status was also statistically significant ($p < .001$). The findings here are again somewhat unsurprising, as they corroborate the findings of other studies (see Aaronson et al., 1994; Cohen & Dubay, 1990; Cohen & Spector, 1996; Harrington et al., 1998; Harrington et al., 2000; and McGregor et al., 2005). Nonprofit and publicly-owned residential care facilities are positively associated with the dependent variable (O.R. = 1.505). Finally, facility size seems to be a significant predictor of the dependent variable. Medium-sized facilities were 242.2% (O.R. = 3.422) more likely than small facilities to end up in the highest group of RN HPPD. Further, large-sized facilities were even more likely than medium-sized facilities to be in the highest group of RN HPPD. They were 257.4% (O.R. = 3.574) more likely than small facilities to be in the highest group of RN HPPD. Finally, extra-large sized facilities were slightly less likely than medium-sized facilities to be in the highest group of RN HPPD, but were 234.7% more likely than small facilities to be in that group (O.R. = 3.347). Chain status, use of contract workers, the use of volunteers, and service of residents with developmental disabilities and severe mental illnesses were not statistically significant in model 1.

Secondary findings for model 2 were similar to those as in model 1. Acceptance of Medicaid ($p < .001$; O.R. = 1.682; C.I. = 1.337/2.116), admissions policy strictness ($p < .01$; O.R. = .962; C.I. = .937/.988), nonprofit or public ownership ($p < .01$; O.R. = 1.384; C.I. =

1.093/1.753), medium-sized facility ($p < .001$; O.R. = 3.146; C.I. = 2.110/4.689), large-sized facility ($p < .001$; O.R. = 3.006; C.I. = 2.042/4.425), and extra large-sized facility ($p < .001$; O.R. = 2.801; C.I. = 1.861/4.215) were all significant predictors again. In model 2 though, three new variables became significant. Service of residents with developmental disabilities or severe mental illness ($p < .05$; O.R. = .779; C.I. = .615/.986), chain status ($p < .01$; O.R. = .773; C.I. = .615/.972), and use of volunteer workers ($p < .05$; O.R. = 1.363; C.I. = 1.076/1.726) were all significant predictors of the dependent variable in model 2.

Table 4.7 Estimated Net Effects of Factors and Covariates on RN Direct Care HPPD (2010 NSRCF)

	Model 1		**Model 2**	
Variable	O.R.	C.I.	O.R.	C.I.
Clinical IT soph.	1.027* (.011)	1.006/1.049	-	-
Exchange IT soph.	-	-	.974 (.037)	.907/1.047
Admissions strictness	.955*** (.011)	.935/.976	.962** (.014)	.937/.988
Dev. disability or mental illness	.849 (.101)	.696/1.036	.779* (.120)	.615/.986
Medicaid	1.635*** (.100)	1.343/1.991	1.682*** (.117)	1.337/2.116
Organizational characteristics				
Medium-sized facility	3.422*** (.142)	2.591/4.519	3.146*** (.204)	2.110/4.689
Large-sized facility	3.574*** (.139)	2.723/4.691	3.006*** (.197)	2.042/4.425
Extra large-sized facility	3.347*** (.156)	2.464/4.546	2.801*** (.208)	1.861/4.215
Nonprofit or public ownership	1.505*** (.104)	1.228/1.844	1.384** (.120)	1.093/1.753
Chain	.911 (.101)	.747/1.111	.773** (.117)	.615/.972

Table 4.7 - continued

Use of Contract & Vol. Workers				
Contract workers	1.159 (.134)	.891/1.507	1.098 (.161)	.800/1.507
Volunteer workers	1.202 (.097)	.994/1.453	1.363* (.121)	1.076/1.726
Model statistics				
Nagelkerke pseudo R^2	.133		.096	
*Notes. Data are weighted on known population parameters; Model 1 n = 2,286; Model 2 n = 1,475; Odds ratios presented with standard errors in parentheses; Confidence interval level presented for O.R. = 95%; *p < .05; **p < .01; ***p < .001*				

4.2.2 Models 3 and 4

Table 4.8 is displayed below. The table presents the estimate net effects of the factors and covariates in models 3 and 4. The results from model 3 suggest that the variables present do a good job of explaining the dependent variable (Nagelkerke pseudo R^2 = .313). Model 4 estimated the effects of the variables on LPN/LVN direct care HPPD in a subsample of facilities. The results from this model suggest that it does do a good job of explaining the dependent variable (Nagelkerke pseudo R^2 = .346).

4.2.2.1 Impact of Clinical IT Sophistication on LPN/LVN Direct Care HPPD

While model 1 examined the impact of clinical IT sophistication on RN direct care HPPD, model 3 examined the impact of clinical IT sophistication on LPN/LVN direct care HPPD. Recall that it was hypothesized that residential care facilities with more sophisticated clinical IT systems would exhibit greater LPN/LVN staffing efficiency than residential care facilities with less sophisticated clinical IT systems. The results from model 3 do not suggest that this is the case, although the confidence interval is both above and below one (O.R. = 1.005; C.I. = .984/1.027). Clinical IT sophistication is not a significant predictor of the dependent variable in this model though.

4.2.2.2 Impact of Exchange IT Sophistication on LPN/LVN Direct Care HPPD

Recall that model 4 examined the impact of exchange IT sophistication on LPN/LVN direct care HPPD. Hypothesis 4 stated that, in those facilities with clinical IT applications, those with more sophisticated exchange capabilities would exhibit greater LPN/LVN staffing efficiency than those facilities with less sophisticated exchange systems. In other orders, the exchange IT sophistication was expected to have a negative relationship with the dependent variable in model 4. The results from model 4 suggest that this is not the case and, in fact, the relationship is the opposite of the relationship specified in hypothesis ($p < .05$; O.R. = 1.107; C.I. = 1.019/1.202). The effect is quite small though. One additional exchange capability increases the likelihood of being in the highest group of LPN/LVN HPPD by 10.7%.

4.2.2.3 Other Findings

Nine other variables were statistically significant predictors of the dependent variable in model 3. Admissions policies strictness ($p < .05$; O.R. = .971; C.I. = .950/.993), service of residents with developmental disabilities or mental illnesses ($p < .001$; O.R. = .698; C.I. = .572/.851), and acceptance of Medicaid as a form of payment ($p < .01$; O.R. = .760; C.I. = .623/.928) were all statistically significant and negatively associated with the dependent variable. The negative relationship between service of residents with developmental disabilities or mental illnesses and LPN/LVN HPPD is quite surprising and unexpected. These facilities were 30.2% less likely to be in the high group of the dependent variable. While it was thought that these types of residents would require more intensive care, this does not appear to be the case here. Additionally, ownership ($p < .001$; O.R. = 1.945; C.I. 1.573/2.405), chain status ($p < .01$; O.R. = 1.354; C.I. = 1.113/1.646), and the use of volunteer workers ($p < .01$; O.R. = 1.354; C.I. = 1.113/1.646) were all statistically significant and positively associated with the dependent variable. Specifically, nonprofit and public-owned facilities were 94.5% more likely than private for-profit facilities to be in the highest group of LPN/LVN HPPD. Further, chain members were

35.4% more likely than non-chain members to be in the highest group of the dependent variable. Finally, medium-sized facility ($p < .001$; O.R. = 4.084; C.I. = 2.948/5.658), large-sized facility ($p < .001$; O.R. = 10.474; C.I. = 7.655/14.331), and extra large-sized facility ($p < .001$; O.R. = 13.563; C.I. = 9.535/19.292) were all statistically significant and positively associated with the dependent variable. Interestingly, the relationship between facility size and LPN/LVN HPPD was different than the relationship between facility size and RN HPPD. With RN HPPD, the O.R. decreased at the move from large-sized facility to extra large-sized facilities. This was not the case here.

Eight other variables were statistically significant predictors of the dependent variable in model 4. Again, acceptance of Medicaid ($p < .01$; O.R. = .720; C.I. = .577/.900) and service of residents with developmental disabilities or severe mental illness ($p < .01$; O.R. = .702; C.I. = .564/.873) were both statistically significant and negatively associated with the dependent variable. Admissions policies strictness was not statistically significant this time. The use of volunteer workers ($p < .01$; O.R. = 1.376; C.I. = 1.099/1.724), chain status ($p < .01$; O.R. = 1.389; C.I. = 1.108/1.740), and ownership status ($p < .001$; O.R. = 2.031; C.I. = 1.580/2.611) were all statistically significant and positively associated with the dependent variable. Finally, medium-sized facility ($p < .001$; O.R. = 4.592; C.I. = 3.001/8.170), large-sized facility ($p < .001$; O.R. = 13.661; C.I. = 8.379/22.271), and extra large-sized facility ($p < .001$; O.R. = 15.860; C.I. = 9.507/26.459) were all statistically significant again and positively associated with the dependent variable.

Table 4.8 Estimated Net Effects of Factors and Covariates on LPN/LVN Direct Care HPPD (2010 NSRCF)

	Model 3		**Model 4**	
Variable	O.R.	C.I.	O.R.	C.I.
Clinical IT soph.	1.005 (.011)	.984/1.027	-	-

Table 4.8 - continued

Exchange IT soph.	-	-	1.107* (.042)	1.019/1.202
Admissions strictness	.971* (.011)	.950/.993	.982 (.013)	.957/1.008
Dev. disability or mental illness	.698*** (.101)	.572/.851	.702** (.111)	.564/.873
Medicaid	.760** (.102)	.623/.928	.720** (.114)	.577/.900
Organizational characteristics				
Medium-sized facility	4.084*** (.166)	2.948/5.658	4.592*** (.255)	3.001/8.170
Large-sized facility	10.474*** (.160)	7.655/14.331	13.661*** (.249)	8.379/22.271
Extra large-sized facility	13.563*** (.180)	9.535/19.292	15.860*** (.261)	9.507/26.459
Nonprofit or public ownership	1.945*** (.108)	1.573/2.405	2.031*** (.128)	1.580/2.611
Chain	1.354** (.100)	1.113/1.646	1.389** (.115)	1.108/1.740
Use of Contract & Vol. Workers				
Contract workers	1.130 (.139)	.861/1.483	1.092 (.146)	.820/1.454
Volunteer workers	1.285* (.097)	1.063/1.554	1.376** (.115)	1.099/1.724
Model statistics				
Nagelkerke pseudo R^2	.313		.346	
*Notes. Data are weighted on known population parameters; Model 3 n = 2,285; Model 4 n = 1,474; Odds ratios presented with standard errors in parentheses; Confidence interval level presented for O.R. = 95%; *p < .05; **p < .01; ***p < .001*				

4.2.3 Models 5 and 6

Table 4.9, displayed below, presents the estimated net effects of the variables in models 5 and 6 on personal care aide direct care HPPD. The results from the models suggest that both models do an acceptable job of explaining the dependent variables. In the case of model 5, the Nagelkerke pseudo R^2 was .179. In the case of model 6, the Nagelkerke pseudo R^2 was .262.

4.2.3.1 Impact of Clinical IT Sophistication on Personal Care Aide Direct Care HPPD

Model 5 examined the impact of clinical IT sophistication on personal care aide direct care HPPD. In chapter 2, it was hypothesized that, all else equal, residential care facilities with more sophisticated clinical IT systems would exhibit greater personal care aide staffing efficiency than residential care facilities with less s sophisticated clinical IT systems. In other words, the relationship was expected to be negative between the focal independent variable and the dependent variable in this model. In the case of model 5, clinical IT sophistication does not appear to be a significant predictor of the dependent variable (O.R. = 1.021; C.I. = .999/1.043).

4.2.3.2 Impact of Exchange IT Sophistication on Personal Care Aide Direct Care HPPD

Model 6 examined the impact of exchange IT on personal care aide direct care HPPD in facilities that had at least one clinical IT application in use. Recall that in chapter 2, it was hypothesized that residential care facilities with more sophisticated exchange capabilities would exhibit greater personal care aid staffing efficiency than residential care facilities with less sophisticated exchange information systems. In other words, it was expected that a negative relationship between the primary independent variable and the dependent variable. This appears to be that case, although that effect is not statistically significant (O.R. = .968; C.I. = .890/1.052).

4.2.3.3 Other Findings

Six variables were shown to be statistically significant in model 5. As in the other models, admissions strictness was negatively associated with the dependent variable ($p < .001$; O.R. = .923; C.I. = .901/.945). A one unit increase in admissions strictness decreased the likelihood of ending up in the highest group of personal care aide HPPD by 8.7%. Additionally service of residents with developmental disabilities or severe mental illness ($p < .001$; O.R. =

.772; C.I. = .578/.855) and acceptance of Medicaid ($p < .01$; C.I. = .638/.934) were again negatively associated with the dependent variable. Interestingly, medium-sized facility was not statistically significant in this model, although large-sized facility ($p < .001$; O.R. = .186; C.I. = .258/.429) and extra large-sized facility ($p < .001$; O.R. = .186; C.I. = .138/.252) were statistically significant. In this model though, they were negatively associated with the dependent variable. Ownership status was also statistically significant ($p < .01$), although negatively associated (O.R. = .724; C.I. = .587/.892) with the dependent variable in this model. Nonprofit and public facilities were 27.6% less likely to be in the highest group of personal care aide HPPD.

Eight Variables were shown to be statistically significant in model 6. Again, admissions policies strictness ($p < .001$; O.R. = .914; C.I. = .88/.940), service of residents with developmental disabilities or mental illness ($p < .01$; O.R. = .722; C.I. = .569/.915), and acceptance of Medicaid ($p < .01$; O.R. = .728; C.I. = .579/.916) were all statistically significant and negatively associated with the dependent variable. Ownership was statistically significant ($p < .05$) as well and negatively associated with dependent variable (O.R. = .761; C.I. = .600/.965). Utilization of volunteers was also negatively associated with the dependent variable ($p < .05$; O.R. = .790; C.I. = .642/.971). Finally, large-sized facility ($p < .001$; O.R. = .195; C.I. = .132/.288) and extra large-sized facility ($p < .001$; O.R. = .100; C.I. .064/.158) were statistically significant and negatively associated with the dependent variable. As opposed to model 5, medium-sized facility was statistically significant this time ($p < .01$; O.R. . 558; C.I. = .384/.809).

Table 4.9 Estimated Net Effects of Factors and Covariates on Personal Aide Direct Care HPPD (2010 NSRCF)

	Model 5		**Model 6**	
Variable	O.R.	C.I.	O.R.	C.I.
Clinical IT soph.	1.021 (.011)	.999/1.043	-	-
Exchange IT soph.	-	-	.968 (.043)	.890/1.052

Table 4.9 - continued

Admissions strictness	.923*** (.012)	.901/.945	.914*** (.014)	.888/.940
Dev. disability or mental illness	.703*** (.100)	.578/.855	.722** (.121)	.569/.915
Medicaid	.772** (.097)	.638/.934	.728** (.117)	.579/.916
Organizational characteristics				
Medium-sized facility	.819 (.127)	.639/1.052	.558** (.190)	.384/.809
Large-sized facility	.333*** (.129)	.258/.429	.195*** (.200)	.132/.288
Extra large-sized facility	.186*** (.153)	.138/.252	.100*** (.231)	.064/.158
Nonprofit or public ownership	.724** (.107)	.587/.892	.761* (.121)	.600/.965
Chain	1.142 (.092)	.953/1.368	1.013 (.111)	.814/1.260
Use of Contract & Vol. Workers				
Contract workers	1.007 (.125)	.788/1.288	.904 (.154)	.668/1.223
Volunteer workers	.843 (.091)	.705/1.008	.790* (.106)	.642/.971
Model statistics				
Nagelkerke pseudo R^2	.179		.262	
*Notes. Data are weighted on known population parameters; Model 5 n = 2,282; Model 6 n = 1,472; Odds ratios presented with standard errors in parentheses; Confidence interval level presented for O.R. = 95%; *p < .05; **p < .01; ***p < .001*				

4.3 Discussion

Models 1, 3, and 5 were designed to test the impact of clinical IT applications on efficiency. Only the estimates in model 1 were statistically significant. Further the estimates from model 1 suggest that hypothesis one did not hold. In fact, the relationship was opposite of that which was specified, but the effect was quite marginal. In models 3 and 5, the effect was marginal again[6], although it was not statistically significant in both cases, which is a significant finding in itself. The effect is very small in all cases, so it may be dangerous to make any major conclusions here, other than mentioning that the hypotheses did not hold in each of these cases. In model 1, one could ask why might it be that the hypothesis did not hold. Why does the effect seem to be different than that seen in other settings (see Pierpont & Thilgen, 1995; Wong et al., 1998)? It is possible that, while clinical IT did not lead to increased efficiency in a strictly input-output sense, it may lead to increased face-to-face time, which has been linked with quality of care. Pierpont and Thilgen (1995) observed this, although they also found decreases in documentation and information-gathering time. If this were the case here, the models would not be able to capture that. Some other method(s), such as observation or time-motion studies, would need to be used in conjunction. It might also be the case that health IT truly did lead to decreased efficiency (at least in RNs). In the literature review earlier, it was suggested that increased time was needed to needed to learn the systems. Increased time may also be spent at the computer, further decreasing efficiency (Krall, 1995; Tierney et al., 1993). Another potential explanation might be that only larger facilities have the necessary technical expertise and capital to build a more sophisticated IT system. These larger facilities appear to have higher HPPD as well. It is possible that the size-related variables in the models did not adequately control for this issue. Finally, it may also be that the commercially available systems used by residential care facilities do not lead to some of the same impacts seen in the in-house built systems of other care settings, such as hospitals. Hospitals often have the capital to build in-house, customized information systems, whereas residential care facilities often do not. Almost all of the research on health IT concerns these in-house built systems. It would be good for future research to explore some of these potential issues.

Models 2, 4, and 6 were designed to test the impact of exchange information systems on nurse efficiency. Ordered logit was run on a subpopulation of residential care facilities that

[6] Confidence intervals were both above and below 1.000 though. This makes it difficult to make any conclusions about the direction and nature of the relationship that exists.

had clinical IT applications. A statistically significant effect was seen in only one of the models, model 4. In this model, a slight positive effect was seen, so the hypothesis did not hold. Again, the reasons for this may be similar to some of the reasons suggested in the previous paragraph. With increasing exchange capabilities, nurses might find themselves in front of the computer more frequently, becoming less efficient. In models 2 and 6, the effect was in the direction hypothesized, although the effect was not significant in either case. Further, the confidence intervals for both of the estimates were below and above 1.000. Not much can be gleaned from these estimates. The mean score on the information exchange index was .70 out of 8. This suggests that exchange capabilities are underdeveloped and underutilized in residential care facilities. A likely problem here is that of low base rates and range restriction. For the purposes of this study, the low mean score on the information exchange score probably reduced correlation and ultimately made it harder to find a significant effect. Future research should take this issue into account.

Other findings emerged from the models as well. Some of these additional estimates are unsurprising. In every model, except model 4, strictness of admissions policies was shown to be a significant predictor of the dependent variable. Admissions strictness was shown to be negatively associated with the dependent variable in each case. In other words, the stricter a facility's admissions policies, the lower the facility's HPPD. While admissions policies have not been studied, they do capture some elements that have been studied elsewhere. For example, admissions policies will influence the types of residents living in the facility, the intensity of care needed, and ultimately HPPD. This finding is consistent with other studies that have suggested these elements, such as patient mix and intensity of care, to be important (Blegen, Vaughn, & Vojir, 2008). Another variable, acceptance of Medicaid payment, was significant in each of the models. This finding is not surprising and fits with the existing literature (Munroe, 1990; Nyman, 1988). Interestingly though, the variable is positively associated with the dependent variable in model 1 and 2, but it is negatively associated with the dependent variables in models 3, 4, 5, and 6. These estimates suggests that Medicaid participants staff greater numbers higher-skilled nurses, while those who do not participate in Medicaid staff higher numbers lower skilled nurses. Ownership status is another variable that seems to influence HPPD in the same manner as participation in Medicaid. In each model, ownership status was statistically significant. In models 1, 2, 3, and 4 public and nonprofit facilities were positively associated with the dependent variables. This fits with the existing literature (see Aaronson et al, 1994; Cohen & Dubay, 1990; Cohen & Spector, 1996; Harrington et al., 1998; Harrington et al., 2000; and McGregor et al., 2005). Interestingly though, public and nonprofit facilities were negatively associated with the dependent variables in models 5 and 6, suggesting that these facilities employ higher skilled nurses than for-profit facilities.

A few of the other estimates are a bit more surprising. For instance, service of residents with developmental disabilities or mental illness was negatively associated with the dependent variable and significant and all of the models, except model 1. Recall that it was originally thought that this variable would be positively associated with the dependent variables, because these types of patients were thought to require more intensive care. The results suggest that this is not the case, although it remains to be seen why. Another surprising result was the positive association between the use of volunteer workers and the dependent variables. In model 6 though, the relationship was the opposite direction. It is possible that this may be due to larger facilities making use of volunteer workers and maintaining greater HPPD levels. The smallest facilities may have no need for volunteer workers.

While not the primary reason for undertaking this thesis, when viewed as a set, the results of the analyses also provide some interesting insight into the profile of the country's residential care facilities, a care setting that not much is known about, but is likely to become increasingly important as the country's population grows greyer. As other studies have suggested, facility size seems to be a crucial predictor of staffing levels. First, when viewed together, the models suggest that larger facilities favor higher staffing levels of RNs and

LPN/LVNs versus smaller residential care facilities. Conversely, smaller facilities seem to prefer personal care aides. There may be a couple of reasons for this. First, larger facilities have the capital necessary to attract and hire more educated and more costly nurses, such as RNs. Second, larger facilities likely have a greater need for more skilled nurses. Smaller facilities may be able to get by just hiring more skilled contract nurses when needed. The results also suggest that past a certain point, at least for RNs, economies of scale may be reached for the largest of residential care facilities (100+ beds). When considered as a whole, the results also suggest that residential care facilities that accept Medicaid prefer to staff higher numbers of RNs. Conversely, those who do not accept Medicaid seem to favor lower skilled nurses. Furthermore, the results suggest that nonprofit or publicly-owned facilities will staff greater numbers of higher-skilled nurses, in particular LPNs/LVNs, while for-profit facilities prefer personal care aides and lower-skilled nurses over higher-skilled nurses. This may come as no surprise to many. For-profit facilities will be looking to maximize surplus, through means such as keeping labor costs low. One way to do that would be through higher a higher percentage of lower-skilled care providers. While not statistically significant in a few of the models, it appears as though non-chain membership facilities staff higher levels of higher-skilled nurses, while chain members staff higher levels of lower-skilled nurses.

CHAPTER 5

CONCLUSIONS

The previous chapter presented descriptive statistics and the estimates obtained from the models. Further, a brief discussion of the results followed. The final chapter of this thesis covers the author's conclusions on the study. Specifically, the contributions to the existing body of work are discussed in section 5.1. In this portion of the final chapter, four modest contributions are identified: a further understanding of nurse efficiency and health IT, a better understanding of efficiency across different types of nurses, the relationship of exchange information systems to nurse efficiency, and the context in which the study was conducted. Next, the limitations of the study are identified and presented. Finally, suggestions for future research are offered.

5.1 Contribution to the Existing Body of Work

5.1.1 Nurse Efficiency and Health IT

A major rationale in conducting this study was that the relationship between health IT and nurse efficiency had been understudied in general. Most of the efficiency studies conducted have been focused on physicians. Additionally, most of these types of studies concerned themselves with one or two applications at a time, primarily electronic health records and/or decision support systems. More research was needed on nurses and on a wider range of health IT applications. This study added to a small body of literature on the relationship between nurse efficiency and health IT. It found that, contrary to the specified hypotheses, a small, negative relationship existed between clinical IT sophistication and efficiency. Only in model 1 was this finding statistically significant though. Not only was this finding contrary to the hypotheses, but this finding was also contrary to those found in the literature. Additionally, a finding of no efficiency effect for several of the models is significant. This adds to the literature that health IT may be poorly implemented or not worth the cost from a purely efficiency perspective.

5.1.2 Efficiency Across Different Types of Nurses

Earlier in this thesis, nursing efficiency studies in the existing literature were criticized for focusing primarily on RNs. Few of the studies of this type make distinction between RNs and other nurses and few focus at all on LPNs/LVNs. Even fewer focus on aides, although they provide a good portion of the care, particularly in care settings such as residential care facilities. This lack of focus was cited as a rationale for the study. As this was the case, a distinction was made between the different types of nurses and models were built for each level of nurse. Although effects seemed to be slightly different, but similar across nursing types, the effects on different types of nurses is a contribution nonetheless.

5.1.3 Exchange Information Systems

To the best of my knowledge, this is the first study to examine the relationship between the exchange function of health IT and nurse efficiency. In chapter two, the existing literature was criticized for focusing almost exclusively on clinical IT applications. This primary focus on clinical applications is understandable as they are far more frequently used than information exchange. A focus on implementing health information exchange capabilities has only come about in the past few years and these capabilities are rare in most care settings, especially in those outside of hospitals and physicians’ offices. The estimates from one of the three models in which exchange capabilities were considered was statistically significant (Model 4). The estimates from this model suggested that efficiency gains were not seen. In models 2 and 6, the estimates were not statistically significant, although the expected relationship was observed.

5.1.4 Context

To the best of my knowledge, this is the first study to examine health IT in residential care facilities, broadly conceived. Additionally, this is the first study conducted using data from the 2010 NSRCF. The public-use data files were released fairly recently in December 2011. The setting and data used, makes this study a contribution. In other words, the context in which the study was conducted is one of its strengths. In the literature review of this study, it was suggested that most of the studies examining the relationship of health IT and nurse efficiency had been conducted in hospitals, especially large academic hospitals. This trend in the literature was criticized and put forth as one of the primary rationales for conducting the study. While there is likely to be some disagreement here, authors have argued that context is extremely important. This is particularly true in healthcare settings (Dopson, Fitzgerald, & Ferlie, 2008). While the primary variables under study here are similar across settings (many of the health IT applications are across all settings), the nature of the care being provided is important. Additionally, patient mix and the makeup of the people providing the care will be important and may influence staff efficiency. For instance, different types of nurses have different levels of education and different skill levels. This is likely to influence the ability to grasp a particular technology, how technology is used, and the various outcomes associated with it. Further, a profile of the staffing patterns of America's residential care facilities emerged.

5.2 Limitations of the Study

As with any study, there are limitations in the present study. The limitations of this study primarily have to with the nature of the data and the nature of the phenomena under study. More specifically, several seemingly important control variables were left out.

5.2.1 Quality of Care

Unfortunately, the quality of care provided by residential care facilities was not controlled for in this study. The quality of care provided by a facility is almost certain to have a major influence on a measure such as HPPD. All else equal, it is likely that a facility that seeks to provide a high quality of care may require a greater number of direct care HPPD across the board. Alternatively, if a facility provides a lower quality of care, they may require fewer direct care HPPD. With that said, quality of care is a concept that is quite difficult to measure for any study. Competing views about what constitutes quality of care abound.

5.2.2 Time Effects

In addition to missing data on quality of care, this study is limited by the inability to control for time effects. We know that, as with any new technology, physicians and nurses must first learn how to use a new application. Initial drops in productivity may be seen along with frustration and resistance, but studies do suggest that these feelings may subside as users become more proficient at using the technologies (for example see Krall, 1995).

5.2.3 Changing Patient Mix and Intensity of Care

This study was cross-sectional in nature and did not control for a facility's changing patient mix and changes in intensity of care. The measure of efficiency used here, direct care HPPD, is a snapshot of a facility at a point in time. It is likely that the value of this measure will change throughout the year as residents cycle in and out of the facility. This dynamic may change the intensity of care required. For instance, if a resident that requires a great amount of care joins the facility, the measure of efficiency is likely to change. Likewise, if patients requiring more intensive care are replaced with patients that require less care, the measure of efficiency is likely to change again.

5.2.4 Separate Care Units

This study did not control for whether or not a facility had a separate care unit. This is another limitation of this study. Residential care facilities will occasionally have separate care units. For instance, a facility might have a unit dedicated to Alzheimer's patients or others residents that require more intensive care or a different type of care. Further, these units may staff differently than others in the facility and may exhibit higher or lower levels of HPPD. Additionally, health IT applications may influence these units differently. In other words, the effect may be different (i.e. stronger/weaker, opposite direction).

5.2.5 Extensive Transformation of Variables

The transformations and collapsing of the variables in the public-use data file probably influenced the effects by increasing measurement error, thereby making significant effects harder to find. For instance, the ownership type variable was originally coded as three categories: private for-profit, private nonprofit, and state, county, or local government. This originally coding was collapsed into two categories by the survey administrators: private for-profit and nonprofit or state, county, or local government. In this case, it might have been interesting to be able to make comparisons between public and nonprofit facilities. In another example, facility size (number of beds) was coded into four categories. Coding facility size in this manner then influenced the coding of HPPD, which takes facility size into account. Because facility size was coded into four categories and not as a continuous variable, so was HPPD. The manner in which these variables were coded most likely led to less precise estimates and probably influenced effects. These efforts were made on the part of the survey administrators to protect the identities of the survey participants. This is understandable, but it makes the results less precise.

5.3 Suggestions for Future Research

In future studies, researchers should seek to control for some of the potential confounding variables mentioned in the previous section of this chapter, including quality of care. These are variables that may influence efficiency. Some of them, such as the existence of separate care units, may be easier to measure and control for than other. No matter how strong this study , some of the variables missing from it are just too important. This undoubtedly influenced the results and obscured the true effect. Ultimately, it limits some of the conclusions that can be drawn from it.

Future researchers interested in this topic might want conduct a holistic study in which efficiency and labor productivity is considered at the organizational level in combination with observational and time-motion studies. This would allow researchers to test whether or not health IT increase face-to-face care time, although it does not increase efficiency at the macro-level.

More research is needed on health information exchange. Future research might also further consider the impact of health information exchange on physician and nurse efficiency. This is an area that is badly in need of research. This study attempted to begin filling this gap, but much more attention is needed. Here, researchers might consider designing time-motion and observational studies. These could be similar to the studies conducted regarding some of the clinical applications. Researchers could also do pre-post studies as well. Tasks could be documented before and after implementation. Researchers should also consider range restriction issues, as the technology is relatively immature and underutilized.

Future research might also consider how time influences the subsequent impact of health IT on efficiency. Failure to consider temporal issues may further decrease the effect of health IT on efficiency. We have some idea that initial resistance and decreased efficiency may be seen soon after implementation. Researchers might ask *when* it is that users become acquainted with an application enough that productivity picks up or *how long* it takes for productivity to return to normal or even increase. One way to go about this might be to conduct longitudinal studies

Additionally, future researchers might want to consider the relationship between efficiency and health IT applications in a greater variety of settings. This study was conducted in a new setting, residential care facilities. There is a whole host of additional settings that need attention. These settings contain a variety of services provided, a variety of patients, and different staff mixes. Not only will health IT become increasingly important in the future, but additional care settings will be called on increasingly as well.

APPENDIX A

VARIABLES USED IN THE STATISTICAL MODELS

Survey Question Number	Variable Name	Survey Question Text	Original Code Categories	Notes
	FACSIZE	Facility size defined by the number of beds reported in resident selection questionnaire	1=SMALL (4-10 beds) 2=MEDIUM (11-25 beds) 3=LARGE (26-100 beds) 4=EXTRA LARGE (Over 100 beds)	IV (Control)
F_S14	CHAIN	Is this facility owned by a chain, group, or multi-facility system?	1=YES 2=NO	IV (Control)
Derived from F_S15	OWN2	What is the type of ownership of this facility? Private for profit, private nonprofit, or state, county, or local government	1=PRIVATE, FOR PROFIT 2=PRIVATE NONPROFIT OR STATE/COUNTY/LOCAL GOVT	IV (Control)
Derived from F_A17, F_A18	ANYDDMI	Does the facility currently serve any persons with developmental disabilities (e.g., mental retardation, autism, or Down syndrome) or those with severe mental illness (e.g., schizophrenia, psychosis)? Exclude Alzheimer's disease or other dementias.	1=YES 2=NO -8=DON"T KNOW	IV (Control)
F_A22	MEDICAID	Is this residential facility certified or registered to participate in Medicaid?	1=YES 2=NO -8=DON'T KNOW	IV (Control)
F_A34	CONTRACT	Does this facility use contract workers to provide direct care to residents?	1=YES 2=NO	IV (Control)
F_A35	VOLWORK	During the past 7 days or last work week, did your facility use any volunteers to help your residents or this facility's staff in any way?	1=YES 2=NO	IV (Control)
F_B1a	ADEMER	In terms of this facility's admission policy, do you admit a resident who is UNABLE TO LEAVE THE FACILITY IN AN EMERGENCY WITHOUT HELP?	1=YES 2=NO 3=NO SPECIFIC POLICY – WE MAKE DECISIONS ON A CASE BY CASE BASIS -9=NOT ASCERTAINED	IV (Control) *Used in comput. of admissions index
F_B1b	ADCOG	In terms of this facility's admission policy, do you admit a resident who HAS	1=YES 2=NO 3=NO SPECIFIC	IV (Control) *Used in

		MODERATE TO SEVERE COGNITIVE IMPAIRMENT, THAT IS, THE RESIDENT DOES NOT KNOW WHO THEY ARE?	POLICY – WE MAKE DECISIONS ON A CASE BY CASE BASIS -9=NOT ASCERTAINED	comput. of admissions index
F_B1c	ADBEH	In terms of this facility's admission policy, do you admit a resident who EXHIBITS PROBLEM BEHAVIOR SUCH AS WANDERING, TEMPER OUTBURSTS, OR COMBATIVE BEHAVIOR TO OTHER RESIDENTS?	1=YES 2=NO 3=NO SPECIFIC POLICY – WE MAKE DECISIONS ON A CASE BY CASE BASIS -9=NOT ASCERTAINED	IV (Control) *Used in comput. of admissions index
F_B1d	ADSNC	In terms of this facility's admission policy, do you admit a resident who NEEDS SKILLED NURSING CARE ON A REGULAR BASIS?	1=YES 2=NO 3=NO SPECIFIC POLICY – WE MAKE DECISIONS ON A CASE BY CASE BASIS -9=NOT ASCERTAINED	IV (Control) *Used in comput. of admissions index
F_B1e	ADMON	In terms of this facility's admission policy, do you admit a resident who NEEDS DAILY MONITORING FOR A HEALTH CONDITION LIKE ASSISTANCE TAKING INSULIN OR MONITORING BLOOD SUGAR?	1=YES 2=NO 3=NO SPECIFIC POLICY – WE MAKE DECISIONS ON A CASE BY CASE BASIS -9=NOT ASCERTAINED	IV (Control) *Used in comput. of admissions index
F_B1f	ADURINE	In terms of this facility's admission policy, do you admit a resident who is REGULARLY INCONTINENT OF URINE?	1=YES 2=NO 3=NO SPECIFIC POLICY – WE MAKE DECISIONS ON A CASE BY CASE BASIS -9=NOT ASCERTAINED	IV (Control) *Used in comput. of admissions index
F_B1g	ADFECES	In terms of this facility's admission policy, do you admit a resident who is REGULARLY INCONTINENT OF FECES?	1=YES 2=NO 3=NO SPECIFIC POLICY – WE MAKE DECISIONS ON A CASE BY CASE BASIS -7=REFUSAL -9=NOT ASCERTAINED	IV (Control) *Used in comput. of admissions index
F_B1f	ADLIFT	In terms of this facility's admission policy, do you admit a resident who NEEDS TWO PEOPLE	1=YES 2=NO 3=NO SPECIFIC POLICY – WE MAKE	IV (Control) *Used in comput. of

		TO HELP THEM GET IN AND OUT OF BED OR NEEDS A HOYER LIFT TO GET IN AND OUT OF BED?	DECISIONS ON A CASE BY CASE BASIS -9=NOT ASCERTAINED	admissions index
F_B1j	ADDRUG	In terms of this facility's admission policy, do you admit a resident who HAS A HISTORY OF DRUG OR ALCOHOL ABUSE?	1=YES 2=NO 3=NO SPECIFIC POLICY – WE MAKE DECISIONS ON A CASE BY CASE BASIS -8=DON'T KNOW -9=NOT ASCERTAINED	IV (Control) *Used in comput. of admissions index
F_B1k	ADEOLC	In terms of this facility's admission policy, do you admit a resident who REQUIRES END OF LIFE CARE?	1=YES 2=NO 3=NO SPECIFIC POLICY – WE MAKE DECISIONS ON A CASE BY CASE BASIS -9=NOT ASCERTAINED	IV (Control) *Used in comput. of admissions index
F_B3a	DCEMER	In terms of this facility's discharge policy, do you discharge a resident who is UNABLE TO LEAVE THE FACILITY IN AN EMERGENCY WITHOUT HELP?	1=YES 2=NO 3=NO SPECIFIC POLICY – WE MAKE DECISIONS ON A CASE BY CASE BASIS -9=NOT ASCERTAINED	IV (Control) *Used in comput. of discharge index
F_B3b	DCCOG	In terms of this facility's discharge policy, do you discharge a resident who HAS MODERATE TO SEVERE COGNITIVE IMPAIRMENT, THAT IS, THE RESIDENT DOES NOT KNOW WHO THEY ARE?	1=YES 2=NO 3=NO SPECIFIC POLICY – WE MAKE DECISIONS ON A CASE BY CASE BASIS -9=NOT ASCERTAINED	IV (Control) *Used in comput. of discharge index
F_B3c	DCBEH	In terms of this facility's discharge policy, do you discharge a resident who EXHIBITS PROBLEM BEHAVIOR SUCH AS WANDERING, TEMPER OUTBURSTS, OR COMBATIVE BEHAVIOR TO OTHER RESIDENTS?	1=YES 2=NO 3=NO SPECIFIC POLICY – WE MAKE DECISIONS ON A CASE BY CASE BASIS -9=NOT ASCERTAINED	IV (Control) *Used in comput. of discharge index
F_B3d	DCSNC	In terms of this facility's discharge policy, do you discharge a resident who NEEDS SKILLED NURSING CARE ON A REGULAR BASIS?	1=YES 2=NO 3=NO SPECIFIC POLICY – WE MAKE DECISIONS ON A CASE BY CASE BASIS	IV (Control) *Used in comput. of discharge index

			-9=NOT ASCERTAINED	
F_B3e	DCMON	In terms of this facility's discharge policy, do you discharge a resident who NEEDS DAILY MONITORING FOR A HEALTH CONDITION LIKE ASSISTANCE TAKING INSULIN OR MONITORING BLOOD SUGAR?	1=YES 2=NO 3=NO SPECIFIC POLICY – WE MAKE DECISIONS ON A CASE BY CASE BASIS -9=NOT ASCERTAINED	IV (Control) *Used in comput. of discharge index
F_B3f	DCURINE	In terms of this facility's discharge policy, do you discharge a resident who is REGULARLY INCONTINENT OF URINE?	1=YES 2=NO 3=NO SPECIFIC POLICY – WE MAKE DECISIONS ON A CASE BY CASE BASIS -9=NOT ASCERTAINED	IV (Control) *Used in comput. of discharge index
F_B3g	DCFECES	In terms of this facility's discharge policy, do you discharge a resident who is REGULARLY INCONTINENT OF FECES?	1=YES 2=NO 3=NO SPECIFIC POLICY – WE MAKE DECISIONS ON A CASE BY CASE BASIS -1=LEGITIMATE SKIP -9=NOT ASCERTAINED	IV (Control) *Used in comput. of discharge index
F_B3f	DCLIFT	In terms of this facility's discharge policy, do you discharge a resident who NEEDS TWO PEOPLE TO HELP THEM GET IN AND OUT OF BED OR NEEDS A HOYER LIFE TO GET IN AND OUT OF BED	1=YES 2=NO 3=NO SPECIFIC POLICY – WE MAKE DECISIONS ON A CASE BY CASE BASIS -8=DON'T KNOW -9=NOT ASCERTAINED	IV (Control) *Used in comput. of discharge index
F_B3j	DCDRUG	In terms of this facility's discharge policy, do you discharge a resident who ABUSES DRUGS OR ALCOHOL?	1=YES 2=NO 3=NO SPECIFIC POLICY – WE MAKE DECISIONS ON A CASE BY CASE BASIS -1=LEGITIMATE SKIP -8=DON'T KNOW -9=NOT ASCERTAINED	IV (Control) *Used in comput. of discharge index
F_B3k	DCEOLC	In terms of this facility's discharge policy, do you discharge a resident who REQUIRES END OF LIFE CARE?	1=YES 2=NO 3=NO SPECIFIC POLICY – WE MAKE DECISIONS ON A CASE BY CASE BASIS -7=REFUSAL	IV (Control) *Used in comput. of discharge index

			-9=NOT ASCERTAINED	
F_A49	EHRS	Other than for accounting or billing purposes, does this facility use Electronic Health Records?	1=YES 2=NO -9=NOT ASCERTAINED	IV *Used in comput. of clinical IT index
Derived from F_A50	ITDEM	Does the facility computerized capabilities have? RESIDENT DEMOGRAPHICS.	1=YES 2=NO -8=DON'T KNOW -9=NOT ASCERTAINED	IV *Used in comput. of clinical IT index
Derived from F_A50	ITMDINFO	Does the facility computerized capabilities have? MEDICAL PROVIDER INFORMATION	1=YES 2=NO -8=DON'T KNOW -9=NOT ASCERTAINED	IV *Used in comput. of clinical IT index
Derived from F_A50	ITFUNC	Does the facility computerized capabilities have? FUNCTIONAL ASSESSMENTS	1=YES 2=NO -8=DON'T KNOW -9=NOT ASCERTAINED	IV *Used in comput. of clinical IT index
Derived from F_A50	ITSERPLN	Does the facility computerized capabilities have? INDIVIDUAL SERVICE PLANS	1=YES 2=NO -8=DON'T KNOW -9=NOT ASCERTAINED	IV *Used in comput. of clinical IT index
Derived from F_A50	ITNOTE	Does the facility computerized capabilities have? CLINICAL NOTES, SUCH AS MEDICAL HISTORY AND DAILY PROGRESS NOTES	1=YES 2=NO -8=DON'T KNOW -9=NOT ASCERTAINED	IV *Used in comput. of clinical IT index
Derived from F_A50	ITPROB	Does the facility computerized capabilities have? PATIENT PROBLEMS LIST	1=YES 2=NO -8=DON'T KNOW -9=NOT ASCERTAINED	IV *Used in comput. of clinical IT index
Derived from F_A50	ITRXADM	Does the facility computerized capabilities have? MEDICATION ADMINISTRATION	1=YES 2=NO -8=DON'T KNOW -9=NOT ASCERTAINED	IV *Used in comput. of clinical IT index
Derived from F_A50	ITRXLIST	Does the facility computerized capabilities have? MAINTAINING LIST OF RESIDENT'S MEDICATIONS	1=YES 2=NO -8=DON'T KNOW -9=NOT ASCERTAINED	IV *Used in comput. of clinical IT index
Derived from F_A50	ITALLERG	Does the facility computerized capabilities have? MAINTAINING ACTIVE MEDICATION	1=YES 2=NO -8=DON'T KNOW -9=NOT ASCERTAINED	IV *Used in comput. of clinical IT

		ALLERGY LIST		index
Derived from F_A50	ITPRESC	Does the facility computerized capabilities have? ORDERS FOR PRESECRIPTIONS	1=YES 2=NO -8=DON'T KNOW -9=NOT ASCERTAINED	IV * Used in comput. of clinical IT index
Derived from F_A50	ITCONTRA	Does the facility computerized capabilities have? WARNING OF DRUG INTERACTIONS OR CONTRAINDICATIONS	1=YES 2=NO -8=DON'T KNOW -9=NOT ASCERTAINED	IV * Used in comput. of clinical IT index
Derived from F_A50	ITORDER	Does the facility computerized capabilities have? ORDERS FOR TESTS	1=YES 2=NO -8=DON'T KNOW -9=NOT ASCERTAINED	IV * Used in comput. of clinical IT index
Derived from F_A50	ITVIEW	Does the facility computerized capabilities have? VIEWING LABORATORY/IMAGING RESULTS	1=YES 2=NO -8=DON'T KNOW -9=NOT ASCERTAINED	IV * Used in comput. of clinical IT index
Derived from F_A50	ITREMIND	Does the facility computerized capabilities have? REMINDERS FOR GUIDELINE BASED INTERVENTIONS OR SCREENING TESTS	1=YES 2=NO -8=DON'T KNOW -9=NOT ASCERTAINED	IV * Used in comput. of clinical IT index
Derived from F_A50	ITDISCH	Does the facility computerized capabilities have? DISCHARGE AND TRANSFER SUMMARIES	1=YES 2=NO -8=DON'T KNOW -9=NOT ASCERTAINED	IV * Used in comput. of clinical IT index
Derived from F_A50	ITPUBLIC	Does the facility computerized capabilities have? PUBLIC HEALTH REPORTING	1=YES 2=NO -8=DON'T KNOW -9=NOT ASCERTAINED	IV * Used in comput. of clinical IT index
Derived from F_A51	ITMD	Does this facility's computerized system support electronic health information exchange with PHYSICIANS?	1=YES 2=NO -1=LEGITIMATE SKIP -8=DON'T KNOW -9=NOT ASCERTAINED	IV *Used in comput. of exchange IT index
Derived from F_A51	ITNH	Does this facility's computerized system support electronic health information exchange with NURSING HOME?	1=YES 2=NO -1=LEGITIMATE SKIP -8=DON'T KNOW -9=NOT ASCERTAINED	IV *Used in comput. of exchange IT index
Derived from	ITHOSP	Does this facility's computerized system	1=YES 2=NO	IV *Used in

F_A51		support electronic health information exchange with HOSPITAL?	-1=LEGITIMATE SKIP -8=DON'T KNOW -9=NOT ASCERTAINED	comput. of exchange IT index
Derived from F_A51	ITPHARM	Does this facility's computerized system support electronic health information exchange with PHARMACY?	1=YES 2=NO -1=LEGITIMATE SKIP -8=DON'T KNOW -9=NOT ASCERTAINED	IV *Used in comput. of exchange IT index
Derived from F_A51	ITLAB	Does this facility's computerized system support electronic health information exchange with LABORATORY/TESTS?	1=YES 2=NO -1=LEGITIMATE SKIP -8=DON'T KNOW -9=NOT ASCERTAINED	IV *Used in comput. of exchange IT index
Derived from F_A51	ITLTC	Does this facility's computerized system support electronic information health exchange with OTHER HEALTH OR LONG TERM CARE PROVIDER?	1=YES 2=NO -1=LEGITIMATE SKIP -8=DON'T KNOW -9=NOT ASCERTAINED	IV *Used in comput. of exchange IT index
Derived from F_A51	ITPERS	Does this facility's computerized system support electronic health information exchange with RESIDENT'S PERSONAL HEALTH RECORD	1=YES 2=NO -1=LEGITIMATE SKIP -8=DON'T KNOW -9=NOT ASCERTAINED	IV *Used in comput. of exchange IT index
Derived from F_A51	ITPHR	Does this facility's computerized system support electronic health information exchange with PUBLIC HEALTH REPORTING?	1=YES 2=NO -1=LEGITIMATE SKIP -8=DON'T KNOW -9=NOT ASCERTAINED	IV *Used in comput. of exchange IT index
Derived from F_A3, F_A33A	RNHPPD2	RN direct care hours per patient day (HPPD)	1=0 HPPD 2=0.1-0.25 HPPD 3=0.26-0.HPPD 4=MORE THAN 0.5 HPPD -8=DON'T KNOW	DV *Models 1 and 2
Derived from F_A3, F_A33B	LPNHPPD2	LPN/LVN direct care hours per patient day (HPPD)	1=0 HPPD 2=0.1-0.25 HPPD 3=0.26-0.5 HPPD 4=MORE THAN 0.5 HPPD -8=DON'T KNOW	DV *Models 3 and 4
Derived from F_A3,	AIDEHPPD2	Personal care aide direct care hours per patient day (HPPD)	1=0-0.9 HPPD 2=1.0-1.9 HPPD 3=2.0-2.9 HPPD	DV * Models 5 and 6

F_A33c			4=3 or MORE HPPD -8=DON'T KNOW	

REFERENCES

Aaronson, W.E., Zinn, J.S., & Rosko, M.D. (1994). Do for-profit and not-for-profit nursing homes behave differently?, *The Gerontologist*, *34*(6), 775-786.

Abookire, S.A., Teich, J.M., Sandige, H., Paterno, M.D., Martin, M.T., Kuperman, G.J., et al. (2000). Improving allergy alerting in a computerized physician order entry system. *Proceedings of the American Medical Informatics Association Symposium*, *USA*, 2-6.

Agency for Healthcare Research and Quality (AHRQ). (2012). *Patient safety primers: Computerized provider order entry*. Retrieved February 1, 2012, from http://psnet.ahrq.gov/primer.aspx?primerID=6

Allison, P.D. (1999). *Logistic regression using the SAS system: Theory and application*. Cary, NC: SAS Institute.

Allison, P.D. (2001). *Missing Data*. Sage University Papers Series on Quantitative Applications in the Social Science, 07-136. Thousand Oaks, CA: Sage.

Arshad, U., Mascolo, Cecilia, M., & Mellor, M. (n.d.). *Exploiting mobile computing in health-care*. Retrieved February 3, 2012, from http://www.cl.cam.ac.uk/~cm542/papers/iwsawc.pdf

Ash, J.S., Gorman, P.N., & Hersh, W.R. (1998). Physician order entry in U.S. hospitals. *Proceedings of the AMIA Annual Symposium*, 235-239.

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

Baird, T.K., Broekemeier, R.L., & Anderson, M.W. (1984). Effectiveness of a computer-supported refill reminder system. *American Journal of Hospital Pharmacy*, *41*(11), 2395-2397.

Barnett, G.O. (1984). The application of computer-based medical-record systems in ambulatory practice. *The New England Journal of Medicine*, *310*(25), 1643-1650.

Barrett, J., Barnum, R., Gordon, B., & Pesut, R. (1975). Final report on the evaluation of the implementation of a medical information system in a general community hospital (NTIS PB248340). Columbus, OH: Battelle Columbus Labs.

Bates, D.W., Kuperman, G.J., Jha, A., Teich, J.M., Orav, E.J., Ma'luf, N. et al. (1997). Does the computerized display of charges affect inpatient ancillary test utilization? *Archives of Internal Medicine*, *157*(21), 2501-2508.

Bates, D.W., Leape, L.L., Cullen, D.J., Laird, N., Petersen, L.A., Teich, J.M. et al. (1998). Effect of computerized physician order entry and a team intervention on prevention of serious medication errors. *Journal of the American Medical Association*, *280*(15), 1311-1316.

Bates, D.W., Teich, J.M., Lee, J., Seger, D., Kuperman, G.J., Ma'Luf, N., et al. (1999a). The impact of computerized physician order entry on medication error prevention. *Journal of the American Medical Informatics Association*, *6*(4), 313-321.

Bates, D.W., Kuperman, G.J., Rittenberg, E., Teich, J.M., Fiskio, J., Ma'luf, N. et al. (1999b). A randomized trial of a computer-based intervention to reduce utilization of redundant laboratory tests. *American Journal of Medicine*, *106*(2), 144-150.

Berner, E., Webster, G., Shugerman, A., Jackson, J., Algina, J., Baker, A. et al. (1994). Performance of four computer-based diagnostic systems. *New England Journal of Medicine*, *330*(25), 1792-1796.

Blegen, M.A., Vaughn, T., & Vojir, C.P. (2008). Nurse staffing levels: Impact of organizational characteristics and registered nurse supply. *Health Services Research*, *43*(1), 154-173.

Borooah, V.K. (2002). *Logit and probit: Ordered and multinomial models*. Sage University Papers Series on Quantitative Applications in the Social Sciences, 07-138. Thousand Oaks, CA: Sage.

Bourbonniere, M., Feng, Z., Intrator, O., Angelelli, J., & Mor, V. (2006). The use of contract licensed nursing staff in U.S. nursing homes. *Medical Care Research and Review*, *63*(1), 88-109.

Buchbinder, S.B., & Buchbinder, D. (2007). Managing healthcare professionals. In Buchbinder, S.B. and Shanks, N.H. (Eds.), *Introduction to health care management* (pp.231-264). Sudbury, MA: Jones and Bartlett Publishers.

Bush, G.W. (2004). *2004 State of the Union Address*. Retrieved February 9, 2012, from http://www.americanrhetoric.com/speeches/stateoftheunion2004.htm

Cannon, D.S., & Allen, S.N. (2000). A comparison of the effects of computer and manual reminders on compliance with a mental health clinical practice guideline. *Journal of the American Medical Informatics Association*, *7*(2), 196-203.

Chaudhry, B., Wang, J., Wu, S., Maglione, M., Mojica, W., Roth, E. et al. (2006). Systematic review: Impact of health information technology on quality, efficiency, and costs of medical care. *Annals of Internal Medicine*, *144*, 747-752.

Chen, P., Tanasijevic, M.J., Schoenenberger, R.A., Fiskio, J., Kuperman, G.J., & Bates, D.W. (2003). A computer-based intervention for improving the appropriateness of antiepileptic drug level monitoring. *American Journal of Clinical Pathology*, *119*, 432-438.

Christiansen, J. (1999). Health IT and privacy: The legal perspective. *MD Computing*, *16*(4), 15-16.

Clark, D. (2000). Old wine in new bottles: Delivering nursing in the 21st century. *Journal of Nursing Scholarship*, *32*(1), 11-15.

Classen, D.C., Pestotnik, S.L., Evans, R.S., Lloyd, J.F., Burke, J.P. (1997). Adverse drug events in hospitalized patients. Excess length of stay, extra costs, and attributable mortality. *Journal of the American Medical Association*, *277*(4), 301-306.

Chertow, G.M., Lee, J., Kuperman, G.J., Burdick, E., Horsky, J., Seger, D.L., et al. (2001). Guided medication dosing for inpatients with renal insufficiency. *Journal of the American Medical Association*, *286*(22), 2839-2844.

Chin, H.L., & Wallace, P. (1999). Embedding guidelines into direct physician order entry: Simple methods, powerful results. *Proceedings of the American Medical Informatics Association Symposium*, *USA*, 221-225.

Choplin, R., Boehme, J.M., & Maynard, C.D. (1992). Picture archiving and communication systems: An overview. *Radiographics*, *12*, 127-129.

Cohen, J.W., & Dubay, L.C. (1990). The effects of Medicaid reimbursement and ownership on nursing home costs, case mix, and staffing. *Inquiry*, *27*(2), 183-200.

Cohen, J.W., & Spector, W.D. (1996). The effect of Medicaid reimbursement on quality of care in nursing homes. *Journal of Health Economics*, *15*(1), 23-48.

Cordero, L., Kuehn, L., Kumar, R.R., & Mekhjian, H.S. (2004). Impact of computerized physician order entry on clinical practice in a newborn intensive care unit. *Journal of Perinatology*, *24*(2), 88-93

Cross, M. (2000, March/April). Cases: Making a connection: Kaiser Permanente's web strategy. Internet Healthcare Magazine, 30-32.

Demakis, J.G., Beauchamp, C., Cull, W.L., Denwood, R., Eisen, S.A., Lofgren, R., et al. (2000). Improving residents' compliance with standards of ambulatory care: Results from the VA Cooperative Study on Computerized Reminders. *Journal of the American Medical Association*, *284*(11), 1411-1416.

Dexter, P.R., Wolinsky, F.D., Gramelspacher, G.P., Zhou, X.H., Eckert, G.J., Waisburd, M., et al. (1998). Effectiveness of computer-generated reminders for increasing discussions about advance directives and completion of advance directive forms. A randomized, controlled trial. *Annals of Internal Medicine*, *128*(2), 102-110.

Dexter, P.R., Perkins, S.M., Maharry, K.S., Jones, K., & McDonald, C.J. (2004). Inpatient computer-based standing orders vs physician reminders to increase influenza and pneumococcal vaccination rates: A randomized trial. *Journal of the American Medical Association*, *292*(19), 2366-2371.

Dick, R., & Steen, E. (1991). *The computer-based patient record: An essential technology for healthcare*. Washington, DC: Institute of Medicine & National Academy Press.

Dopson, S., Fitzgerald, L., & Ferlie, E. (2008). Understanding change and innovation in healthcare settings: Reconceptualizing the active role of context. *Journal of Change Management*, *8*(3-4), 213-231.

Dunham-Taylor, J., & Pinczuk, J.P. (2006). Health are financial management for nurse managers. Sudbury, MA: Jones and Bartlett Publishers.

Evans, R.S., Larsen, R.A., Burke, J.P., Gardner, R.M., Meier, F.A., Jacobson, J.A., et al. (1986). Computer surveillance of hospital-acquired infections and antibiotic use. *Journal of the American Medical Association*, *256*(8), 1007-1011.

Evans, R.S., Pestotnik, S.L., Classen, D.C., Bass, S.B., & Burke, J.P. (1992) Prevention of adverse drug events through computerized surveillance. *Proceedings of the Annual Symposium on Computer Applications in Medical Care*, *USA*, 47-441.

Evans, R.S., Classen, D.C., Stevens, L.E., Pestotnik, S.L., Gardner, R.M., Lloyd, J.F., et al. (1993). Using a hospital information system to assess the effects of adverse drug events. *Proceedings of the Annual Symposium on Computer Application in Medical Care*, *USA*, 161-165.

Evans, R.S., Classen, D.C., Pestotnik, S.L., Lundsgaarde, H.P., & Burker, J.P. (1994). Improving empiric antibiotic selection using computer decision support. *Archives of Internal Medicine*, *154*(8), 878-884.

Evans, R.S., Pestotnik, S.L., Classen, D.C., Clemmer, T.P., Weaver, L.K., Orme, J.F., et al. (1998). A computer-assisted management program for antibiotics and other antiinfective agents. *New England Journal of Medicine*, *338*(4), 232-238.

Evans, R.S., Pestotnik, S.L., Classen, D.C., Burke, J.P. (1999). Evaluation of a computer-assisted antibiotic-dose monitor. *Annals of Pharmacotherapy*, *33*(10), 1026-1031.

Fihn, S.D., McDonell, M.B., Vermes, D., Henikoff, J.G., Martin, D.C., Callahan, C.M. et al. (1994). A computerized intervention to improve timing of outpatient follow-up: A multicenter randomized trial in patients treated with warfarin. National Consortium of Anticoagulation Clinics. *Journal of General Internal Medicine*, *9*(3), 131-139.

Fung, E.Y., & Leung, B. (2009). Do automated dispensing machines improve patient safety? *Canadian Journal of Hospital Pharmacy*, *62*(6), 516-519.

Garr, D.R., Ornstein, S.M., Jenkins, R.G., & Zemp, L.D. (1993). The effect of routine use of computer-generated preventive reminders in a clinical practice. *American Journal of Preventive Medicine*, *9*(1), 55-61.

Garrido, T., Jamieson, L., Zhou, Y., Wiesenthal, A., & Liang, L. (2005). Effect of electronic health records in ambulatory care: Retrospective, serial, cross sectional study. *BMJ*, *330*, 581-584.

General Accounting Office (GAO). (1992, May 20). Medical ADP systems: Composite health care system is not ready to be deployed, #92-54. Washington, DC: United States General Accounting Office, Information Management and Technology Division.

Graber, M.A., & VanScoy, D. (2003). How well does decision support software perform in the emergency department?, *Emergency Medicine Journal*, *20*(5), 426-428.

Gunter, T.D., Terry, N.P. (2005). The emergence of national electronic health record architectures in the United States and Australia: Models, costs, and questions. *Journal of Medical Internet Research*, *7*(1), e3.

Harrell, F.E. (2001). *Regression modeling strategies: With applications to linear models, logistic regression and survival analysis*. New York: Springer.

Harrington, C., Carrillo, H., Mullan, J., & Swan, J.H. (1998). Nursing facility staffing in the states: the 1991 to 1995 period. *Medical Care Research and Review*, *55*(3), 334-363.

Harrington, C., Zimmerman, D., Karon, S.L., Robinson, J., & Beutel, P. (2000). Nursing home staffing and its relationship to deficiencies. *The Journals of Gerontology. Series B, Psychological Science and Social Sciences*, *55*(5), S278-S287.

Harrington, C., Swan, J.H., & Carrillo, H. (2007). Nurse staffing levels and Medicaid reimbursement rates in nursing facilities. *Health Services Research*, *42*(3 pt. 1), 1105-1129.

Harris Interactive. (2002). European physicians, especially in Sweden, Netherlands, and Denmark, lead U.S. in use of electronic medical records. *Harris Interactive Health Care News*, *2*(16).

Hartz, A.J., Krakauer, H., Kuhn, E.M., Young, M., Jacobsen, S.J., Gay, G., et al. (1989). Hospital characteristics and mortality rates. *New England Journal of Medicine*, *321*(25), 1720-1725.

Healthcare Information and Management Systems (HIMSS). (n.d.). *Fact sheet: Transforming healthcare for all Americans*. Retrieved February 9, 2012, from http://www.himss.org/asp/ContentRedirector.asp?ContentId=50742

Igbaria, M., Livari, J., & Maragahh, H. (1995). Why do individuals use computer technology? A Finnish case study. *Information & Management*, *29*(5), 227-238.

Jadad, A. (1999). Promoting partnerships: Challenges for the internet age. *British Medical Journal*, *319*, 761-764.

Kerr, E.A., Smith, D.M., Hogan, M.M., Krein, S.L., Pogach, L., Hofer, T.P., et al. (2002). Comparing clinical automated, medical record, and hybrid data sources for diabetes quality measures. *Joint Committee Journal on Quality Improvement*, *28*(), 555-565.

Khoury, A.T. (1997). Finding value in EMRs (electronic medical records). Health Management Technology, 18(1997), 34-36.

Khoury, A.T. (1998). Support of quality and business goals by an ambulatory automated medical record in Kaiser Permanente of Ohio. *Effective Clinical Practice*, *1*(2), 73-82.

Kilgore, M.L., Flint, D., & Pearce, R. (1998). The varying impact of two clinical information systems in a cardiovascular intensive care unit. *Journal of Cardiovascular Management*, *9*(2), 31-35.

Kissinger, K., & Borchardt, S. (Eds.). (1996). *Information technology for integrated health systems: Positioning for the future*. New York: John Wiley & Sons.

Koppel, R., Metlay, J.P., Cohen, A., Abaluck, B., Localio, A.R., Kimmel, S.E., et al. (2005) Role of computerized physician order entry systems in facilitating medication errors. *Journal of the American Medical Association*, *293*(10), 1197-1203.

Kovner, C., & Gergen, P.J. (1998). Nurse staffing levels and adverse events following surgery in U.S. hospitals. *Image: The Journal of Nursing Scholarship*, *30*(4), 315-321.

Krall, M.A. (1995). Acceptance and performance by clinicians using an ambulatory electronic medical record in an HMO. *Proceedings of the Annual Symposium on Computer Applications in Medical Care*, *USA*, 708-711.

Kramer, T.L., Owen, R.R., Cannon, D., Sloan, T.L., Thrush, C.R., Williams, D.K., et al. (2003). How well do automated performance measures assess guideline implementation for new-onset depression in the Veterans Health Administration? *Joint Commission Journal on Quality and Safety*, *29*(9), 479-489.

Kucher, N., Koo, S., Quiroz, R., Cooper, J.M., Paterno, M.D., Soukonnikov, B., et al. (2005). Electronic alerts to prevent venous thromboembolism among hospitalized patients. *New England Journal of Medicine*, *352*(), 969-977.

Kuperman, G.J., Gardner, R.M., & Pryor, T.A. (1991). HELP: A dynamic hospital information system. Computers and Medicine. New York: Springer-Verlag.

Kuperman, G.J., Teich, J.M., Tanasijevic, M.J., Ma'Luf, N., Rittenberg, E., Jha, A., et al. (1999). Improving response to critical laboratory results with automation: Results of a randomized controlled trial. *Journal of the American Medical Informatics Association*, *6*(6), 512-522.

Larsen, R.A., Evans, R.S., Burker, J.P., Pestotnik, S.L., Gardner, R.M., & Classen, D.C. (1989). Improved perioperative antibiotic use and reduced surgical wound infections through use of computer decision analysis. *Infection Control and Hospital Epidemiology*, *10*(7), 316-320.

Lee, F., Teich, J.M., Spurr, C.D., & Bates, D.W. (1996). Implementation of physician order entry: User satisfaction and self-reported usage patterns. *Journal of the American Medical Informatics Association*, *3*(1), 42-55.

Litzelman, D.K., Dittus, R.S., Miller, M.E., & Tierney, W.M. (1993). Requiring physicians to respond to computerized reminders improves their compliance with preventive care protocols. *Journal of General Internal Medicine*, *8*(6), 311-317.

Manheim, L.M., Feinglass, J., Shortell, S.M., & Hughes, E.F.X. (1992). Regional variation in Medicare hospital mortality. *Inquiry*, *29*(1), 55-66.

Mayes, R., & Berenson, R.A. (2006). Medicare prospective payment and the shaping of U.S. health care. Baltimore: The Johns Hopkins University Press.

McDonald, C.J. (1976a). Protocol-based computer reminders, the quality of care, and the non-perfectibility of man. *New England Journal of Medicine*, *295*(24), 1351 - 1355.

McDonald, C.J. (1976b). Use of a computer to detect and respond to clinical events: Its effect on clinician behavior. *Annals of Internal Medicine*, *84*(2), 162-167.

McDonald, C.J., Wilson, G.A., & McCabe, G.P. (1980). Physician response to computer reminders. *Journal of the American Medical Association*, *244*(14), 1579-1581.

McDonald, C.J., Hui, S.L., Smith, D.M., Tierney, W.M., Cohen, S.J., Weinberger, M., et al. (1984). Reminders to physicians from an introspective computer medical record. A two-year randomized trial. *Annals of Internal Medicine*, *100*(1), 130-138.

McDonald, C.J., Blevins, L., Tierney, W., & Martin, D. (1988). The Regenstrief medical records. *MD Computing*, *5*(5), 34-47.

McDonald, C.J., Hui, S.L., & Tierney, W.M. (1992). Effects of computer reminders for influenza vaccination on morbidity during influenza epidemics. *MD Computing*, *9*(5), 304-312.

McGregor, M.J., Cohen, M., McGrail, K., Broemeling, A.M., Adler, R.N., Schulzer, M., et al. (2005). Staffing levels in not-for-profit and for-profit long-term care facilities: Does type of ownership matter? *Canadian Medical Association Journal*, *172*(5), 645-649.

Medicare Payment Advisory Commission (MedPac). (2004). Report to the Congress: New approaches in Medicare. Retrieved February 2, 2012 from http://www.medpac.gov/documents/June04_Entire_Report.pdf

Mekhjian, H.S., Kumar, R.R., Kuehn, L., Bentley, T.D., Teater, P., Thomas, A., et al. (2002). Immediate benefits realized following implementation of physician order entry at an academic medical center. *Journal of the American Medical Informatics Association*, *9*(5), 529-539.

Miller, R., & Geissbuhler, A. (1999). Clinical diagnostic decision support systems – an overview. In E. Berner (Ed.), Clinical decision support systems: Theory and practice (p. 3-34). New York: Springer-Verlag.

Moss, A.J., Harris-Kojetin, L.D., Sengupta,M., et al. (2011). Design and operation of the 2010 National Survey of Residential Care Facilities. National Center for Health Statistics. Vital Health Stat 1(54).

Mullett, C.J., Evans, R.S., Christenson, J.C., Dean, J.M. (2001). Development and impact of a computerized pediatric antiinfective decision support program. *Pediatrics*, *108*(4), E75.

Munroe, D.J. (1990). The influence of registered nurse staffing on the quality of nursing home care. *Research in Nursing & Health*, *13*(4), 263-270.

National Research Council. (2001). *Crossing the quality chasm: A new health system for the 21st century*. Washington, DC: The National Academies Press.

Nyman, J.A. (1988). Excess demand, the percentage of Medicaid patients, and the quality of nursing home care. *The Journal of Human Resources*, *23*(1), 76-92.

Ornstein, S.M., Garr, D.R., Jenkins, R.G., Musham, C., Hamadeh, G., & Lancaster, C. (1995). Implementation and evaluation of a computer-based preventive services system. *Family Medicine*, *27*(4), 260-266.

Overhage, J.M., Tierney, W.M., & McDonald, C.J. (1996). Computer reminders to implement preventive care guidelines for hospitalized patients. *Archives of Internal Medicine*, *156*(14), 1551-1556.

Overhage, J.M., Tierney, W.M., Zhou, X.H., & McDonald, C.J. (1997). A randomized trial of “corollary orders” to prevent errors of omission. *Journal of the American Medical Informatics Association*, *4*(5), 364-375.

Overhage, J., Suico, J., McDonald, C. (2001a). Electronic laboratory reporting: Barriers, solutions, and findings. *Journal of Public Health Management and Practice*, *7*(6), 60-66.

Overhage, J.M., Perkins, S., Tierney, W.M., & McDonald, C.J. (2001b). Controlled trial of direct physician order entry: Effects on physcians' time utilization in ambulatory primary care internal medicine practices. *Journal of the American Medical Informatics Association*, *8*(4), 361-371.

Pierpont, G.L., & Thilgen, D. (1995). Effect of computerized charting on nursing activity in intensive care. *Critical Care Medicine*, *23*(6), 1067-1073.

Pizziferri, L., Kittler, A.F., Volk, L.A., Honour, M.M., Gupta, S., Wang, S. et al. (2005). Primary care physician time utilization before and after implementation of an electronic health record: A time-motion study. *Journal of Biomedical Informatics*, *38*(3), 176-188.

Poissant, L., Pereira, J., Tamblyn, R., & Kawasumi, Y. (2005). The impact of electronic health records on time efficiency of physicians and nurses: A systematic review. *Journal of the American Medical Informatics Association*, *12*(5), 505-516.

Poon, E.G., Jha, A.K., Christino, M., Honour, M.M., Fernandopulle, R., Middleton, B., et al. (2006). Assessing the level of healthcare information technology adoption in the United States: A snapshot. *BMC Medical Informatics and Decision Making*, *6*(1).

Robert Wood Johnson Foundation. (2006). *Health information technology in the United States: The information base for progress*. Princeton, NJ: Robert Wood Johnson Foundation.

Rollman, B.L., Hanusa, B.H., Lowe, H.J., Gilbert, T., Kapoor, W.N., & Schulberg, H.C. (2002). A randomized trial using computerized decision support to improve treatment of major depression in primary care. *Journal of General Internal Medicine*, *17*(7), 493-503.

Rossi, R.A., & Every, N.R. (1997). A computerized intervention to decrease the use of calcium channel blockers in hypertension. *Journal of General Internal Medicine*, *12*(11), 672-678.

Safran, C., Rind, D.M., Davis, R.B., Ives, D., Sands, D.Z., Currier, J., et al. (1995). Guidelines for management of HIV infection with computer-based patient's record. *Lancet.*, *346*(8971), 341-346.

Sanders, D.L., & Miller, R.A. (2001). The effects of clinician ordering patterns of a computerized decision support system for neuroradiology imaging studies. *Proceedings of the American Medical Informatics Association Symposium*, *USA*, 583-587.

Schoech, D. (1999). *Human services technology: Understanding, designing, and implementing computer and internet applications in the social services*. Binghmaton, NY: The Haworth Press.

Schriger, D.L., Baraff, L.J., Rogers, W.H., & Cretin, S. (1997). Implementation of clinical guidelines using a computer charting system. Effect on the initial care of health care workers exposed to body fluids. *Journal of the American Medical Association*, *278*(19), 1585-1590.

Shackman, G. (2001). Sample size and design effect. *Paper presented at the Albany Chapter of the American Statistical Association*. Retrieved on March 26, 2012 from http://www.albany.edu/~areilly/albany_asa/confweb01/abstract/Download/shackman.pdf

Shi, L. (2007). *Managing human resources in health care organizations*. Sudbury, MA: Jones and Bartlett Publishers.

Shojania, K.G., Yokoe, D., Platt, R., Fiskio, J., Ma'luf, N., & Bates, D.W. (1998). Reducing vancomycin use utilizing a computer guideline: Results of a randomized controlled trial. *Journal of the American Medical Informatics Association*, *5*(6), 554-562.

Shortliffe, E.H. (2005). Strategic action in health information technology: Why the obvious has taken so long. *Health Affairs*, *24*(5), 1222-1233.

Staggers, N., Thomspon, C.B., & Snyder-Halpern, R. (2001). History and trends in clinical information systems in the United States. *Journal of Nursing Scholarship*, *33*(1), 75-81.

Stata. (1999). *Stata reference manual release 6*. College Station, TX: Stata Press.

Steele, M.A., Bess, D.T., Franse, V.L., & Graber, S.E. (1989). *Cost effectiveness of two interventions for reducing outpatient prescribing costs*. Annals of Pharmacotherapy, *23*(6), 497-500.

Tech Target. (2012a). *Definition: Electronic medical billing*. Retrieved on February 1, 2012 from http://searchhealthit.techtarget.com/definition/electronic-medical-billing

Tech Target. (2012b). *Definition: Clinical decision support system (CDSS)*. Retrieved on February 1, 2012 from http://searchhealthit.techtarget.com/definition/clinical-decision-support-system-CDSS

Teich, J.M., Merchia, P.R., Schmiz, J.L., Kuperman, G.J., Spurr, C.D., & Bates, D.W. (2000). Effects of computerized physician order entry on prescribing practices. *Archives of Internal Medicine*, *160*(18), 2741-2747.

Tierney, W.M., Hui, S.L., & McDonald, C.J. (1986). Delayed feedback of physician performance versus immediate reminders to perform preventive care. Effects on physician compliance. *Medical Care*, *24*(8), 659-666.

Tierney, W.M., McDonald, C.J., Martin, D.K., & Rogers, M.P. (1987). Computerized display of past test results. Effect on outpatient testing. *Annals of Internal Medicine*, *107*(4), 569-574.

Tierney, W.M., McDonald, C.J., Hui, S.L., & Martin, D.K. (1988). Computer predictions of abnormal test results. Effects on outpatient testing. *Journal of the American Medical Association*, *259*(8), 1194-1198.

Tierney, W.M., Miller, M.E., Overhage, J.M., & McDonald, C.J. (1990). The effect on test ordering of informing physicians of the charges for outpatient diagnostic tests. *New England Journal of Medicine*, *322*(21), 1499-1504.

Tierney, W.M., Miller, M.E., Overhage, J.M., & McDonald, C.J. (1993). Physician inpatient order writing on microcomputer workstations. Effects on resource utilization. *Journal of the American Medical Association*, *269*(3), 379-383.

Toso, M.E. (2012). *Cost accounting and cost accounting systems in health care organizations*. Retrieved on February 2, 2012 from http://www.trinethealth.com/Articles/Cost%20Acctg%20&%20Cost%20Acctg%20Systems%20in%20Healthcare%20Org.pdf

United State Department of Health and Human Services (HHS). (2012). *Recovery Act-Funded Programs*. Retrieved, February 9, 2012, from http://www.hhs.gov/recovery/programs/index.html#Health

Warner, H., Toronto, A., Veasey, L., & Stephenson, R. (1961). A mathematical approach to medical diagnosis: Application to congenital heart disease. *Journal of the American Medical Association*, *177*(3), 177-183.

Weiderhold, G., & Perreault, L. (1990). Hospital information systems. In E.H. Shortliffe & L.E. Perreault (Eds.), Medical informatics: Computer applications in healthcare (p. 219-242). Reading, MA: Addison-Wesley.

Weiner, J., Lux, L., Johnson, R., & Greene, A.M. (2010). *National Survey of Residential Care Facilities: Sample frame construction and benchmarking report* (Prepared for Office of Disability, Aging and Long-Term Care Policy Office of the Assistant Secretary for Planning and Evaluation, Contract #HHS-100-03-0025 Interagency Agreement #10-HS06-894-CPCD-6) Washington, DC: U.S. Department of Health and Human Services.

Willson, D., Ashton, C., Wingate, N., Goff, C., Horn, S., Davies, M., et al. (1995). Computerized support of pressure ulcer prevention and treatment protocols. *Proceedings of the Annual Symposium of Computer Applications in Medical Care*, *USA*, 646-650.

Wilson, G.A., McDonald, C.J., & McCabe, G.P. Jr. (1982). The effect of immediate access to a computerized medical record on physician test ordering: A controlled clinical trial in the emergency room. *American Journal of Public Health*, *72*(7), 698-702.

Wong, D.H., Gallegos, Y., Weinger, M.B., Clack, S., Slagle, J., & Anderson, C.T. (2003). Changes in intensive care unit nurse task activity after installation of a third-generation intensive care unit information system. *Critical Care Medicine*, *31*(10), 2488-2494.

BIOGRAPHICAL INFORMATION

Jason D. Smith received his B.A. in political science from the University of Minnesota – Twin Cities in May of 2010. He continued his education at the University of Texas – Arlington, where he received his M.A. in Urban Affairs in May of 2012 at the School of Urban and Public Affairs. In the Fall of 2012, he will begin the doctoral program in public administration at the Maxwell School of Citizenship and Public Affairs, Syracuse University.