Managing Human Capital in Supply Chains:

Perspectives on Technological Advancement and Social Responsibility

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Dedication

To my family -- my parents, grandmother, sister and all relatives -- for all their love, understanding and support.

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To my wife, Di Zhao, and my son, Xuanyuan Liu.

Abstract

Managing human capital and technology is critical for sustainable and responsible operations in global supply chains. Facing new technologies and the necessity for the appropriate accompanying skills in global supply chains, organizations must manage well both the technology and the human capital, and must do so both internally and externally. This dissertation focuses on integrating technology and human capital in supply chains, with special emphasis on improving long-term operational sustainability and social responsibility. The investigation unfolds in four arenas: 1) technology development; 2) human capital; 3) work design; and 4) working conditions. Following this conceptual structure, I employ statistics, econometrics, and data analytics to analyze complex data sets from the health care and garment manufacturing industries, providing empirical evidence relating to the four areas and identifying current challenges for maintaining sustainable development in the supply chains of these industries.

This dissertation is organized into three essays. Focusing on the health care industry, Essay I investigates how workforce capabilities shape the implementation effectiveness of Clinical Decision Support (CDS) systems, one critical component of an Electronic Health Record (EHR) system. Under the knowledge management framework of technology, the dissertation develops a model on the integration between explicit knowledge embedded in the technology system and tacit knowledge from workforce capabilities, and their impact on care delivery effectiveness in clinical organizations. The results show that more extensive CDS system implementation can enhance care delivery effectiveness, while low levels of related workforce capabilities have a significantly negative impact. The findings on the interaction relationships between the two types of knowledge vary across the types of workforce capabilities. Specifically, trainer needs (i.e., low workforce capability in training on information technology use) negatively

moderate the relationship between CDS and care delivery effectiveness, suggesting that this type of workforce capability can strengthen the effectiveness of CDS. However, both informatics needs (i.e., low workforce capability in health informatics skills), and EHR/IT staff needs (i.e., low workforce capability in preparing and maintaining EHR/IT systems) have positive moderating effects. Counter-intuitively, we find that these two types of workforce capability, in fact, dampen the effectiveness of CDS. These findings indicate that a complex relationship exists for the integration of explicit and tacit knowledge related to technology implementation.

Essay II investigates how geographical, socioeconomic, organizational, and technological contexts affect telemedicine use and its effectiveness in the health care industry. The dissertation employs the technology-organization-environment (TOE) framework as the theoretical underpinning to examine antecedents and consequences of telemedicine adoption in clinics. Combining data from multiple sources relevant to clinical organizations, our empirical analysis indicates that differences in geographic location characteristics and organizational barriers have significant impact on telemedicine adoption. Specifically, rural and low poverty regions are positively associated with telemedicine adoption, while cost and low local demand are barriers. We further examine the implication of telemedicine adoption on organizational outcomes. The results suggest that telemedicine adoption is related to the effectiveness of care delivery in clinics. More extensive use of telemedicine is associated with greater care delivery effectiveness. However, examining the interaction among technologies, we find that telemedicine reduces the effectiveness of CDS systems – i.e., the benefit of telemedicine is greater in clinics with a lower level of CDS adoption.

Essay III uses the Bangladesh ready-made garment (RMG) industry to investigate how buyers in the global garment industry coordinate and collaborate to improve working conditions in supplier factories in Bangladesh. In line with the literature on supply chain trust and risk management, the dissertation explores the implications of three types of working condition risks on buyer sourcing strategy. We characterize these risks as structural risk, fire risk, and electrical risk. We collect data from two large consortiums: North American retailers comprise the Alliance for Bangladesh Worker Safety (Alliance), and European retailers comprise the Accord on Fire and Building Safety in Bangladesh (Accord). We examine the implications of each type of risk for buyer trust and buyer sourcing strategy. The empirical results support the contention that buyers are sensitive to working condition risks in a supplier factory. When working condition risks in a supplier factory increase, buyer trust in the factory decreases. Our analysis, however, shows that this relationship varies with the type of the risk. Specifically, among the three types of studied risks, fire and electrical risks are associated with decreased buyer trust, while structural risk has a marginal negative effect. Further, the negative relationship between working condition risks and buyer trust is contingent on the size of the supplier factory. The results indicate that for a given level of risk, buyers have greater trust in larger factories compared to smaller factories. This may imply that buyers expect large factories to share the responsibility and take corrective actions toward improving working conditions.

In conclusion, the dissertation provides new, theoretically grounded empirical insights into managing human capital and technology for sustainable and responsible operations in global supply chains. It echoes the call from the extant literature that organizations are expected to have important and integral social, psychological, and ecological responsibilities. My research contributes to the development of supply chain management theory and applies these theories to real world industrial practice. The dissertation concludes with a discussion of the key findings from each of the three essays. Limitations and directions for future research are also identified.

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Chapter 1

Introduction to the Dissertation

1.1. Human Capital and Technology in Supply Chains

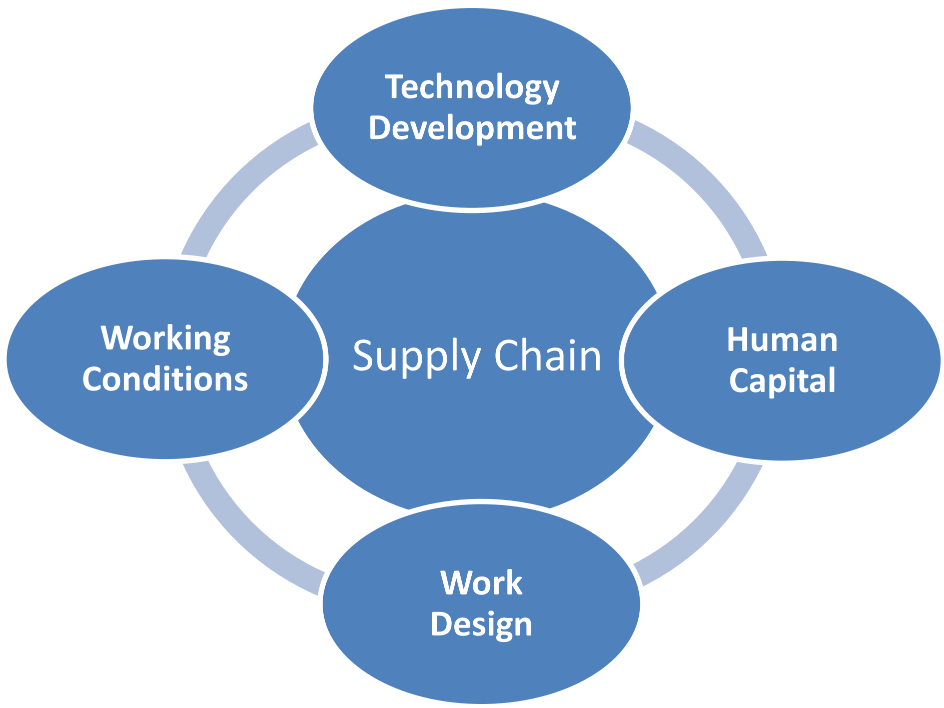
> *"[Babbage aimed] to point out the effects and the advantages which arise from the use of tools and machines; … and to trace both the causes and the consequences of applying machinery to supersede the skill and power of the human arm… The advantages which are derived from machinery and manufactures seem to arise principally from three sources: The addition which they make to human power. The economy they produce of human time. The conversion of substances apparently common and worthless into valuable products." (Babbage 1832, p. 6,8)*

> *"What that first bit of Enquire code [World Wide Web] led me to was something much larger, a vision encompassing the decentralized, organic growth of ideas, technology, and society… The Web is more a social creation than a technical one. I designed it for a social effect - to help people work together - and not as a technical toy. The ultimate goal of the Web is to support and improve our web like existence in the world. We clump into families, associations, and companies. We develop trust across the miles and distrust around the corner. What we believe, endorse, agree with, and depend on is representable and, increasingly, represented on the Web. We all have to ensure that the society we build with the Web is of the sort we intend." (Berners-Lee and Fischetti 1999, p. 1,123)*

Managing human capital and technology sustainably and responsibly becomes increasingly critical for organizational competitiveness and survival in global supply chains. Nowadays, supply chains of goods and services increasingly span the globe (Pigors and Rockenbach 2016, Bartley 2007). Concurrently, work involved with the production of goods and services is increasingly distributed across firm and country boundaries (Sinha and Van de Ven 2005). The global distribution of work is largely driven by technology advancement, coupled with the availability of complementary human capital. The benefits are enormous. Babbage (1832, p. 7) pointed out that, "the accumulation of skill and science which has been directed to diminish the difficulty of producing manufactured goods, has not been beneficial to that country alone in which it is concentrated; distant kingdoms have participated in its advantages." Starting from Babbage's inquiry, it is well perceived that organizations must manage well both technology and human capital when they face new technologies and demand for new skills.

The evolution of industry presents new challenges for the fundamental role of organizations in managing technology and human capital. *First*, business organizations are increasingly competing on technology development. Based on U.S. patent application statistics, business firms file more than 80% of patent applications, while government and individuals together constitute the remaining 20%; the number of applications by both U.S. and non-U.S. firms has increased exponentially since the 1970s (USPTO 2016). *Second*, the relevant human capital often determines the success of technology development and use in practice. Taking the health care industry, for example, the "digital doctor" (i.e., the practice of medicine with the involvement of or contribution from electronic information) illustrates the unique requirement of the combination of physicians and information technology to create better care delivery (Wachter 2015). *Third*, the work design in supply chains has the potential to bridge divides among different communities. The World Bank reports that people and organizations from different communities and regions receive vastly differing "digital dividends" – differential returns from digital technologies in terms of growth, jobs and services, and such dividends can further impact local people and potential economic growth (World Bank 2016). *Fourth*, global supply chains need to improve social responsibility. Social performance is particularly important for firms transacting in foreign jurisdictions, and organizations need to improve the social performance of upstream business partners, primarily in developing countries (Distelhorst et al. 2016). The substandard workplace for workers in a supply chain factory may raise concerns about the social impact of production and lead to reputational risk for multinational firms (Short et al. 2015). The four dimensions of human capital in supply chains are illustrated in Figure 1-1.

Figure 1-1. Dissertation Dimensions



This dissertation focuses on integrating technology and human capital in supply chains, with special emphasis on improving long-term operational sustainability and social responsibility. Although the fundamental needs of managing technology and human capital have remained largely the same over time, new technologies and challenges require further exploration on their role in the new contexts (e.g., different technologies, new regulations, and industry change). This dissertation focuses on two industry scenarios -- 1) health care industry and 2) global garment industry. Both industries serve as ideal empirical settings for the inquiry on different combinations of the above dimensions, and span the spectrum from a high technology – high professional industry (health care) to a low technology – limited skilled industry (global garment).

A current example of new technology adoption and use includes information management in health care industry. The practices of sharing information have been shifted from "pneumatic tubes" to electronic health systems for evidence-based care delivery (Wachter 2015). This dissertation focuses on Clinical Decision Support (CDS) Systems and Telemedicine -- two critical but distinct components in management of health information in the health care industry. CDS systems encompass a variety of tools and approaches to "enhance decision-making in the clinical workflow" (Department of Health and Human Services 2013), which aims for "delivering clinical knowledge and intelligently filtered patient information to clinicians and/or patients for the purpose of improving healthcare processes and outcomes" (Osheroff 2009, p. 9). The adoption and implementation of CDS systems by health care providers has occurred at a rapid pace. U.S. law mandates use of CDS systems for the ordering of advanced diagnostic imaging in the Medicare program starting in 2017 (Hussey et al. 2015, Anon. 2014, p. 218). Currently, for Minnesota clinics and hospitals with information infrastructure, 90% routinely use CDS systems (i.e., medication guides and alerts) and over 80% of hospitals have fully implemented CDS functionalities for drug-drug interactions and drug allergy alerts (MDH 2014, Minnesota Department of Health 2014).

Telemedicine, the second information technology component in the health care industry examined in this dissertation, projects a growth pattern similar to CDS in recent years. Telemedicine is a set of technologies and capabilities that enable patients to remotely access clinical care via secure information and communication technologies, overcoming the traditional limitations of distance (American Telemedicine Association 2015, Nalugo et al. 2014, Weinstein et al. 2014, Paul 2006). It can include the use of mobile devices and applications. The global telemedicine market value reached $17.8 billion in 2014, and is expected to achieve $35.0 billion in 2020 (Market Research Store 2016, Research and Markets 2015b, 2015a). The increase may be further strengthened by health insurance reimbursement, which started covering remote and virtual physician visits in 2015 (BusinessWire 2015). Telemedicine has the potential to provide inexpensive, convenient, and improved health care with more options for patients (Field and Grigsby 2002). When it can reduce distance constraints and improve utilization of health care resources across clinics, telemedicine may provide a means to increase affordability for a larger patient population (Sinha and Kohnke 2009). Telemedicine could help reduce hospital admissions, facilitate early interventions, prevent the need for crisis management, monitor patient health status (Anker et al. 2011), and decrease access disparity (Weinfeld et al. 2012, Gibbons and Casale 2010), as well as reallocate health care resources to cover larger areas (Singh and Wachter 2008, Mitka 2003).

The second industry scenario for this dissertation is the global garment industry. Business operational processes is no longer constrained in one region or country, and the global supply chain of the garment industry is one example, which interlinks human capital and technology in the value chain – i.e., from supplier factories and buyer firms to consumers, government agencies, policymakers, and NGOs. Bangladesh garment factories, one empirical setting for this dissertation, serve as suppliers for major retailers in North America and Europe. Bangladesh plays a critical role in the ready-made garment (RMG) industry — it is the third largest exporter to the U.S., after China and Vietnam (Anner 2015), and the second largest overall exporter in the world after China (Evans

2015). In a recent McKinsey survey, nearly 90% of chief purchasing officers projected Bangladesh as the No. 1 sourcing "hot spot" over the next 5 years (Berg et al. 2011). Currently, Bangladesh's RMG industry sector employs nearly 4 million mostly female workers (Mahr and Habib 2013), and clothing accounts for 80% of total exports, at $22 billion (Evans 2015). In terms of employment, contribution to reducing poverty levels, and overall GDP growth, Bangladesh's RMG industry sector continues to be the foremost industry sector within the country. The sample data for this dissertation includes more than 1600 garment (supplier) factories in Bangladesh. The global distribution of work to developing countries is largely driven by the lower costs of labor and materials coupled with the availability of skilled labor necessary to perform relevant work in such countries (Miller 2015, Locke et al. 2009). Notwithstanding these benefits, designing and managing global supply chains whose reach extends into supplier factories in developing countries often involves the stark reality of substandard working conditions in such factories, often referred to as "sweatshops." Recent illustrative examples include the widely publicized building collapse and fires due to poor maintenance in Bangladesh RMG factories (Greenhouse 2013), routine overwork in Chinese electronic manufacturing units (Svensson 2012), and inadequate worker safety procedures in Samsung's manufacturing unit in Brazil (Pearson 2013).

1.2. Relevance of the Dissertation and Research Questions

Combining the above industry scenarios on technology, human capital, and global supply chains, this dissertation aims to explore antecedents and consequences of technology adoption, identify the role of human capital in technology adoption, and investigate factors that impact socially responsible operations.

For technology and human capital management, on the one hand, some literature supports a general positive impact of technology adoption (Wachter 2015, Agarwal et al. 2010, Longman 2010, Osheroff 2009). On the other hand, scholars find heterogeneous outcomes from information technology use across organizations, including differences across environmental and organizational contexts (Aral et al. 2012, Aral and Weill 2007, Park et al. 2007, Zhu et al. 2006, Klein and Sorra 1996), technological context (Dey et al. 2013, Queenan et al. 2011, Zhu et al. 2006), and the sequencing and complexity of technologies (Angst et al. 2011). Deeper exploration, then, is necessary to understand how health care organizations manage technological capabilities of physicians and nurses and use health information technology for quality health care delivery.

At the same time, scholars have begun exploring the management of corporate social responsibility beyond temporal profit maximization (Distelhorst et al. 2016, Besiou and Van Wassenhove 2015, Briscoe et al. 2015, Carroll et al. 2012, King 2008) in settings where business transactions transcend firm and country boundaries (Short et al. 2015, Porter and Kramer 2011, Freeman 1984). Corporate social responsibility encompasses the notion that organizations need to conduct business "*to do good, to do well, to do the right thing in the right way*" (Carroll et al. 2012, p. 9). The literature calls for empirical research on socially responsible operations in the global supply chain (Distelhorst et al. 2016, Besiou and Van Wassenhove 2015, Guo et al. 2015, Plambeck and Taylor 2015, Short et al. 2015, Toffel et al. 2015). Such calls are extremely urgent in research on global supply chains, because the current literature has provided limited attention to this topic with emerging studies focusing mainly on theoretical and anecdotal explorations. One possible explanation for the paucity of research on this topic in the operations and supply chain management literature is that the concept of corporate social responsibility is often perceived as distant and disconnected from traditional operational performance metrics of efficiency and effectiveness (Das et al. 2008). Second, with the rapid servitization of North American and European economies over the last two decades and significant offshoring of manufacturing jobs from these economies, it is often assumed that the partnering suppliers in developing countries provide satisfactory workplace for employees in terms of health and safety. However, such assumption on the socially responsible operations is not true. Organizations continue to use traditional criteria to contract with supplier factories without deliberating much about the particular circumstances surrounding the newly added stakeholders, like the employees in an international factory (Briscoe et al. 2015, King 2008). The dissertation aims to fill the research gap by investigating the implications of operations practices on corporate social responsibility and working conditions improvement in a supplier factory in the global supply chain.

To extend the current literature to enrich our understanding of organizations' role in managing human capital and technology, the dissertation reviews several relevant theories, develops conceptual frameworks, and derives research questions from real world problems. Synthesizing these problems with the operations management literature, two main research questions then arise as to develop technological capability for health care organizations and to establish socially responsible operations in global supply chain. More specifically,

1) How do organizations manage health information technology investment and develop the technological capability of physicians and nurses to provide quality health care to a larger population?

2) How do buyers encompass socially responsible operations and improve working conditions in a supplier factory?

In summary, centering on technological advancement and social responsibility issues, the dissertation echoes the call from the extant literature that organizations are expected to have important and integral social, psychological, and ecological responsibilities. This research contributes to the development of supply chain management theory and applies this theory to real world industrial practice.

1.3. Outline of the Dissertation

The rest of the dissertation is organized as follows. In the remainder of the introduction I provide a brief summary of the three studies. In chapter two, I describe in detail the first study which looks at enablers and barriers to developing the capabilities of physicians and nurses to use a new technology to deliver high quality and cost effective care. In chapter three, I describe the details of the mechanisms on how socioeconomic, geographical, organizational and technological antecedents impact the adoption and use of telemedicine in health care delivery. In chapter four, I expand the scope of industry to global supply chains, and investigate how buyer firms from developed, advanced-industrialized countries that source products from manufacturing firms in developing countries can improve working conditions in these supplier factories. Finally in chapter five, I summarize the key takeaways, conclude the dissertation, discuss the contribution to the academic literature and its implication for practitioners, and provide potential directions of future research.

1.3.1. Essay I: Evaluating the Implementation Effectiveness of Clinical Decision Support (CDS) Systems: The Enabling Role of Health Care Provider Capability

Essay I investigates the enablers and barriers to developing the capabilities of physicians and nurses to use a new technology to deliver high quality and cost effective care in the health care industry. Information technology (IT) adoption in the health care setting has rapidly expanded in recent years. Clinical Decision Support (CDS) systems, one critical component of an Electronic Heath Record (EHR) system, encompass a variety of tools and approaches for “delivering clinical knowledge and intelligently filtered patient information to clinicians and/or patients for the purpose of improving healthcare processes and outcomes” (Osheroff, 2009). Adoption and implementation of CDS systems by health care providers has occurred at a rapid pace.

The magnitude of benefits regarding the degree of implementation after the technology adoption is still under debate. More critically, we need to obtain deeper understanding on the organizational factors that can amplify or dampen the impact of technology on organizational performance. From the knowledge management perspective of technology, we examine the impact of explicit knowledge development through increased technology implementation on organizational performance. We further investigate the combined effect of workforce capabilities, one critical part of tacit knowledge in organizations, and the high level of technology implementation in organizations. Thus, we develop a model on the integration between explicit knowledge embedded in the technology system and tacit knowledge from workforce capabilities, and their impact on care delivery effectiveness.

Using a unique dataset collected across clinics and medical groups, our analysis shows that more extensive CDS system implementation has a significant positive effect on care delivery effectiveness, while low workforce capabilities, or workforce needs, have a significant negative impact. These results provide evidence of the critical roles of both explicit and tacit knowledge on care delivery in clinics. In terms of their combined effect, we find that how workforce capabilities interact with CDS systems varies across specific types of workforce capabilities. Specifically, trainer needs (i.e., low workforce capability in training on information technology use) negatively moderate the relationship between CDS and care delivery effectiveness, while both informatics needs (i.e., low workforce capability in health informatics skills), and EHR/IT staff needs (i.e., low workforce capability in preparing and maintaining EHR/IT systems) have positive moderating effects. Our findings suggest that a complex relationship exists on the integration between explicit and tacit knowledge from technology implementation. Our study contributes to management of technology in health care organizations, and provides practical insights relating to implementation of health technology and the necessary workforce capabilities.

1.3.2. Essay II: Evaluating Telemedicine Adoption in Clinics: Accounting for Socioeconomic, Geographical, Organizational and Technological Antecedents

Essay II involves a theoretically grounded empirical analysis on how socioeconomic, geographical, organizational and technological antecedents impact the adoption and use of telemedicine in health care delivery. Telemedicine – i.e., technology-enabled remote delivery of clinical care – is a means to improve patient access to health care services. Little research has investigated the antecedents and consequences of telemedicine adoption. This study develops an integrated framework on telemedicine adoption for clinics, with related antecedents from geographical, socioeconomic and organizational contexts, and consequences on care delivery effectiveness in the technological context. Although their use has historically grown slowly and unevenly across specialties, there may be a timely opportunity to expand telemedicine practices following the rapid adoption of clinical decision support (CDS) systems. CDS systems, one critical component of electronic health record (EHR) systems, provide evidence based decision-making tools for clinical care. This study aims to improve our understanding of the factors influencing clinic-level telemedicine adoption, and investigate whether telemedicine and CDS interact on the care delivery effectiveness.

We test the proposed framework using a novel empirical dataset with clinic and medical group level information. We find that differences in geographic location characteristics and organizational barriers lead to variation in telemedicine adoption. Specifically, rural and low poverty regions are positively associated with telemedicine adoption, while cost and low local demand are barriers. Telemedicine adoption is related to the effectiveness of care delivery in clinics. More extensive use of telemedicine is associated with higher care delivery effectiveness. However, telemedicine negatively interacts with CDS – i.e., the benefit of telemedicine is greater in clinics with a lower level of CDS adoption. Thus, our findings provide guidance to clinics on how to choose adoption levels of telemedicine and CDS to maximize the potential of both technologies on care delivery effectiveness.

1.3.3. Essay III: Evaluating Working Conditions in Supplier Factories: An Empirical Analysis of Global Sourcing From Developing Countries

Essay III expands the scope of industry to global supply chain, and investigates how buyer firms from developed, advanced-industrialized countries that source products from manufacturing firms in developing countries can improve working conditions in these supplier factories. With supply chains now extending into developing countries, time and again, working conditions in supplier factories have been found to be unsafe. In this study, we focus on factories in the Bangladesh ready-made garment (RMG) industry that supplies North American and European retailers. These retailers have adopted an innovative approach to improve the working conditions of supplier factories by forming consortiums. The consortium of North American retailers is the Alliance for Bangladesh Worker Safety (Alliance). The consortium of European retailers is the Accord on Fire and Building Safety in Bangladesh (Accord). The central question addressed in this study is: How do working conditions in a supplier factory impact buyer trust in the supplier? We characterize supplier factory working conditions in terms of three types of risks—namely, structural risk, fire risk, and electrical risk. Next, we examine the implications of each type of risk for buyer trust—measured as the number of buyers contracting with the factory. The empirical analysis is conducted using detailed archival data on safety inspection reports of the two consortiums, Alliance and Accord.

The results of the empirical analysis support the contention that buyers are sensitive to working condition risks in a supplier factory, i.e., as working condition risks in a supplier factory increase, buyer trust in the factory decreases; however, this relationship varies with the type of the risk. Specifically, among the three types of risks, fire and electrical risks are associated with decreased buyer trust, while structural risk has a marginal effect. Further, the negative relationship between working condition risks and buyer trust is moderated by the size of the supplier factory. That is, for a given level of risk, buyers trust larger factories more, expecting them to take corrective actions toward improving working conditions, compared to smaller factories. The above findings highlight the marketplace implications of risks related to working conditions in supplier factories and suggest that the competitiveness of a supplier factory in a developing country is inversely related to the level of working condition risks in the factory.

Chapter 2

Evaluating the Implementation Effectiveness of Clinical Decision Support (CDS) Systems: The Enabling Role of Health Care Provider Capability

2.1. Introduction

Management of technology has become increasingly critical for organizational success. One example is the increased adoption of Clinical Decision Support (CDS) Systems in health care industry. CDS systems encompass a variety of tools and approaches to "enhance decision-making in the clinical workflow" (Department of Health and Human Services 2013), which aim for "delivering clinical knowledge and intelligently filtered patient information to clinicians and/or patients for the purpose of improving healthcare processes and outcomes" (Osheroff 2009, p. 9). As critical components in Electronic Heath Record (EHR) system, the adoption and implementation of CDS systems by health care providers occurred at a rapid pace. For Minnesota clinics and hospitals with EHR system, 90% routinely used CDS systems (i.e., medication guides and alerts) and over 80% of hospitals have fully implemented CDS functionalities for drug-drug interactions and drug allergy alerts (MDH 2014b, Minnesota Department of Health 2014). Such growth is associated with the rapid adoption of EHR system. For example, the adoption rate of EHR system in Minnesota has been 93% for clinics and 99% for hospitals, respectively. From a national perspective, 70% of physicians from the Surescritps network had already been e-prescribing with it by April 2014 (Gabriel and Swain 2014). From the perspective of states, the e-prescribing rate by physicians has reached 40% for all states, and 70% for at least 28 states. It seems that clinics and hospitals recognizes the benefits of the new information technology system and begins to incorporate these technology into their current practices (Wachter 2015, Agarwal et al. 2010, Longman 2010, Osheroff 2009). Technology adoption in health care, thus, provides us with a valid setting to obtain a deeper understanding of the interaction among components of knowledge management.

Research on the effectiveness of CDS systems and related technology has gained momentum in recent years, addressing technology capability, order of technology implementation, computerized physician order entry and application of meaningful use. Operational performance of providers is found to positively related to the stage of electronic medical record capability, although we need to be cautionary about the self-selection issue in the choice of stage and higher stages of electronic medical record capability may not be beneficial to all providers (Dey et al. 2013). The literature also finds that the sequence of implementation and integration of medical technologies do matter, and hospitals perform better when they integrate foundational and complex technologies first, such as cardiology information system and cardiology catheterization laboratory (Angst et al. 2011). Computerized physician order entry (CPOE) systems can detect and reduce safety issues regarding over dosing, medication allergy, and adverse drug interactions (Ransbotham and Overby 2010), as well as improve patient satisfaction (Queenan et al. 2011). Recognizing the difference between adoption and use of various functions in EHR system, including CDS, the U.S. federal government has been taking steps to maximize the implementation effectiveness and potential of quality improvement (Centers for Medicare & Medicaid Services 2014). The literature shows that meaningful use incentives significantly and consistently improve quality of care, particularly in historically disadvantaged hospitals such as small, non-teaching, or rural hospitals (Lin et al. 2014).

Whereas the literature sheds lights solely on health information technology adoption and implementation, more research is needed to address the development of relevant technological capability for meaningful use (Dey et al. 2013). The integration between workforce capabilities and technology implementation in health care is often overlooked. The question raised by Alavi and Leidner (2001) is still largely unanswered -- "what are the consequences of increasing the breadth and depth of available knowledge, via information technology, on organizational performance?" Workforce capability is one essential part of tacit knowledge as an organization resources, and the technology system can be viewed as explicit knowledge part of an organization (Gaimon and Bailey 2013, Shamsie and Mannor 2013, Gaimon 2008, Alavi and Leidner 2001, Nonaka 1994). Gaimon (2008) points out that the new capabilities offered by technology adoption are themselves "developed, implemented, and used by the [organization's] workforce." Greater benefits for organizations can be supported by the unique stocks of tacit knowledge, given that explicit knowledge can be disseminated (Shamsie and Mannor 2013, Pisano 1994). This study follows this rationality and aims to provide a systematic understanding of how tacit knowledge interacts with explicit knowledge in using CDS systems in health care.

Empirical evidences support the role of integration of knowledge from various sources for higher organizational performance. For example, current literature emphasizes systematic knowledge management, resulting from the synergistic effects of integrating work design, technical infrastructures and workforce capabilities on organizational impact (Posthuma et al. 2013, Kong et al. 2012, Osheroff 2009, Lin et al.

2006, Sinha and Van de Ven 2005). Such knowledge can enhance technology system effectiveness, employee competencies, commitment, productivity, and the following overall organizational impact. Lack of appropriate level of workforce capabilities and related knowledge may become a barrier for providers and organizations to realize the potential benefits of increased implementation level of health technology (Dey et al. 2013, p. 334). Successful work systems should entail intensive recruitment, selection, and on-going training of workers, and compensation that supports worker commitment (Bishop 2014). And the appropriate alignment between workers and the working systems can enhance operational and financial effectiveness and efficiency (Posthuma et al. 2013). Therefore, workforce skills are critical determinants of high performance work systems (Preuss 2003).

We argue that the integration between knowledge embedded in workforce capabilities and knowledge embedded in CDS system implementation is critical for health care organizational performance (Gaimon 2008, Alavi and Leidner 2001, Nonaka 1994). *First*, we aim to understand the impact of increased explicit knowledge through higher level of CDS system on care delivery effectiveness in health care setting from organizational perspective. *Second*, we consider the interaction between explicit knowledge and tacit knowledge in technology implementation. The incorporation of CDS system may require workforce to make justified and reasonable decisions, and to update their decisions based on the existing knowledge base, accumulated system information, and the uncertainty in the process (Kong et al. 2012, Lin et al. 2006). Therefore, organizations may need better to align workforce capabilities and CDS system implementation to generate, store and manage knowledge during the health care delivery process (Osheroff 2009). Taking into account the dynamic development of knowledge in organization, where both technology system and workforce need to support "creation, transfer, and application of knowledge in organizations" (Alavi and Leidner 2001), we ask two specific questions in this study,

1. What is the effect of higher implementation level of CDS systems and related workforce capabilities on care delivery effectiveness, separately?

2. How do workforce capabilities interact with CDS systems on care delivery effectiveness?

Through the lens of knowledge based view (KBV) of organizations, this research develops a model on the workforce capabilities (i.e., tacit knowledge) in the context of CDS system implementation (i.e., explicit knowledge), and investigates their interaction on care delivery effectiveness. We propose that health care delivery effectiveness relies on the joint effect between explicit knowledge and tacit knowledge -- i.e., implementation level of CDS systems and related workforce capabilities. The knowledge creation and transfer through implementation of CDS systems and workforce capabilities development may further enhance organizational learning during the interaction among the two dimensions. As a whole, workforce capabilities need to be better aligned with process and technology elements in order to optimize the outcomes of current practices and overall information system performance (Flynn and Saladin 2006, Meyer and Collier 2001).

We empirically investigate our research questions using unique dataset from the Minnesota Department of Health and Minnesota e-Health Initiative survey, which monitored on EHR system adoption and use in 2013 and 2014. The survey aims to capture comprehensively the CDS systems and other health IT adoption, utilization and exchanging in all clinics and hospitals in Minnesota (MDH 2014b). The survey has 2232 observations at clinics level that adopted EHR system, of which there are 222 and 199 medical groups in 2013 and 2014. This data allows us to examine the effect of CDS system implementation and related workforce capabilities and address our research questions.

Using Hierarchical Linear Modeling (HLM) analysis and controlling for the health care organizational structures, we find that CDS system implementation has a positive effect on care delivery effectiveness, while low workforce capabilities has a negative effect on care delivery effectiveness. These findings support the critical role of tacit and explicit knowledge on organizational performance. In terms of their combined effect, we find heterogonous effect for different types of low workforce capabilities, including EHR/IT staff needs (i.e., low workforce capability in preparing and maintaining EHR/IT systems), informatics staff needs (i.e., low workforce capability in health informatics skills) and trainer needs (i.e., low workforce capability in training on information technology use). Specifically, trainer needs has a negative moderating effect on the relationship between CDS system implementation and care delivery effectiveness. It indicates that this type of workforce capability can complement with technology implementation, and increase organizational knowledge performance. However, informatics and EHR/IT staff needs have positive moderating effects. Our findings suggest that complex relationship exists on the integration between explicit and tacit knowledge from technology implementation. Our study contributes to knowledge management during technology adoption and implementation in health care organizations. It also provides practical insights relating to implementation of health technology and development of necessary workforce capabilities. Thus, our research framework and analysis echo the proposition of a need for stronger interface between OM and human capital management in health care setting in the extant literature (Boudreau et al. 2003).

The next section covers the literature review of the knowledge creation and transfer in organization and complementarities between implementation of CDS systems and related workforce capabilities. We propose an integrated research model on relationships among these constructs. In the following section, to examine the proposed research model, we provide a detailed analysis strategy on empirical model, measures and analysis. We then report the results and discuss the associated implications. In the last section, we discuss the theoretical and practical contribution of this study, as well as identify potential areas for future research.

2.2. Literature and Theory

We ground our theoretical model development of CDS implementation following the Knowledge Based View of organizations (KBV). KBV conceptualizes organizations as entities for developing, transferring, applying, and integrating knowledge (Macher and Boerner 2012, Alavi and Leidner 2001, Grant 1996, Kogut and Zander 1992). Knowledge is defined as justified beliefs that determine the capability for effective action (Linderman et al. 2004, Sabherwal and Becerra-Fernandez 2003, Nonaka 1994). The main goal of organizational knowledge management is to effectively and efficiently transform materials, human skills, and current organizational knowledge into goods or services that meet customer needs. The form of organizational knowledge can be documents, policies, procedures, and human minds, or the flow in conversations, training, and reporting (Sabherwal and Becerra-Fernandez 2003, Alavi and Leidner 2001). KBV emphasizes organizational capabilities and competencies in reconfiguring resources to develop knowledge (Nag and Gioia 2012, Teece 1986, Nelson and Winter 1982), which is the most strategic resource of an organization. In general, knowledge-based resources that are difficult to imitate, are socially complex, immobile and heterogeneous in form are major determinants of organizational capabilities.

Organizations need to manage two types of knowledge, explicit knowledge and tacit knowledge (Shamsie and Mannor 2013, Nonaka and von Krogh 2009, Linderman et al. 2004, Alavi and Leidner 2001, Nonaka 1994). Explicit knowledge is accessible through conscious communication, while tacit knowledge is hard to formalize and communicate and is deeply rooted in action, commitment, and involvement in a specific context (Nonaka 1994). Technology adoption can augment the management of storage and retrieval of organizational explicit knowledge. The technology system is one element of organizational capabilities (Gaimon 2008), and can be used to systematize, enhance, and expedite large-scale knowledge management (Alavi and Leidner 2001).

Compared to explicit knowledge, tacit knowledge is usually obtained through subconscious practices and experiences, and is more complex and specific in nature (Shamsie and Mannor 2013, Macher and Boerner 2012, Alavi and Leidner 2001, DeCarolis and Deeds 1999, Kogut and Zander 1992). One key source of tacit knowledge is from the individual workers in an organization (Gaimon 2008, Alavi and Leidner 2001, Argote 1999, Nonaka 1994). For example, a firm's productivity can gain from learning-by-doing by individual workers (Argote 1999). The potential organizational capabilities supported by technology systems are developed, implemented and used by the firm's workforce (Gaimon 2008). Therefore, in knowledge management, workers need to gather knowledge (Haas 2006), understand, learn the information, build knowledge stocks (Alavi and Leidner 2001), conduct new discovery (Gaimon and Bailey 2013), and form experience on technology use by developing routines, expertise, and mechanisms (Macher and Boerner 2012). In addition, the relationship between explicit and tacit knowledge can be dynamic, and each can be converted into the other by various systematic approaches across individuals, groups and organizations (Alavi and Leidner

2001, Nonaka 1994). Thus, the combination of tacit and explicit knowledge can help organization to successfully manage knowledge.

Organizations should manage knowledge across their hierarchy levels of individual employee, team, unit, firm, and inter-firm network (Bardhan et al. 2013, Macher and Boerner 2012, Rothaermel and Hess 2007, Macher 2006, Sabherwal and Becerra-Fernandez 2003, Crossan et al. 1999). Knowledge management should focus on knowledge creation and learning across levels, and researchers need to look it at the individual, firm, and network level (Rothaermel and Hess 2007). Crossan, Lane and White (1999) provide a framework of organizational learning that contains four processes – intuiting, interpreting, integrating, and institutionalization – that occur over individual, group, and organization levels. In their framework, each level is responsible for specific processes, and not every process occurs at every level. The cognitive development, organizational impacts, and the role of individuals are highlighted in the theory of KBV (Sabherwal and Becerra-Fernandez 2003, Grant 1996, Kogut and Zander 1992). At the same time, the flow of knowledge across levels also impacts the outcome of organizational knowledge management (Nonaka and von Krogh 2009, Nonaka 1994). Knowledge can start with the individual, and organizations integrate the knowledge; the process can also be reversed, organizations can obtain knowledge from other sources, and individuals need to internalize the knowledge in their work practices. The latter process for individual can be called “re-experience what others go through” (Sabherwal and Becerra-Fernandez 2003).

Moving from individuals to the organizational level, knowledge management can occur at organizational and group levels (i.e., a group refers to a parent organization consisting of one or more affiliated subsidiaries). The interplay between group and organizational knowledge includes synthesis, combination and specification. The reconfiguring process of various knowledge components from multiple levels can be complex. For example, organizations can develop knowledge through identifying the best practices that lead to high performance in comparing practices at the employee level. Also, from an individual organization (e.g., clinics) to all member organizations in the same organizational group (e.g., medical group), group knowledge can be created by employing the large knowledge pool and prioritizing the critical core knowledge components for all members in the group. Therefore, group level knowledge for one organization can be assimilated from external members within the same groups without creating them directly.

Related and relevant theoretical models include Quality Management (e.g., Total Quality Management), organizational learning and Socio-technical Systems. Similar to manufacturing strategy elements of environmental technology portfolio management as a structural element and quality improvement capabilities as an infrastructure element, CDS systems belong to the structural dimension (i.e., technology component), while workforce capabilities belong to the infrastructural dimension (i.e., labor practices and training components) (Klassen and Whybark 1999, Hayes and Wheelwright 1984, Skinner 1974). The integration of quality management practices and organizational knowledge can lead to improved performance (Linderman et al. 2004). The organizational learning literature focuses on how organizations can integrate newly adopted technology and maintain a positive learning curve by developing workforce capabilities and skills (Tucker 2007, Wiersma 2007, Sorenson 2003, Pisano et al. 2001, Levin 2000, Argote 1999, Adler and Clark 1991).

Our theoretical approach is also similar to Socio-technical Systems Theory that emphasizes the joint optimization of the technical and social systems, two independent but linked organizational systems (Molina et al. 2007, Short et al. 2007, Manz and

Stewart 1997, Trist 1981). These two systems are supplementary and complementary, and their fit can improve organizational performance.

Although the argument on the combination of technology and workforce capabilities is similar across theories, the KBV framework may be more appropriate in the setting of CDS system implementation for several reasons. *First*, the purpose of CDS systems is to promote better decision making in clinical workflow by integrating clinical knowledge and technical knowledge (Osheroff 2009). KBV is closely related to the functions and goals of CDS systems. We focus on whether the organization has both the CDS functions and workforce capabilities to best use the CDS system to improve outcomes. *Second*, the combined knowledge from CDS systems and the workforce is relevant at different organizational levels in care delivery. KBV treats the transfer of knowledge from one level to another as an essential characteristic of knowledge management, while other theoretical frameworks often solely emphasize learning at an individual employee level. *Third*, the meaningful use of technology in health care delivery requires the organization to align workforce capabilities and technology systems for quality care provision. Organizations may deviate from such a meaningful use improvement goal in providing quality care if they simply focus on these dimensions separately, for more immediate goals of cost reduction, failure prevention, or profit maximization. Thus, we this study is guided by KBV, as it aligns with the goals in this study.

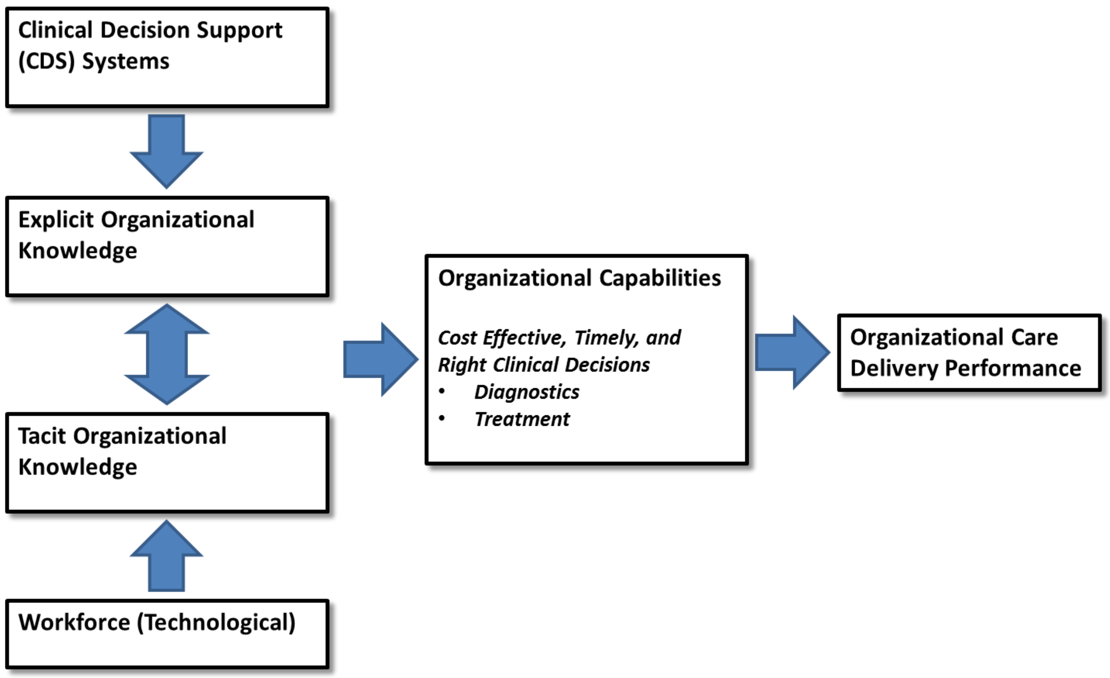
In summary, KBV emphasizes the management of both explicit and tacit knowledge in organizations across organizational hierarchy levels. From this perspective, we investigate how an organization develops and integrates: 1) explicit knowledge from implementation of CDS systems, 2) tacit knowledge from workforce capabilities, and 3) meaningful use of CDS systems by integrating the important contributions of explicit and tacit knowledge vis-à-vis the combined technology and capabilities for higher care delivery effectiveness.

2.2.1. KBV for CDS Systems and Workforce Capabilities

Knowledge management is relevant to KBV framework during technology adoption in health care. Health care involves knowledge intensive practices and requires dynamic process of knowledge update enabled by various types of technology (Bardhan et al. 2013, Kong et al. 2012, Osheroff 2009). During the last three decades, the storage, flow, and decision making in knowledge management is exponentially amplified by the electronic means resulted from Information Technology advancement. Health care sector, especially, benefits from similar tools such as the electronic medical records (EMR) and related healthcare information technology (HIT) to improve the delivery of care (Dey et al. 2013, Osheroff 2009). We apply KBV framework for CDS system implementation in health care, and examine the interaction between explicit and tacit knowledge for higher organizational outcome. As discussed above, we propose that CDS systems represent the explicit knowledge, and tacit knowledge includes workforce capabilities. As shown in Figure 2-1, the integration between two types of knowledge can enhance organizational capability in knowledge management, which leads to better organizational outcome (i.e., care delivery in clinics).

Healthcare systems and providers make efforts to improve CDS system implementation for greater health care delivery effectiveness. Care delivery effectiveness is the focus of knowledge management outcome in this study. We argue that knowledge management is directly related to care delivery in clinics and medical groups. And we define health care delivery effectiveness as the extent to which the implementation of health IT helps clinical organizations on multiple desired outcomes (Osheroff 2009). Clearly, clinics and hospitals are initiating stakeholders that try to implement CDS system for improvement of care delivery, which can impact medication safety and health care quality for patients (Osheroff 2009).

Figure 2-1. Model on Knowledge Management in CDS systems



To increase patient care quality and safety and to reduce medication errors, clinics and hospitals need to carefully design and incorporate CDS systems into their current work-flow and align the system with organizational goals (MDH 2014b, Department of Health and Human Services 2013, Osheroff 2009). CDS systems include explicit knowledge delivery interventions, including documentation forms and templates, patient data presentation and summaries, order and prescription creation facilitators, protocol and pathway support, references information and alerts and reminders (MDH 2014b, Department of Health and Human Services 2013, Kong et al. 2012, Osheroff 2009). Similarly to other health IT, CDS systems can provide explicit knowledge management platform to capture, store, retrieve, share, monitor, and analyze patient-specific health record.

KBV provides a useful theoretical lens for understanding how knowledge is created and integrated, in implementing CDS for clinical organizations to achieve improved performance in care delivery. We propose a model on the knowledge management process for CDS and workforce capabilities in Figure 2-1. Health care delivery practices involve extensive and complex knowledge for decision making in diagnostics and treatment, aggregating individual patient data, population-based characteristics, and knowledge bases from clinical trials, system biology, and health care systems longitudinally and cross-sectionally (Demirezen et al. 2016, El-Rab et al. 2016, Helm et al. 2016, Hoffman et al. 2016, Yu 2015). CDS systems, that relate individual patient health data to established rule-based knowledge, can assist in precise clinical decision making and health management (Yu 2015). The new and explicit knowledge enabled by CDS systems can be: 1) shared information related to medical literature and educational material (e.g., disease information and clinical guideline); 2) situational awareness for specific health data (e.g., drug-drug interaction alerts); or 3) computational medicine for a patient-specific intervention (e.g., guidance on drug dosage given the particular patient).

The medicine literature has examined the import role of CDS systems for knowledge management in clinical pharmacogenetics (Hoffman et al. 2016), oncology (Yu 2015), and clinical practice guideline formation (El-Rab et al. 2016). Helm et al. (2016) also propose a multi-methodology model to reduce hospital readmissions by using individual patient data to establish an empirical prediction model. Overall, CDS systems provide a rules engine that combine available knowledge resources with individual patient data for clinical decision making in the normal clinical workflow (Osheroff 2009). Organizational capabilities related to care delivery should grow with knowledge and learning accumulate from established clinical routines, localized knowledge and expertise, and integration of knowledge (Macher and Boerner 2012, Macher 2006). Thus, CDS systems have the potential to improve clinical performance, for example, through medical error reduction, and thus, concurrently reduce the cost of care delivery (Demirezen et al. 2016), avoid unnecessary readmissions (Helm et al. 2016).

The literature on IT and technology adoption also support its critical role in organizational performance. Treating IT assets as critical resource (Aral et al. 2012, Aral and Weill 2007, Banker et al. 2006, Zhu et al. 2006), integration between the knowledge-intensive work and IT applications is new frontier for Operations Management research (Bardhan et al. 2013, Sodero et al. 2013, Zhou and Benton 2007). And the process of invention, adoption, and deployment of new technology and process improvements can help organization to create unique capability and obtain sustainable competitive advantage (Sodero et al. 2013, Barney 1991, Schumpeter 1934). However, beyond adoption, empirical evidence still lacks on the magnitudes of benefit in higher level of CDS system implementation.

Workforce capabilities refer to the organizational capabilities in supporting, maintaining and exploring the technology system for organizational goal. It is one important component of tacit knowledge. Besides the computerized data, health care organization needs to rely on workforce knowledge and a reasoning or inferencing mechanism for quick informed decision and appropriate action in care delivery (Osheroff 2009). Considering the implementation stages in CDS systems, organizational knowledge may also change, from learning specific knowledge to fulfill the system operational activities to solving new problems (Nag and Gioia 2012). The knowledge in the latter requires more reflection, critiques, and questions during the interaction between CDS systems and employees. Empirical studies on IT adoption and use find the importance of experience, specialized skills and know-how in organizational capabilities (Tambe and Hitt 2014, Shamsie and Mannor 2013, Macher and Boerner 2012, Aral and

Weill 2007). The tacit knowledge can partly explain why some organizations are moving faster and archiving higher performance in new technology use (Tambe and Hitt 2014). Thus, we integrate both explicit and tacit knowledge on clinic care delivery.

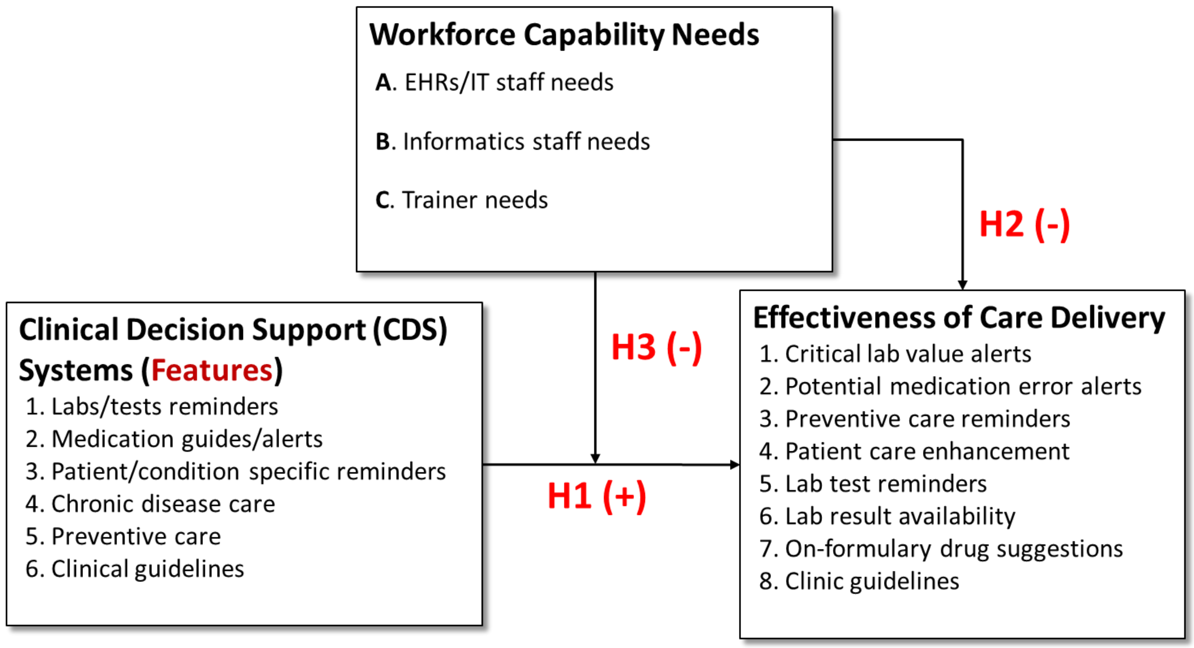
2.2.2. The Conceptual Model

Considering CDS implementation and workforce capabilities in health care, we develop an integrated model on their interaction on care delivery effectiveness as shown in Figure 2-2. Drawing upon our earlier discussion, we posit that care delivery effectiveness depends not only on levels of CDS implementation, but also the workforce capabilities and their joint interaction. Our model reflects the integration requirement between technology system and other organizational factors (Lin et al. 2014, Dey et al. 2013, Alavi and Leidner 2001).

To construct the model, we first investigate the effect of CDS implementation level. Rather than one snapshot of adoption event, we consider the incremental implementation in CDS systems. Organizations may strategically choose one component of CDS system to meet the adoption requirement, either for its own need or policy push. For comprehensive systems like CDS, we examine whether it has consistent and positive effect on care delivery effectiveness. We expect that there is positive effect.

We further investigate the role of workforce capabilities on organizational outcome, and its interaction effect with CDS systems. We argue that knowledge from the implementation of CDS systems and that from workforce capabilities can interact with each other, and jointly shape the resultant health care delivery effectiveness. Moreover, we control clinic level and medical group level in knowledge management. We can also better access the specific effect of the CDS systems and workforce capabilities at two levels, and identify the underlying mechanisms that facilities the technology role on organizational outcome.

Figure 2-2. Research Model for CDS systems



2.2.3. Hypothesis Development

2.2.3.1. Implementation of CDS Systems

Explicit knowledge from implementation of CDS systems can help clinics to increase organizational effectiveness. When successfully adopted CDS systems, all tools in the systems should be able to provide clinicians or patients with clinical knowledge and patient-related information, which is intelligently filtered or presented at appropriate times (MDH 2014a). The enhanced decision making process and optimized clinical workflow should improve care delivery, and ultimately increase patient care. However in practice, CDS system use is not one-off action, but a process with various stages (Dey et al. 2013, Osheroff 2009). The process includes interaction between organizational practices and the various functions of CDS systems, and generation of new knowledge during the clinical uncertainty, feasibility and flexibility of functions, and inference and learning complexity. It fits the technology adoption and utilization stages in heal care. For example, Minnesota clinical organizations general flow the three stage of model -- i.e., adopt, utilize and exchange – for EHR and CDS systems (MDH 2014a, p. 15). More functions and tools are added to the baseline when the system is initially adopted. However, little research investigates how implementation of CDS systems interacts with organization for better outcome (Dey et al. 2013).

First, the adoption of CDS system may directly add new knowledge to existing knowledge stock. The new technology can provide substantial explicit knowledge in large scale to current knowledge management (Alavi and Leidner 2001). The most obvious element is the coded knowledge imbedded in the tools and functionality, like clinical database, patient data report, templates, guidelines, and all kinds of computerized alerts and reminders. These timely knowledge and reminders can extend doctors' existing decision making capability. More importantly, the linked data across systems can provide more specific about the individual patient. When provided better information, clinicians may find solution to a critical problem, and discover new knowledge for new areas. Thus, clinicians can provide better clinic decisions to the individual patient. The practical role of CDS system adoption and other heath IT has been recorded in the literature. For example, the development and use of CDS systems and others can help health care providers analyze and gain insight from patient data in real-time and make appropriate decisions (Mainous et al. 2013, Anton et al. 2009). Similar insight and support are gained from computerized order entry systems (Jaspers et al. 2011, Devine et al. 2010) and automated prescribing alerts (Scott et al. 2011). Therefore, CDS system can provide more explicit knowledge to clinicians.

Second, the increased levels of CDS system may increase the functionality of the overall technology system, and better coordinate with other organizational capability. The dynamic knowledge creation and application process will help organization to achieve higher performance (Salomon and Martin 2008, Teece et al. 1997). This is because organizations can benefit more from the larger knowledge pool and new opportunities for learning and knowledge spillovers. The learning from previous experience can help organization avoid unnecessary waste and speed up the implementing the new functions. Also, organizations can obtain greater CDS system performance due to the increased scale in CDS system, when all tools can function to their potential by design. For example, in studying R&D activity, Marcher (2006) argues that knowledge developed and accumulated in one activity can be transferred to other activities with little cost, but with significant performance benefits. Besides, the increased level of CDS systems can leverage the disruption during the new technology implementation (Boone and Ganeshan 2001). The earlier experience and existing technological base can help organizations to reduce the chance of failure. Therefore, the greater net benefit is possible in higher level of CDS systems.

Organizations may further achieve larger benefits when they can integrate high level of CDS system with other systems. The explicit knowledge may not only facilitate daily clinical practice like clinical decision making, but also improve the efficiency in order entry and health information exchange (Lin et al. 2014, Dey et al. 2013). When integrating more CDS system functions with health care practices in the whole medical group, it is more likely that best practices of CDS interventions and care practices can be diffused to all members in a positive way. This synthesis in the technology systems, thus, may lead to increased capability. For example, when carefully implemented, these information technologies can positively impact medical, process, and clinical outcomes

(Parsons et al. 2012, Banas et al. 2011, Crandall et al. 2007). Following the above logic, we expect to see a positive relationship between higher implementation level of CDS systems and increased health care delivery effectiveness.

> *H1: The implementation level of CDS systems is positively related to care delivery effectiveness, ceteris paribus.*

2.2.3.2. Workforce Capabilities as Complementarities

Workforce capabilities development can be a critical and complementary factor that enables CDS system adoption and use for greater health care delivery effectiveness. The heath IT related skill of employees determines organizational knowledge competence. This is especially the true in knowledge intensive setting in health care industry, where workers have responsibility for decision making related to patients and establishing routine practices. From KBV, workers can contribute to the tacit knowledge of an organization (Alavi and Leidner 2001, Nonaka 1994). Such tacit knowledge can be in forms of experience, routines, state of knowledge and understanding, skills, expertise, and know-how. It can also be the social interaction among workers in group and organization. The importance of workforce capabilities is supported by broader literature on organization and IT management. Alignment between workforce and other organizational elements can significantly improve workforce efficiency (Dill et al. 2013), worker commitment (Bishop 2014), worker productivity (Singer and Vogus 2013, Vogus et al. 2010), organizational functions, operational and financial performance (Posthuma et al. 2013). Therefore, it is important to include workforce capabilities in the studying CDS systems for high performance health care delivery (Preuss 2003).

The management literature shows that complementary organizational practices can determine productivity and firm performance during IT adoption. Aral, Brynjolfsson and Wu (2012) test three-way complementarities among performance pay, human resource analytics and information technology use, and find that the system of complements creates a disproportionately larger productivity premium than a system missing one or more elements. Studying organizational choice in different stages of EMR, Dey, Sinha and Thirumalai (2013) find that there is systematic self-selection considering technological, organizational, and environmental contexts. And simply incentivizing higher stage selection of EMR capability may not lead to the realization of the potential benefits of that stage. In addition, worker IT skills and related know-how can generate productivity spillovers when a firm adopts new IT innovations (Tambe and Hitt 2014). In their study on the mobility of workers and investment on new IT projects, Tambe and Hitt (2014) find that the mobility of IT workers can contribute to productivity growth as much as 20% - 30%. Their results indicate that worker skills might be a critical resource that facilitates the use of CDS systems to improve health care delivery. However, few studies examine the performance implications of the co-presence of IT and highly skilled workers (Aral and Weill 2007).

We focus on workforce capabilities and their implications on health care delivery. We argue that different types of workers possess unique and valuable skills and knowledge, which can enable CDS system to achieve higher health care delivery (Nag and Gioia 2012). First, to make CDS systems work well after the adoption, workers need to have related skills to meaningfully interact with the systems, including filtering the information, organizing and presenting the information to support current workflow (Department of Health and Human Services 2013, Osheroff 2009). This interaction may happen in clinicians who have learned how to use the system, or in the supporting staff who prepare and maintain the systems, and educate others. Otherwise, organizations may suffer from performance loss during the early stage of adoption. The lack of basic skills in the system may hinder the whole organization from achieving the optimal functioning (Shamsie and Mannor 2013, Kogut and Zander 1992). Second, workers may develop new skills and knowledge in the process during the implementation of technology, like capability of integrating and configuring existing IT functions, skills in identification and selection of optimal template, changing the reasoning and inferencing mechanism (Kong et al. 2012, Osheroff 2009). New knowledge development is encouraged and essential in health care.

We operationalize workforce capabilities in clinics from the several types of workers during the CDS implementation. Workers are responsible for providing quality information to the technology system and conducting meaningful interpretation and inferences the information in decision making (Preuss 2003). For example, in quality management, individuals need develop capabilities to understand and interpret the statistical process control charts and other information before they take appropriate actions. If health care lack needed skills for the technology systems, it is expected that the organization would have lower outcome. Therefore, we hypothesize that,

H2: Lack of workforce capabilities, i.e. EHR/IT staff needs, informatics staff needs, and trainer needs, negatively relate to care delivery effectiveness, ceteris paribus.

2.2.3.3. The Interaction between Implementation of CDS Systems and Workforce Capabilities

We investigate the joint effect between implementation level of CDS systems and workforce capabilities on health care delivery. Within an organizational context, the contingency between explicit and tacit knowledge can determine the efficiency in knowledge creation and transfer (Kogut and Zander 1992). This argument aligns with the process of conversion between tacit knowledge and explicit knowledge (Nonaka 1994). And this is especially important for health care delivery, where technology adoption and implementation is not the final stage. Both the technology and workforce should support each other for higher clinical knowledge. We argue that high level of CDS systems and skilled workforce can complement with each other for knowledge creation and transfer (Osheroff 2009).

Workforce capabilities can strengthen the benefits from CDS system implementation. During CDS system use, the knowledge creation process can occur in the format of "learning by doing" and "learning before doing" (Pisano 1994). When increasing implementation of CDS systems, organizations need to configure their functions based on existing routines and redesign the process of health reporting and quality improvement. It provides an opportunity for the organization to learn new functions, new processes and configurations from CDS systems. When workers have higher level of skills, the organization as a whole would learn faster in solving the existing problems, establishing new practices and routines, and integrating new CDS systems with existing workflow. Similarly, higher level of CDS systems can also enable workers to have greater knowledge scope for search. In this case, workers can reflect and develop critical thinking on more critical problems (Nag and Gioia 2012). A larger platform may also enable workers to engage in sharing, communicating, and discussing the current issues. The social interaction may further stimulate tacit knowledge creation, and transformation between tacit and explicit knowledge. For example, after successfully using medication guides and alerts, clinics may expand this knowledge to develop more sophisticated chronic disease care plans and lab/test reminders.

Studying the integration effect between CDS systems and workforce capabilities on health care delivery, we follow the moderating effect approach. Compared to organizations with higher level of worker capabilities, those lacking in certain types of workforce may not achieve the potentially maximum benefits performance from CDS systems. We hypothesize that,

H 3: Lack of workforce capabilities negatively interacts with CDS systems on health care delivery effectiveness, ceteris paribus.

2.3. Method

2.3.1. Data

To measure the progress how Minnesota clinics adopt, utilize and exchange information among Electronic Health Record system, the Minnesota Department of Health and Minnesota e-Health Initiative collected monitoring data on EHR system adoption and use in 2013 and 2014 (Soderberg 2014). The goal of the dataset is to "measure Minnesota's status on achieving state and national goals to accelerate adoption and use of electronic health records and other health IT to achieve interoperability of health information; identify gaps and barriers to enable effective strategies and efficient use of resources; help develop programs and inform decisions at the local, state and federal levels of government; support community collaboration efforts" (MDH 2014a). From 2013 to 2014, 1286 of 1623 Minnesota clinics completed the data and the participant rate was 79% (Minnesota Department of Health 2013), or 140 of 148 (95%) Minnesota acute and specialty care hospitals provided the data (Minnesota Department of Health 2014). For clinics, 87% (1,114) have an Electronic Health Record system installed and in use. We focus on clinics with EHRs in use and exclude those without the system from the sample.

In our sample, 88% clinics use at least one clinical decision support (CDS) tool and 57% use three or more.

2.3.2. Dependent Variable

Care delivery effectiveness. We measure *care delivery effectiveness* as the extent to which the system helps providers in reporting, improving delivery quality and patient safety. This is a critical indicator for technology management, and it informs organizations whether the technology implementation performs as intended. Organizations should regularly conduct the evaluation in knowledge management (Gaimon and Bailey 2013), to make sure that generated clinical knowledge by the CDS is accurate, up-to-date, and delivered in the appropriate way (Osheroff 2009). Specifically, the outcome variable is measured by the effectiveness in multiple dimensions of care delivery in the general setting of Electronic Health Record system use. The composite score in a clinic reflects whether the technical system contributes to, 1) critical lab alerts, 2) medication error alerts, 3) preventive care reminders, 4) patient care improvement, 5) needed lab alters, 6) lab result availability, 7) on-formulary drug order; and 8) guidelines. Each item is measured as yes (1) or no (0), and we obtain the sum of all items to measure care delivery effectiveness, which ranges from 0 to 8.

2.3.3. Independent Variables

Clinical Decision Support (CDS) systems. We measure CDS by the use of CDS systems that are built into an EHR system to support enhanced patient care (MDH 2014a). Investment and implementation of CDS systems produce real value only after they are used effectively to support efficient workflow and effective clinical decisions during the delivery of healthcare to individuals and populations (Minnesota Department of Health 2013). Based on the patient demand and organizational needs, clinics can decide how many components or features of CDS system should be implemented. CDS is measured by whether an organization uses the following dimensions, 1) Automated reminders for missing labs and tests; 2) Chronic disease care plans and flow sheets; 3) Clinical guidelines based on patient problem list, gender, and age; 4) Medication guides/alerts; 5) Patient specific or condition specific reminders; 6) Preventive care services due. Each dimension is measured by a dummy variable, and then we sum the scores up to measure CDS. In the analysis, we scale the sum compared to the ground mean. This approach would allow us to explore the higher order effect in analysis, without introducing collinearity issue.

Workforce capabilities. Workforce capabilities relating to technology adoption and use are critical and complementary factors that enable CDS adoption and use for greater health care effectiveness. They can determine organizational competence in tacit knowledge across levels. Besides, workforce also carry on specific responsibility during the technology support and use (Osheroff 2009). We operationalize workforce capabilities in clinics with reverse coded approach, which indicates low workforce capability or organizational needs for staff that have skills in facilitating technical system. Specifically, we measure three types of needs for skills, 1) *EHR/IT staff needs*, 2) *informatics staff needs*, and 3) *trainer needs*. First, we measure *EHR/IT staff needs* as the needs in organizations regarding to staff who can design, customize, prepare, and maintain EHR and general IT for clinical use. It ranges from 0 to 3, and we standardize it with mean of 0. Second, we use dummy variable to measure the *informatics staff needs*, which indicates whether a clinic has needs for informatics nurses, clinicians, or other related staff. Third, in a similar way, we measure *trainer needs* with a dummy variable that indicates whether a clinic has needs for trainers in the use of technical system.

2.3.4. Control Variables

We include several control variables that might affect health care delivery. We control for *clinic size* by using the natural logarithm of total number of providers. Similarly, the medical group size may affect the process in EHR system use. We introduce dummy variables to control for the medical group size based on the number of clinics for a medical group, and *small medical group* indicates a clinic belongs to a medical group which have 5 or fewer clinics in our sample. To capture the difference in geographical location of clinics, we use a dummy variable, *rural vs. urban location*, to indicate whether the rural-urban commuting area (RUCA) code is ≥ 7 (i.e, 1 for rural and 0 for urban). This code indicates whether a clinic is located outside metropolitan, urban, or micropolitan region (MN Office of Rural Health and Primary Care 2011). The focal activities in clinics may also determine the number of CDS systems and the consequent health care delivery effectiveness, and we use a dummy variable, *specialty vs. primary care*, with specialty care (1) or primary care (0). The EHR system vendors might introduce specific requirements of skills and capabilities and result in different health care delivery effectiveness. Therefore we use dummy variable, using *vendor system from EPIC*, to control for the effect of the dominate vendor. Since there are two year data for majority of clinics, we control for the year effect the duplicated inclusion of the same clinic. The stage of Electronic Health Record system or other health IT may also determine the outcome in health care delivery effectiveness (Dey et al. 2013). We take into account four related progress or stage variables. Use of an Office of the National Coordinator for Health Information Technology *(ONC)-certified EHR system*, and *application for meaningful use incentive* (*MU*), are two dummy variables that indicate whether the clinic join other incentives program in the adoption and use EHR system (Lin et al. 2014). We also use dummy variables, *E-prescribing of non-controlled substances*, to indicate whether the clinic has over 80% of prescriptions that are e-prescribed; and the level of electronic documentation used, to indicate whether the clinic is entirely paperless for patient information.

2.3.5. Statistical Analysis Approach

To model the nested levels of organizational structure between clinics and medical groups, we conduct Hierarchical Linear Modeling (HLM) to analyze the data. HLM is widely used to study multilevel data (Raudenbush and Bryk 2002). It overcomes the statistical weaknesses of traditional methods for analyzing nested data, and the analysis would be misleading at clinic level if we fail to control for some unobserved factors from medical group level (Antonakis et al. 2010). The model is also appropriate for the investigation on cross level effect.

We focus on the average medical group level effects on the clinic health care delivery effectiveness, due to that significant proportion of variation in health care delivery effectiveness lies across medical groups. Therefore, we investigate the independent variables at the medical group level (level 2), and we include medical group average CDS and average challenge in workforce capabilities into the level 2, as well as other average control variables. Such analysis would allow us to examine how the overall CDS and workforce capabilities from medical group relate to clinic care deliver outcome.

We specify the statistical model as the following,

Level 1: $Y_{ij} = \beta_{0j} + \epsilon_{ij}$

Level 2: $\beta_{0j} = \gamma_{00} + \gamma_{1j}X_{CDS} + \gamma_{2j}X_{staff\ needs} + \gamma_{3j}X_{CDS} \times X_{staff\ needs} + \delta C_j + \mu_{0j}$

Where:

X – independent variable,
C – control variables at medical level,

j – medical group j,
i – clinic i.

2.4. Results

2.4.1. Descriptive Analysis

For 2232 clinic observations that adopted and implemented Electronic Health Record system, there are 249 medical groups in total. The medical group size varies based on the number of clinics in the data. The number of clinics in a medical group ranges from 1 to 59 with median of 2. The average number of clinics per medical group is 5.02 in 2013 and 5.62 in 2014. Also, there are 101 medical groups which have one clinic in 2013, while 89 in 2014.

The correlation matrix. We show the descriptive statistics and pairwise correlations for variables used at medical group level in our analysis in Table 2-1. On average, 17% of the clinics are from rural areas, and 35% of clinics focus on specialty care activities. Meanwhile, for a medical group average of 88% of clinics have ONC certificate, about 80% of the clinics have participated in meaningful use incentives programs, and over 70% fully implemented paperless charts on patient information or E-Prescribing for non-controlled substances. The correlation matrix indicates that the correlation coefficient between specialty care and health care delivery outcome is -0.39, EHR system vendor in EPIC is positively correlated with health care delivery effectiveness ($r = 0.43$). We find that CDS tools are highly positively correlated with care delivery outcome and the correlation coefficient is 0.65, while the needs for workforce capabilities in EHR/IT staff and trainers are negatively correlated with care delivery outcome, and informatics staff needs have very small direct correlation with care delivery outcome (r = 0.09). Among the independent variables, we find that the correlation between CDS system and EHR

Table 2-1. Descriptive Analysis and Correlation Matrix

Variables	mean	median	sd	min	max	1	2	3	4	5	6	7	8	9	10	11	12	13
1.Overall health care delivery effectiveness	4.44	5.00	2.79	0.00	8.00													
2.Small Medical Group	0.30	0.00	0.46	0.00	1.00	-0.31												
3.Use of ONC-certified EHR system [a]	0.88	1.00	0.30	0.00	1.00	0.25	-0.15											
4.EHR Vendor: Epic	0.40	0.00	0.49	0.00	1.00	0.43	-0.33	0.19										
5.Number of providers in the clinic (log) [a]	2.04	2.05	0.62	-0.69	4.36	0.25	-0.16	-0.02	0.26									
6.Rural vs. urban location [a]	0.17	0.00	0.29	0.00	1.00	-0.01	0.13	-0.10	-0.03	-0.20								
7.Fully use of electronic documentation [a]	0.74	1.00	0.42	0.00	1.00	0.21	-0.10	0.28	0.36	0.16	-0.13							
8.E-prescribing of non-controlled substances [a]	0.73	1.00	0.42	0.00	1.00	0.24	-0.11	0.08	0.22	0.11	0.14	0.13						
9.Application for meaningful use incentive [a]	0.80	1.00	0.37	0.00	1.00	0.25	-0.22	0.32	0.18	0.08	-0.14	0.15	0.10					
10.Specialty vs. primary care [a]	0.35	0.12	0.40	0.00	1.00	-0.39	0.14	-0.11	-0.32	-0.27	-0.28	-0.13	-0.22	-0.07				
11.Number of clinic decision support (CDS) tools [a,b]	0.00	0.23	0.95	-1.55	1.14	0.65	-0.38	0.24	0.52	0.19	0.01	0.25	0.25	0.35	-0.35			
12.EHR/IT staff needs [a,b]	0.00	0.31	0.96	-0.92	2.77	-0.22	0.10	-0.20	-0.28	-0.06	0.09	-0.20	-0.05	-0.11	0.04	-0.13		
13.Informatics staff needs [a]	0.31	0.00	0.44	0.00	1.00	0.09	-0.07	-0.09	0.15	0.18	0.09	0.02	0.21	-0.05	-0.09	0.14	0.06	
14.Trainer needs [a]	0.29	0.00	0.43	0.00	1.00	-0.11	-0.11	-0.08	-0.17	0.10	-0.08	-0.10	0.08	0.03	-0.01	-0.07	0.35	0.10

Note: [a] Average measurement of clinics for each medical group. [b] Normalized measurement for the variable across clinics and years.

system vendor of EPIC is 0.52. CDS system has positive correlation with application for meaningful use incentive (r = 0.35), while negative correlation with Specialty care (r = -0.35). For the focal variables, we do not find serious collinearity issue.

2.4.2. HLM Results

Investigating the factors that affect health care delivery outcome, we present the HLM results in Table 2-2. The factors of interest are workforce capabilities, CDS systems and their interaction. We conduct test to justify the use of HLM method and the focus on the second level (i.e., medical group) analysis. We report the test results in the null model. In the null model without any independent variables, we model care delivery effectiveness with the clinic level (level 1) and medical group level (level 2). It indicates that the medical group can explain 5.61 of the total variation in the outcome of 7.42, and the intra-class correlation is 75.6%. Thus, a majority of variation comes from the medical group level, which justifies our focus on the level 2 in HLM. We then include all control variables in the base model, which significantly improves the model ($\Delta\chi^2 = 254.7, df = 10, p < 0.001$). After that, we add the main effects of predictors, CDS systems and three variables for workforce needs (i.e. EHR/IT staff needs, informatics staff needs and trainer needs), and their interaction effects into the base model, separately. In the full model, we include all CDS systems, workforce needs and their interaction into one model. The addition of the main and interaction effects further improves the base model, as Chi-square tests indicate that all $\Delta\chi^2$ statistics are significant.

The diagnostic analysis results of our model indicate that the data are highly skewed in terms of residuals, which violates the normality assumption. We choose bootstrapping approach to construct the confidence interval for the model inference in Table 2-2, which can relax the assumption of normality. In summary, we find that implementation level of CDS tools has significant positive effect on the outcome variable at medical group level, and the increase in level of CDS tools leads to higher health care delivery effectiveness (in all models). Specially, the estimated coefficient of CDS is 0.94 in the full model. In other words, one more component of CDS is associated with 0.88 score increase in the health care delivery effectiveness, which is significantly positive compared to the 95% bootstrapped confidence interval. Meanwhile, we find evidence supporting the negative effect of workforce needs on health care delivery effectiveness. The estimated main effect is -0.29 for EHR/IT staff needs, -0.32 for informatics staff needs, and -0.93 for trainer needs, all of which are significant. Therefore, when a clinics face workforce needs, they experience lower care delivery effectiveness compared to those without such needs.

The results of the interaction between needs for workforce skills and CDS systems can help us to address the moderating role of workforce needs on the relationship between CDS systems and health care delivery effectiveness. The results show that all of interaction terms are significant. However, the moderating effects are not on the same direction. The result supports the hypothesized negative interaction between trainer needs and CDS systems. It indicates that trainer needs significantly negatively moderates how CDS tools improve health care delivery effectiveness, and the estimated interaction coefficient is -1.07. In contrast, the direction of the interaction term from EHR/IT staff needs and informatics staff needs are opposite of our hypotheses. Rather, they positively interact with CDS on the outcome variable.

We plot the interactions between CDS implementation and workforce needs on health care delivery effectiveness from full model in Figure 2-3. We can see that on average, the health care delivery effectiveness for clinics with workforce needs (dotted line) is lower than those without such needs (solid line), after controlling for other factors at clinic and medical groups. Although three sets of lines are crossed in the plot, the increase associated with implementation level of CDS with workforce needs for (a) EHR/IT or (b) informatics is larger than those without such needs, while the increase is smaller for those with needs for (c) trainers. These results suggest that the way workforce needs affect the implementation effectiveness of CDS systems depends on the specific types of workforce capabilities. Therefore, the evidence doesn't support one universal pattern on how workforce capabilities complement the adoption and implementation of CDS systems in health care setting.

2.4.3. Robustness Analysis

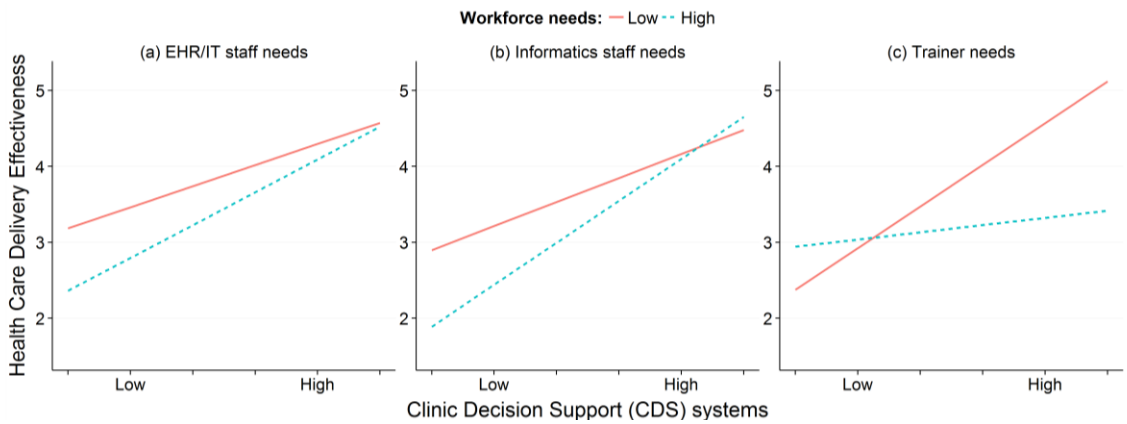
Medical group size varies substantially in our sample data, ranging from 1 to 59. The distribution of the medical group size across clinics is heavily skewed to the right side (large group size). There may be endogeneity concerns on our analysis results. Or the choice of level of CDS implementation may relate to the organizational overall capability in health care provision, which can lead to bias in our estimation. Large medical groups may have more capability and resources to implement CDS systems and achieve greater effectiveness compared to those small medical groups. However, we don't have variables for control from our data set. To investigate whether our results are dependent on the medical group size, we divide the sample of medical groups into three sub-categories with 1) one clinic, 2) 2 - 10 clinics, and 3) more than 10 clinics. We apply ordinary least squares (OLS) regression analysis in the category with one clinic, because the medical group and clinic level collapse into one level, and HLM in other categories. We show the results in Table 2-3. Overall, comparing the direction of the coefficient estimation from the sub-category analysis with our main analysis, we find that the results are qualitatively similar to our main analysis, while some exceptions exist. For example, the results are consistent with main effects of CDS systems, informatics staff needs. For EHR/IT staff and trainer needs, two positive singes of coefficient estimation are found, while others

Table 2-2. Hierarchical Linear Modeling (HLM) on CDS systems Impact at Group Level Only (Bootstrapped CIs in brackets)

Variable	M1: Null	M2: Base	M3: EHR/IT	M4: Informatics	M5: Trainer	M6: Full
Intercept	3.11 *	1.77 *	2.50 *	2.21 *	1.89 *	2.15 *
	[2.81; 3.42]	[0.93; 2.65]	[1.69; 3.34]	[1.33; 3.04]	[1.10; 2.70]	[1.35; 3.00]
Small Medical Group		-0.28	-0.27	-0.32	-0.27	-0.32
		[-0.72; 0.18]	[-0.68; 0.15]	[-0.75; 0.09]	[-0.76; 0.17]	[-0.70; 0.12]
Year: 2014		0.10	0.11	-0.00	0.19 *	0.18 *
		[-0.03; 0.23]	[-0.02; 0.25]	[-0.14; 0.14]	[0.04; 0.33]	[0.04; 0.32]
Use of ONC-certified EHR system [a]		0.92 *	0.77 *	0.77 *	0.97 *	0.86 *
		[0.61; 1.24]	[0.48; 1.08]	[0.45; 1.12]	[0.67; 1.29]	[0.51; 1.18]
EHR Vendor: Epic		-0.06	-0.17	-0.34 *	-0.27	-0.32
		[-0.42; 0.30]	[-0.50; 0.13]	[-0.71; -0.01]	[-0.60; 0.08]	[-0.66; 0.02]
Number of providers in the clinic (log) [a]		0.09	0.12	0.21	0.35 *	0.37 *
		[-0.17; 0.36]	[-0.13; 0.37]	[-0.05; 0.48]	[0.10; 0.58]	[0.12; 0.63]
Rural vs. urban location [a]		0.81 *	0.99 *	1.23 *	1.07 *	1.42 *
		[0.04; 1.63]	[0.21; 1.75]	[0.45; 2.05]	[0.37; 1.82]	[0.62; 2.16]
Fully use of electronic documentation [a]		-1.21 *	-1.39 *	-1.38 *	-1.51 *	-1.63 *
		[-1.50; -0.91]	[-1.71; -1.10]	[-1.69; -1.07]	[-1.81; -1.21]	[-1.93; -1.35]
E-prescribing of non-controlled substances [a]		1.30 *	1.23 *	1.39 *	1.39 *	1.34 *
		[1.09; 1.53]	[1.02; 1.45]	[1.16; 1.60]	[1.15; 1.61]	[1.12; 1.56]
Application for meaningful use incentive [a]		0.91 *	0.84 *	0.84 *	0.78 *	0.79 *
		[0.64; 1.19]	[0.56; 1.09]	[0.57; 1.12]	[0.53; 1.03]	[0.52; 1.04]
Specialty vs. primary care [a]		-0.53 *	-0.83 *	-0.52 *	-0.24	-0.21
		[-1.00; -0.09]	[-1.23; -0.45]	[-0.95; -0.09]	[-0.69; 0.18]	[-0.64; 0.20]
Number of clinic decision support (CDS) tools [a,b]			0.57 *	0.45 *	1.01 *	0.94 *
			[0.43; 0.72]	[0.31; 0.60]	[0.84; 1.20]	[0.76; 1.14]
EHR/IT staff needs [a,b]			-0.52 *			-0.29 *
			[-0.65; -0.38]			[-0.44; -0.16]
Number of clinic decision support (CDS) tools [a,b] x EHR/IT staff needs [a,b]			0.06			0.25 *
			[-0.06; 0.18]			[0.12; 0.38]
Informatics staff needs [a]				-0.48 *		-0.32 *
				[-0.75; -0.20]		[-0.58; -0.06]
Number of clinic decision support (CDS) tools [a,b] x Informatics staff needs [a]				0.62 *		0.50 *
				[0.36; 0.89]		[0.27; 0.74]
Trainer needs [a]					-1.11 *	-0.93 *
					[-1.38; -0.86]	[-1.19; -0.69]
Number of clinic decision support (CDS) tools [a,b] x Trainer needs [a]					-0.96 *	-1.07 *
					[-1.18; -0.73]	[-1.32; -0.84]
AIC	8314.22	8098.57	7979.24	8006.79	7937.72	7852.43
BIC	8331.35	8172.81	8070.61	8098.16	8029.09	7966.64
Log Likelihood	-4154.11	-4036.28	-3973.62	-3987.39	-3952.86	-3906.21
Num. obs.	2232	2232	2232	2232	2232	2232
Num. groups: MedGrp_ID	249	249	249	249	249	249
Chi-Square test		2 vs. 1	3 vs. 2	4 vs. 2	5 vs. 2	6 vs. 2
		254.7*** (df=10)	137.4*** (df=3)	106.5*** (df=3)	176.4*** (df=3)	282.3*** (df=7)
Variance: MedGrp_ID.(Intercept)	5.61	4.95	3.86	4.16	3.87	3.94
Variance: Residual	1.81	1.62	1.56	1.57	1.53	1.45

* 0 outside the confidence interval. [a] Average measurement of clinics for each medical group. [b] Normalized measurement for the variable across clinics and years.

Figure 2-3. The Interaction between Clinical Decision Support Systems and Workforce Needs on Health Care Delivery Effectiveness



four are negative. Similarly, the interaction effect is also consistent between CDS systems and EHR/IT staff needs (and trainer needs). Compared with interaction effects from our main analysis, we find that informatics staff needs have negative moderating effect in large sub-categories (M3), although it is not significant. In addition, we note that the significance level for the coefficient estimation varies substantially compared to main analysis, except the main effect of CDS systems. Therefore, it is important to consider the medical group size effect on health care delivery effectiveness, as we control for in our main analysis.

The outcome variable in our analysis measures multiple dimensions on health care delivery performance, and it reflects the overall agreement that the clinic on the EHR system impact on all dimensions. The measure is appropriate for this study, because we focus on the overall effect from CDS systems and workforce needs, and their effect on organizational care delivery. However, our results may not apply to specific health delivery dimension, like guideline confirmation, medication error alters or patient care enhancement. To increase our confidence on the result of health care delivery effectiveness, we construct four alternative measures of the health care delivery outcome.

The first one is *alerts* -- we focus on the medication, lab, drug order and prevention alerts and reminders, and obtain the total of utility score of EHR systems on these dimensions. The second one is *quality* -- we measure quality as the sum of utility of EHR system on benchmarks/clinical priority development, data sharing with providers, clinical guidelines set up, and professional development support. The third one is *patient care* -- we investigate the role of independent variables and effects on patient care enhancement. And the fourth outcome variable is *guideline* -- we study how clinics adhere to clinical guidelines using EHR system.

We follow different analysis approaches for the alternative outcome variables, because *alerts* and *quality* are measured as continues variables, while *patient care* and *guidelines* as binary outcomes. We apply HLM to test the model on alerts and quality. As for patient care and guidelines, we use Generalized Linear Mixed Model (GLMM) with multivariate normal random effects using Penalized Quasi-Likelihood. The results for the four alternative health care delivery outcome measurements are reported in Table 2-4. The significantly positive effect of CDS systems is supported by all models, while the main effects of workforce needs vary. All workforce needs negatively relates to clinical guidelines. For *trainer needs*, results indicate that they have significantly negative impact on alerts and patient care enhancement, too. *Informatics staff needs* have further significantly negative effect on patient care enhancement, while *EHR/IT staff needs* show similar negative effect on alerts and quality. Consistent with the full model on health care delivery outcome, the interaction effect between CDS systems and informatics staff and trainer needs are all significant on the alternative measures of health care delivery performance. Overall, our results are robust and qualitatively similar on various measures of health care delivery performance.

The use of bootstrap method helps us to relax the assumption about the data distribution, though it becomes less efficient when we conduct inference analysis. We rerun our model with the assumption of normality in the residuals, and report the p-value in M1 in Table 2-4. The results are similar to the full model in Table 2-2. In summary, our findings on CDS systems, workforce needs and their interaction effect on health care delivery effectiveness are consistent and robust, regardless different measure of health care delivery performance and statistical analysis approaches.

2.4.4. Endogeneity Issue

Identifying the causal impact of CDS systems and workforce capabilities on the effectiveness of care delivery is a challenging task. Endogeneity issues (e.g. reverse causality, unobserved heterogeneity, or self-selection) can result in overestimated effects in observational studies (Semadeni et al. 2014, Tan and Netessine 2014, Hoogendoorn et al. 2013). The literature primarily addresses such problems using: 1) instrumental variables (e.g., Semadeni et al. 2014, Tan and Netessine 2014), 2) experiment design (e.g., Hoogendoorn et al. 2013, Çelen and Hyndman 2012) and 3) other approaches (e.g., Mindruta 2013). A potential endogeneity issue in our HLM analysis may be unobserved effects from clinics and hospitals. For example, clinics might be highly proficient in care delivery, and a high level of CDS implementation may reflect their strong performance. Due to the limitations in observational research, we cannot access full information on every trait of each clinic. Therefore, the omitted effects may result in bias in our HLM estimation.

We apply additional panel data analysis to assess the robustness of our results. Panel data is helpful for analysis with observations across time periods, and it is flexible to specification with varying assumptions. Our data provide information for each clinic

Table 2-3. Sub-Sample Health Care Delivery Effectiveness across Medical Group Size at Group Level Only

Variable	M1: 1	M2: 2-10	M3: >10
Intercept	2.19 ***	0.51	11.23 *
	(0.62)	[-0.79; 1.73]	[8.74; 13.77]
Year: 2014	0.00	0.15	0.67 *
	(0.30)	[-0.05; 0.36]	[0.37; 0.96]
Use of ONC-certified EHR system [a]	0.41	0.32	-0.48
	(0.41)	[-0.08; 0.71]	[-1.95; 0.83]
EHR Vendor: Epic	0.96 *	1.70 *	0.08
	(0.45)	[0.88; 2.50]	[-0.30; 0.50]
Number of providers in the clinic (log) [a]	0.39 *	0.80 *	-0.64
	(0.17)	[0.39; 1.20]	[-1.39; 0.18]
Rural vs. urban location [a]	0.58	1.62 *	-11.06 *
	(0.44)	[0.45; 2.73]	[-15.40; -6.98]
Fully use of electronic documentation [a]	-0.39	-0.66 *	-9.02 *
	(0.34)	[-1.01; -0.31]	[-10.17; -7.91]
E-prescribing of non-controlled substances [a]	0.61	1.47 *	2.28 *
	(0.34)	[1.13; 1.85]	[1.74; 2.83]
Application for meaningful use incentive [a]	0.28	0.97 *	0.80 *
	(0.32)	[0.59; 1.34]	[0.16; 1.44]
Specialty vs. primary care [a]	-0.94 **	-1.32 *	0.33
	(0.33)	[-2.12; -0.55]	[-0.61; 1.30]
Number of clinic decision support (CDS) tools [a,b]	1.24 ***	0.35 *	4.56 *
	(0.23)	[0.07; 0.64]	[3.55; 5.54]
EHR/IT staff needs [a,b]	-0.09	0.15	-0.02
	(0.18)	[-0.05; 0.38]	[-0.92; 0.76]
Informatics staff needs [a]	-0.37	-0.25	-0.68
	(0.41)	[-0.65; 0.15]	[-2.04; 0.57]
Trainer needs [a]	-0.11	-0.19	1.71 *
	(0.46)	[-0.69; 0.38]	[0.74; 2.70]
Number of clinic decision support (CDS) tools [a,b] x EHR/IT staff needs [a,b]	0.23	0.52 *	1.11 *
	(0.17)	[0.32; 0.72]	[0.51; 1.73]
Number of clinic decision support (CDS) tools [a,b] x Informatics staff needs [a]	0.11	0.05	-0.16
	(0.38)	[-0.37; 0.47]	[-1.24; 0.85]
Number of clinic decision support (CDS) tools [a,b] x Trainer needs [a]	-0.71	-0.14	-5.35 *
	(0.48)	[-0.65; 0.45]	[-6.41; -4.31]
R^2	0.48		
Adj. R^2	0.43		
Num. obs.	187	792	1253
AIC		2621.30	3915.47
BIC		2710.11	4013.01
Log Likelihood		-1291.65	-1938.74
Num. groups: MedGrp_ID		113	26
Variance: MedGrp_ID.(Intercept)		4.24	11.67
Variance: Residual		0.94	1.14

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$ (or 0 outside the confidence interval).. [a] Average measurement of clinics for each medical group. [b] Normalized measurement for the variable across clinics and years.

Table 2-4. Comparison of Alternative Measures of Healthcare Delivery Effectiveness

Variable	M1: Effectiveness	M2: Alerts	M3: Quality	M4: Patient Care	M5: Guidelines
Intercept	2.15 ***	1.17 ***	2.52 ***	-0.57	-1.10
	(0.42)	(0.27)	(0.23)	(1.06)	(1.29)
Small Medical Group	-0.32	0.02	-0.41 ***	-1.48 *	-2.15 ***
	(0.21)	(0.14)	(0.12)	(0.58)	(0.57)
Year: 2014	0.18 *	0.17 ***	0.00	0.04	-0.40 *
	(0.07)	(0.04)	(0.04)	(0.19)	(0.19)
Use of ONC-certified EHR system [a]	0.86 ***	0.68 ***	0.51 ***	2.86 ***	-1.25 *
	(0.16)	(0.10)	(0.09)	(0.51)	(0.54)
EHR Vendor: Epic	-0.32	-0.10	-0.12	0.57	0.53
	(0.17)	(0.11)	(0.09)	(0.34)	(0.36)
Number of providers in the clinic (log) [a]	0.37 **	0.23 **	-0.05	0.49	1.09 **
	(0.13)	(0.08)	(0.07)	(0.30)	(0.37)
Rural vs. urban location [a]	1.42 ***	0.97 ***	0.68 **	0.80	1.68
	(0.38)	(0.25)	(0.21)	(0.80)	(1.03)
Fully use of electronic documentation [a]	-1.63 ***	-1.12 ***	0.17 *	-2.56 ***	-2.61 ***
	(0.15)	(0.09)	(0.08)	(0.39)	(0.43)
E-prescribing of non-controlled substances [a]	1.34 ***	0.73 ***	-0.36 ***	1.54 ***	3.19 ***
	(0.11)	(0.07)	(0.06)	(0.42)	(0.50)
Application for meaningful use incentive [a]	0.79 ***	0.61 ***	0.37 ***	0.81 *	2.17 ***
	(0.13)	(0.09)	(0.07)	(0.39)	(0.48)
Specialty vs. primary care [a]	-0.21	-0.37 **	-0.09	-0.83	-0.10
	(0.21)	(0.13)	(0.11)	(0.46)	(0.56)
Number of clinic decision support (CDS) tools [a,b]	0.94 ***	0.50 ***	0.31 ***	0.72 **	2.98 ***
	(0.09)	(0.06)	(0.05)	(0.26)	(0.31)
EHR/IT staff needs [a,b]	-0.29 ***	-0.13 **	-0.08 *	-0.38	-1.22 ***
	(0.07)	(0.04)	(0.04)	(0.20)	(0.19)
Informatics staff needs [a]	-0.32 *	-0.05	-0.03	-2.45 ***	-1.45 ***
	(0.13)	(0.09)	(0.07)	(0.49)	(0.44)
Trainer needs [a]	-0.93 ***	-0.23 **	0.11	-1.76 ***	-2.42 ***
	(0.13)	(0.08)	(0.07)	(0.48)	(0.36)
Number of clinic decision support (CDS) tools [a,b] x EHR/IT staff needs [a,b]	0.25 ***	0.25 ***	0.04	0.13	-0.32
	(0.06)	(0.04)	(0.04)	(0.19)	(0.19)
Number of clinic decision support (CDS) tools [a,b] x Informatics staff needs [a]	0.50 ***	0.24 **	0.23 ***	0.94 *	1.63 ***
	(0.13)	(0.08)	(0.07)	(0.44)	(0.44)
Number of clinic decision support (CDS) tools [a,b] x Trainer needs [a]	-1.07 ***	-0.43 ***	-0.26 ***	-1.12 *	-2.44 ***
	(0.12)	(0.07)	(0.06)	(0.47)	(0.38)
AIC	7852.43	5858.61	5167.28		
BIC	7966.64	5972.82	5281.50		
Log Likelihood	-3906.21	-2909.30	-2563.64		
Num. obs.	2232	2232	2232	2232	2232
Num. groups: MedGrp_ID	249	249	249		
Variance: MedGrp_ID.(Intercept)	3.94	1.63	1.16		
Variance: Residual	1.45	0.59	0.43		
Num. groups				249	249

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$. [a] Average measurement of clinics for each medical group. [b] Normalized measurement for the variable across clinics and years.

HLM for M1 - M3, and Generalized Linear Models - Penalized Quasi-Likelihood for M4 - M5 across two years (T=2), and we explore the short panel for each clinic to overcome some endogeneity issues in unobserved heterogeneity.

We fit the data with pooling effect, random effect, and first difference effect models. For T=2, fixed effect and first difference models are identical. In fixed effect model,

$$y_{it} = X_{it}\beta + a_i + \epsilon_{it}$$

Where i indicates the clinics, t indicates the year dummy (2013 or 2014), and ϵ_{it} follows normal distribution. The unit effect a_i captures the unobserved effect in our data. In random effect model, a_i is not estimated directly, rather is assumed to follow normal distribution with mean μ_a and variance of σ_a^2. Compared to fixed effect, random effect model can be flexible, as it can incorporate the effect from the individual level.

In first difference model, we can use the variables from the second period minus the previous, to cancel out the specific effect associated with each clinic or hospital, which is not reported in the data set. The model can be written as,

$$\Delta y_{it} = y_{it} - y_{it-1} = \Delta x_{it}\beta + \Delta\epsilon_{it}$$

We report robust analysis with White's adjustment in the standard error estimation, due to heteroscedasticity across clinics and medical groups. Wooldridge's test suggests that unobserved individual effects exist. And the Hausman tests comparing pooling effect, random effect, and first difference model suggest that first difference model is more reliable. We report the analysis results in Table 2-5. The results show that CDS and workforce capability are beneficial to care delivery in organizations, and the interaction between CDS and workforce capability presents. However, the interaction effects are not the same comparing the three types of workforce capability. EHR/IT staff needs and Informatics needs have positive interaction with CDS, while trainers needs have negative interaction. Both random effect and first difference analysis provide strong support to our HLM analysis results.

Comparing panel analysis with our main HLM analysis, the two approaches share similar specification on the individual effect, especially between HLM and random effect model. Yet, panel data analysis ignores the structure between clinics and medical groups, and the latter contributes to large proportion of variation in the care delivery. Thus, we rely on HLM to make conclusions, because it is more appropriate for our data and research focus.

2.4.5. Post Hoc Analysis

Our analysis finds that the increased level of CDS is generally positively associated with organizational effectiveness. We explore how the combination of the individual features in CDS systems leads to higher outcome. CDS systems include the following components: 1) Automated reminders for missing labs and tests (item no. A); 2) Chronic disease care plans and flow sheets (B); 3) Clinical guidelines based on patient problem list, gender, and age (C); 4) Medication guides/alerts (E); 5) Patient specific or condition specific reminders (F); 6) Preventive care services due (G). On the one hand, we try to address the questions on how can organizations optimally achieve higher outcome through increased technology implementation level. For example, Dey et al. (2013) provides cautionary insight that the choice of higher level of technology capability may be self-selected, and organizations may not realize the potential benefits of high level implementation without aligned technological, organizational, and environmental characteristics. Also, considering the integration among various stand-alone technologies, Angst et al. (2011) find that hospitals perform better if they integrated foundational technologies first. On the other hand, clinics may need the recommendations on how to implement technologies, and what are the critical components that affect organization

Table 2-5. Panel Data Analysis

Variable	M1: Pooling	M2: Random Effect	M3: Fixed Effect	M4: First Difference
Intercept	3.66 ***	3.46 ***		0.05
	(0.21)	(0.21)		(0.08)
Small Medical Group	-0.30 **	-0.41 ***	-0.24	-0.25
	(0.10)	(0.12)	(0.34)	(0.34)
Use of ONC-certified EHR system	0.72 ***	0.65 ***	0.59 **	0.58 **
	(0.14)	(0.14)	(0.18)	(0.18)
EHR Vendor: Epic	0.12	0.01	-1.77 ***	-1.75 ***
	(0.11)	(0.12)	(0.23)	(0.24)
Number of providers in the clinic (log)	0.13 **	0.13 **	0.12	0.11
	(0.04)	(0.05)	(0.11)	(0.11)
Fully use of electronic documentation	-0.20	-0.48 ***	-1.59 ***	-1.61 ***
	(0.11)	(0.11)	(0.17)	(0.17)
E-prescribing of non-controlled substances	0.56 ***	0.91 ***	1.66 ***	1.65 ***
	(0.10)	(0.10)	(0.13)	(0.13)
Application for meaningful use incentive	0.01	0.34 **	0.86 ***	0.84 ***
	(0.11)	(0.11)	(0.14)	(0.14)
Specialty vs. primary care	-0.73 ***	-0.66 ***	0.15	0.11
	(0.10)	(0.10)	(0.17)	(0.18)
Rural vs. urban location	-0.15	-0.11		
	(0.12)	(0.14)		
EHR/IT staff needs [b]	-0.29 ***	-0.34 ***	-0.23 **	-0.24 **
	(0.05)	(0.05)	(0.08)	(0.08)
Informatics staff needs	-0.15	-0.16	-0.44 **	-0.45 **
	(0.10)	(0.10)	(0.15)	(0.15)
Trainer needs	-0.24 *	-0.43 ***	-0.81 ***	-0.82 ***
	(0.10)	(0.10)	(0.14)	(0.14)
Number of clinic decision support (CDS) tools	0.74 ***	0.66 ***	0.30 ***	0.30 ***
	(0.03)	(0.03)	(0.05)	(0.05)
EHR/IT staff needs [b] x Number of clinic decision support (CDS) tools	-0.01	0.04	0.14 ***	0.13 ***
	(0.02)	(0.02)	(0.03)	(0.03)
Informatics staff needs x Number of clinic decision support (CDS) tools	0.14 ***	0.15 ***	0.20 ***	0.20 **
	(0.04)	(0.04)	(0.06)	(0.06)
Trainer needs x Number of clinic decision support (CDS) tools	-0.32 ***	-0.40 ***	-0.38 ***	-0.39 ***
	(0.05)	(0.04)	(0.06)	(0.06)
R^2	0.51	0.41	0.32	0.32
Adj. R^2	0.51	0.41	0.13	0.32
Num. obs.	2232	2232	2232	912

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$. [b] Normalized measurement for the variable across clinics. Analysis at clinic level.

most. Therefore, we argue it is important to study the integration of components in CDS system for higher care delivery.

The method we apply here is conditional inference trees, one tool from predictive analysis (Hothorn et al. 2006). This method creates two groups that are maximally different from each other based on the information measure of node selecting the covariate showing the best split. The process in selecting and binary splitting is recursively repeated. The process stops when the global null hypothesis of independence between the response and any of the covariates cannot be rejected at a pre-specified nominal level α. Conditional inference trees are superior to traditional linear regression or other tree methods, because they do not rely on underlying assumptions of linearity and can avoid overfitting.

To understand the predictive relationship between components of CDS systems and care delivery outcome, we use "ctree" function from "partykit" package in R. We base on c_{quad} – type test statistics and Bonferroni correction p-value is used on the stopping criteria, since the components of CDS systems are binary data in nature. We further specify that the minimum sum of weights in a node as 100, before that node to be considered splitting.

The tree results are shown in Figure 2-4. The first split is based on use or not on the components on patient specific reminders (F). The use (1) is on the right, while not use (0) on the left. Next level of splits includes chronic disease care plans (B) and clinical guidelines (C). The third level includes medication guides (E), clinical guidelines (C), and automated reminders (A).

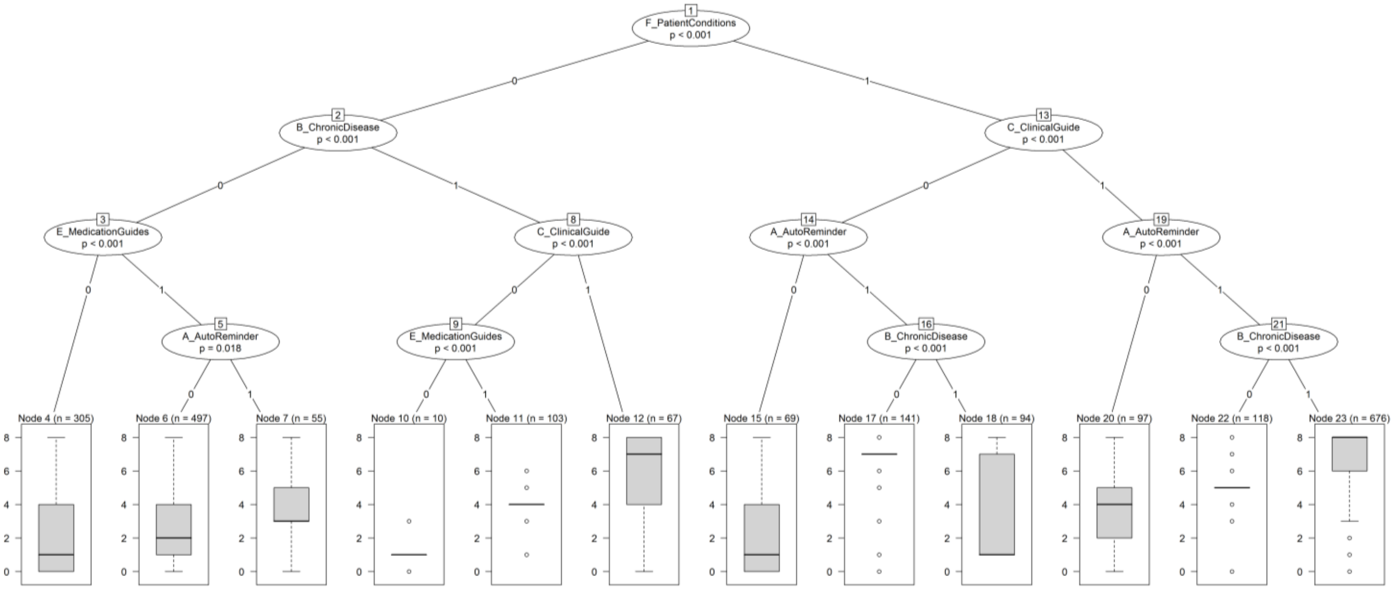
Generally, from left to right, the outcome increases as the use of different components increases. For example, when clinic has the full use of (F-1, C-1, A-1, B-1), the mean of outcome is 6.882; when clinic has no use of any (F-0, B-0, E-0), the mean of outcome is 1.981. The top two nodes with highest mean outcome (above 6) are node 23 (F-1, C-1, A-1, B-1), and node 17 (F-1, C-0, A-1, B-0). And the bottom two nodes (mean outcome below 2) are node 4 (F-0, B-0, E-0) and node 10 (F-0, B-1, C-0, E-0). Of course, there are exception on the outcome when use different combination of the CDS components. The mean outcome from node 7 (F-0, B-0, E-1, A-1) is 3.436, which higher than nodes on its right, node 10 (F-0, B-1, C-0, E-0) and node 15(F-1, C-0, A-0). Same is for node 12 (F-0, B-1, C-1), which has mean outcome 5.687, which is the third highest outcome.

The results from both Figure 2-4 and Table 2-6 indicate that, 1) higher level of CDS is beneficial to clinics generally; 2) interaction between CDS components exists. For example, the joint effect between A and B depends the use in C. The joint effect of B and C (For F-0) is higher than any combination of B, E, and A. Our results reflect the complexity of interaction among individual components in technology adoption and implementation in health care, and some medium-level integration can outperform higher level combination. Therefore, the post hoc analysis has implication for practitioners when they face choice of CDS systems implementation. Future research needs to explore more on the individual components and how they jointly affect the health care delivery.

2.5. Discussion

Our findings contribute to the understanding of knowledge management in an organization for technology implementation (Bardhan et al. 2013, Osheroff 2009, Alavi and Leidner 2001). The knowledge creation and conversion in CDS system implementation and workforce capabilities have significant impact on organizational performance. Our findings on the joint role of CDS systems and workforce capabilities

Figure 2-4. Conditional Inference Trees on Care Delivery Effectiveness for CDS Systems



Note: For each inner node, the selected variable and the Bonferroni-adjusted P values are given. The box plot for care delivery effectiveness for that group is displayed for each terminal node.

Table 2-6. Pairwise Comparison of Performance among Combinations of CDS Components. The Differences between Row and Column Nodes are Reported, with Pairwise t-test Using Bonferroni Correction for p-value.

row	node	F	B	C	A	E	mean	median	sd	N	4	6	7	10	11	12	15	17	18	20	22
1	4						1.96	1	2.26	305											
2	6					x+	2.57	2	2.04	497	0.60**										
3	7				x	x	3.44	3	2.1	55	1.48***	0.87									
4	10		x				1.2	1	1.03	10	-0.76	-1.37	-2.24								
5	11		x			x	4.14	4	0.73	103	2.18***	1.57***	0.70	2.94***							
6	12		x	x			5.69	7	2.88	67	3.73***	3.12***	2.25***	4.49***	1.55***						
7	15	x					2.55	1	2.85	69	0.59	-0.01	-0.89	1.35	-1.59***	-3.14***					
8	17	x			x		6.09	7	2.4	141	4.13***	3.53***	2.66***	4.89***	1.96***	0.41	3.54***				
9	18	x	x		x		3.76	1	2.91	94	1.79***	1.19***	0.32	2.56**	-0.38	-1.93***	1.20**	-2.34***			
10	20	x		x			3.87	4	2.16	97	1.91***	1.30***	0.43	2.67**	-0.27	-1.82***	1.32**	-2.23***	0.11		
11	22	x		x	x		5.2	5	0.95	118	3.24***	2.64***	1.77***	4.00***	1.07**	-0.48	2.65***	-0.89*	1.45***	1.34***	
12	23	x	x	x	x		6.88	8	1.51	676	4.92***	4.32***	3.45***	5.68***	2.75***	1.20***	4.33***	0.79**	3.13***	3.02***	1.68***

Note: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$. + x indicates the component of CDS (i.e., A, B, C, E, F) present.

deepen our understanding in the integration between the two dimensions during technology implementation.

The results indicate that knowledge in CDS system implementation is a critical determinant of health care delivery effectiveness. When a clinic has higher capabilities in adopting and using CDS systems, the explicit knowledge developed and accumulated in CDS systems enables organizations to fully benefit from the systems and establish higher level of efficient use of related tools. This finding on CDS system implementation is consistent with the literature that higher stage of health IT leads to higher healthcare delivery performance (Dey et al. 2013), and that increased level of interoperable and complex technologies can have significant effect in terms of process cost and quality (Angst et al. 2011). It also echoes the recent study in health care on the computerized physician order entry use that the knowledge management and learning during the process increases patient satisfaction (Queenan et al. 2011). Also, our findings generally support the literature on the IT adoption and use in an organization (Aral et al. 2012, Zhu et al. 2006). Our results provide evidences that IT technology implementation can be used to improve organizational knowledge (Alavi and Leidner 2001).

The results also show that the tacit knowledge from relevant workforce capabilities significantly determine health care delivery effectiveness. In a knowledge intensive setting like health care management (Kong et al. 2012, Osheroff 2009), organizational capability and environments can shape the effectiveness of the technology adoption and use (Dey et al. 2013, Aral et al. 2012, Zhu et al. 2006). Our findings on EHR/IT staff, informatics staff and trainers in clinics illustrates that various workforce capabilities for CDS systems are needed for maximum performance. Generally, when a medical group has higher needs (or lower capacity) in related workforce, the clinics perform poorly compared to those without these needs. It indicates that organizations need to better manage the tacit knowledge embedded in the workforce, and enhance workforce skills for higher organizational performance during technology adoption and implementation.

The significant and heterogonous interaction effects between CDS systems and specific workforce needs have implication for technology implementation. Organizations need to pay to the nature of tacit knowledge developed by various types of workforce. Our results support Hess and Rothaeml's (2011) study on the integration between human capital and upstream/downstream innovative activities. It is critical to recognize the "importance of considering not only the heterogeneity of a firm's intellectual human capital but also the relationship between key innovative activities along the knowledge value chain" (Hess and Rothaermel 2011, p. 906). First, we need to consider the specific interaction in the practice rather than assuming a universal effect for all workforces. Our results suggest that we need to pay attention to the various roles of different types of workforce. The different roles of workforce capabilities are also evident in studying occupation composition change (Tambe and Hitt 2012), the tension and compatibility between social and technical aspect of organization (Liu et al. 2006), star scientists and value chain management (Hess and Rothaermel 2011), and policy making on worker mobility and professionalism development (Mithas and Lucas 2010). Thus, an appropriate mix of workforce may be critical for technology implementation success.

Our results suggest that the trainer needs and the associated interaction with CDS system implementation confirm our hypothesis. It may indicate that tacit knowledge from general skill set is complementary to the implementation of CDS systems. When both knowledges increase in an organization, we would observe that they can lead to amplified organizational performance. Such effect may also contribute to the consistent training from various IT adoption projects in the health care. Previous training may reinforce the current CDS system implementation, since training may share similar guidelines and practices.

Different from trainer needs, EHR/IT staff and informatics staff needs affect the relationship between CDS system and health care delivery outcome in opposite ways. Such interaction relationship contradicts to the general complementarity effect between workforce and other organizational factors, including technology (Aral et al. 2012), organizational structure (Rothaermel and Hess 2007), and strategic alliances in the value chain (Hess and Rothaermel 2011). These workforce capabilities may have a more complicated relationship with the technical CDS systems. One explanation for such complexity could be that these two skills are relatively new to organizations, and they need to be further developed by solving the emerging and new problems in the organizations. When CDS system implementation is higher, the system can help solve some of those problems. However, new challenges may come out during the higher level of CDS system implementation, which requires organizations to deploy a complete new skill sets. At the initial stage, an organization can achieve desired outcome by either using higher level of CDS systems or higher level of workforce skills. However, organizations need to keep developing these skills besides their use of current capability. Another reason could be that both workforce skills are developed almost simultaneously with the CDS system implementation. The concurrency requires an organization to split the resources into two parts, and the competition for resources reduces their joint effect on health care delivery performance.

2.6. Conclusions

Reflecting on the knowledge management and learning from KBV of organization and the complementarities of workforce skills in health care IT adoption and implementation, this research captures three key aspects on (1) the impact of CDS system implementation on organizational performance, (2) the role of workforce capabilities development during health IT systems implementation process, and (3) their joint effect on organizational performance. Our research framework contributes to the existing literature on the knowledge management on the integration between workforce capabilities and technology adoption.

Theoretical Contribution

This study extends current research on knowledge creation and transfer among explicit and tacit knowledge which leads to higher organizational performance in health care industry (Dey et al. 2013, Nag and Gioia 2012, Aral and Weill 2007, Preuss 2003, Alavi and Leidner 2001, Nonaka 1994, Pisano 1994). The explicit and tacit knowledge creation and transfer in process of CDS system implementation and workforce capabilities can enable organizations to achieve enhanced performance. Also, our study illustrates the impact of that the knowledge creation and performance at medical group level on health care delivery at clinics, which confirm the knowledge creation locus in the organizational structure (Aral et al. 2012, Pisano 1994). More importantly, we identify the heterogeneous roles of the joint effect between knowledge in CDS system implementation and various types of workforce capabilities. This is similar to previous studies that find the main benefits of adoption and use of health IT in healthcare industry, while we need to pay extra attention to some specific effect in the interaction between the CDS systems with workforce skills, management choice/sequence and other infrastructures (Dey et al. 2013, Kong et al. 2012, Angst et al. 2011, Hess and Rothaermel 2011, Queenan et al. 2011) . It therefore contributes to the current understanding of the integration and interaction among knowledge elements in the health care, and expands the current scope of complementarities in knowledge to a broader domain. Our results indicate that knowledge in certain workforce capabilities, EHR/IT related skills and informatics may need to be continuously updated, in order to accommodate the increased knowledge level of knowledge development in CDS system implementation. The immediate and positive interaction may not be evident in case of new workforce capabilities development.

Managerial Contribution

The findings in this study provide deep insights to practitioners on how to manage CDS system implementation and related workforce capabilities development. First, the direct result provides a complete picture on the integration of CDS system implementation and workforce capabilities. If an organization needs to augment its CDS systems to achieve the maximum impact during the health care delivery process, it should choose to improve both CDS system tools and involve necessary workforce. They might also need to understand how the health care delivery effectiveness is affected by specific workforce skill. On the one hand, the trainers are necessary for CDS system implementation effectiveness on health care delivery effectiveness, and the preparation of such tacit knowledge may complement the CDS systems. Therefore, organizations that increase both level of trainers and CDS system implementation would obtain much higher effectiveness than those who just pursue only one or the other dimension. On the other hand, for the advanced skills like EHR/IT related staff and informatics staff, organizations might decide to improve these skills or improve the CDS system implementation at the initial stage. This is because organization can obtain enhanced performance through either way. Our result may indicate that when CDS system implementation increases, new EHR/IT related staff and informatics staff are necessary for better performance. Thus, in the later stage, organizations may need to keep including more workforce and acquiring new set of these capabilities; otherwise the benefit may be quickly eroded by the obsolete EHR/IT related skills or informatics. Considering the differential joint effect of CDS system implementation and related workforce capabilities, managers need to design an approximate strategy to balance the investment and development in the two areas for optimal organizational performance.

Limitation and Future Study

Our study opens up new avenues of research on the following areas. First, future research can extend this study by exploring the effect of cross-level workforce capabilities and CDS system implementation. More effort is needed to provide a complete view of cross level knowledge creation and transfer from workforce in the technology management. Besides, it is also possible to obtain longitudinal data cross states and countries to confirm the effect of both CDS system implementation and workforce capabilities on health care delivery effectiveness. Such approach can better take into account the unobserved effects embedded in the clinics and medical groups, and overcome the limitation in the narrow coverage of our data. However, researchers need to address the large variation in health care practices across states before any meaningful insights can be obtained from a broader geographic coverage. Third, more research is necessary to understand the dynamics between CDS system adoption and professional knowledge creation in health care. This study doesn't directly examine the health care providers' interaction with the CDS systems. The knowledge from health care providers may exhibit a unique perspective on the integration between CDS systems and workforce capabilities, which requires even more intensive and specialized knowledge in care delivery. Moreover, our study focuses on care delivery effectiveness in the clinics and medical groups, and potential research can be conducted to investigate technology development orientation, capability, context on the technology development in the whole supply chain, like drug and medical equipment industry and IT industry. Comparing the intensity of knowledge sharing and communication within and across organizations, we need to uncover the role of difference and similarity in the technology development and workforce capabilities management in various settings connecting to healthcare industry. One may ask, "how does the interaction between technology development and workforce capabilities management in the upper stream of the supply chain affect the short and long term technology management in health care organizations?"

Chapter 3

Evaluating Telemedicine Adoption in Clinics: Accounting for Socioeconomic, Geographical, Organizational and Technological Antecedents

3.1. Introduction

Organizations increasingly face challenges to maximize potential returns from their extensive investment in information technology (IT) adoption and implementation. Based on studies of the factors that affect technology innovation (Tornatzky and Fleischer 1990), scholars have developed novel explanations of why IT performance varies across organizations, including environmental and organizational contexts (Aral et al. 2012, Aral and Weill 2007, Park et al. 2007, Zhu et al. 2006, Klein and Sorra 1996), technological context (Dey et al. 2013, Queenan et al. 2011, Zhu et al. 2006), and the sequencing and complexity of technologies (Angst et al. 2011). Meanwhile, the idiosyncratic characteristics of new technology adoption in specific circumstances may require novel theory on the management of technology, such as on integration of knowledge management and technology adoption (Paul 2006), the interrelationship between practice and knowledge in organizational management (Nicolini 2011), and concurrent dynamic capability building (Bingham et al. 2015). Given the importance of technological, organizational, and environmental contexts in technology adoption decisions, we empirically investigate concurrent adoption of multiple ITs and how the adoption is related to organizational performance. We choose telemedicine adoption in the organizational context of health care delivery and the related rapid adoption of electronic health record systems as our testing case.

Telemedicine is a set of technologies and capabilities that enable patients to remotely access clinical care via secure information and communication technologies, overcoming the traditional limitations of distance (American Telemedicine Association 2015, Nalugo et al. 2014, Weinstein et al. 2014, Paul 2006). In the domain of telemedicine, the number of “e-visits” was expected to reach 75 million in North America in 2014, a 400% increase from 2012 (Burda 2014, Lee et al. 2014). The increase may be further strengthened by health insurance reimbursement, which started covering remote and virtual physician visits in 2015 (BusinessWire 2015). As technological development continues, telemedicine has potential to provide inexpensive, convenient, and improved health care with more options for patients (Field and Grigsby 2002). When it can reduce distance constraints and improve utilization of health care resources across clinics, telemedicine may provide a means to increase affordability for a larger patient population (Sinha and Kohnke 2009). Telemedicine could help reduce hospital admission, facilitate early intervention, prevent crisis management, monitor patient health status (Anker et al. 2011), and decrease access disparity (Weinfeld et al. 2012, Gibbons and Casale 2010), as well as reallocate health care resources to cover larger areas (Singh and Wachter 2008, Mitka 2003).

Until recently, telemedicine adoption has been fairly slow since its first use 50 years ago. Its popularity has grown slowly relative to other health technology adoptions and unevenly across medical specialties (e.g., rapid adoption in radiology) (Field and Grigsby 2002). Studies suggest that the barriers to adoption may include complex practices and mixed patient profiles (Anker et al. 2011), uncertainty regarding cost-effectiveness, acceptability to participants, and questions regarding quality, safety, privacy, regulation, and finance issues (Mitka 2003, 2009, Singh and Wachter 2008, Field and Grigsby 2002). In contrast, to enhance decision-making in the clinical workflow, Clinical Decision Support (CDS) systems enabled by Electronic Health Record (EHR) systems moved from inception to broad distribution in 10 years (Gabriel and Swain 2014, Angst et al. 2010, Osheroff 2009). There may be a timely opportunity to expand the use of telemedicine practices following the recent rapid adoption of EHR and CDS. However, there is a dearth of empirical evidence on telemedicine adoption from operations management perspectives. In the new era, the ambiguities surrounding the antecedents and consequences of telemedicine adoption in organizations require further investigation (Nicolini 2011, Paul 2006).

To better understand telemedicine adoption in clinics, we employ the **technology-organization-environment (TOE)** framework as the theoretical underpinning (Tornatzky and Fleischer 1990). The TOE framework describes the entire process of development, adoption and implementation of technological innovation in an organization from technological, organizational, and environmental contexts. The three contexts influence both decisions related to IT adoption, as well as the impact of adoption on organization performance. For example, the use of health IT across geographical locations and socio-economic settings, each with unique population characteristics, may face different challenges, leading to varied effectiveness of IT adoption (Weinfeld et al. 2012, Gibbons and Casale 2010, Millery and Kukafka 2010). Studies suggest that researchers need to be cautious about the organizational self-selection issue related to use of technology, and more advanced stages of electronic medical record capabilities may not be beneficial to all providers (Dey et al. 2013). It is also necessary to consider the sequence and complexity of technology adoption (Angst et al. 2011). The context of the health care industry may include unique factors as well. For example, it is important for health care organizations to incorporate usability and perceived usefulness as elements of health IT performance (Ant Ozok et al. 2014), meaningful use incentives and provider characteristics (Lin et al. 2014), patient satisfaction enhancement (Queenan et al. 2011), and health care information technology infrastructure and information processing mechanisms (Gardner et al. 2014, Queenan et al. 2011). These studies suggest that technology adoption in health care settings may be influenced by the specific organizational and environmental contexts, as well as by other technologies. In sum, TOE framework is appropriate for our telemedicine study as it accounts for the relevant contextual factors.

We apply an extended TOE framework and propose an integrated model to capture the antecedents and consequences of telemedicine adoption in clinics. The studied factors of environmental context, geographical location and socioeconomic characteristics may be related to the adoption of telemedicine. Organizational context, including challenges to implement telemedicine, may also be related to adoption. As for consequences, we examine telemedicine in the technological context of existing CDS systems. We expect that telemedicine adoption should improve care delivery effectiveness, as well as enhance the effect of CDS on delivery outcomes. Positioning telemedicine adoption within the studied contexts, we aim to address the following questions:

1. How do the environmental (geographical and socioeconomic) and organizational contexts of a clinic affect the adoption of telemedicine?

2. How does the adoption of telemedicine interact with the technological context of a clinic [i.e., clinical decision support (CDS) system] to impact the effectiveness of care delivery?

To empirically test our framework, we focus on clinics in Minnesota during adoption and implementation of their EHR systems. We obtain secondary data from the Minnesota

Department of Health and Minnesota e-Health Initiative (MDH 2014c). This unique dataset allows us to measure and assess the technological, organizational and environmental contexts during telemedicine adoption, as well as CDS use across organizations. As such, our attempt to integrate insights from the empirical data offers a holistic perspective on the antecedents and consequences of telemedicine adoption in clinics.

This study provides multiple contributions to research and practice in operations management. Our study examines the association of organizational characteristics in conjunction with geographical and socio-economic characteristics on telemedicine adoption based on the TOE framework. The results provide evidence that both environmental and organizational contexts have unique implications for telemedicine adoption. More importantly, telemedicine adoption and CDS use can individually enhance care delivery effectiveness. However, telemedicine adoption negatively moderates the relationship between CDS system use and care delivery effectiveness. This indicates that clinics with lower levels of CDS use tend to benefit more from telemedicine adoption in terms of care delivery. Telemedicine and CDS may have an idiosyncratic nature, and they substitute each other's impact on organization performance. Our findings provide significant insights on the complexity of telemedicine adoption.

The next section covers a literature review of the antecedents and consequences of telemedicine adoption as well as the TOE framework. We propose an integrated research framework and develop our hypotheses to test relationships among these constructs. In the following section, to examine the proposed research framework, we provide detailed reports on statistical models, measures and analysis. We then report the results, discuss the implications, and conclude our analysis. In the last section, we discuss the theoretical and practical contributions of this study, as well as identify potential areas for future research.

3.2. Literature and Theory

3.2.1. Telemedicine in Health Care

Telemedicine refers to the use of real time medical information exchanged via electronic information and communications technologies to provide and aid health care with various participants at a distance (American Telemedicine Association 2015, Nalugo et al. 2014, Weinstein et al. 2014, Paul 2006). Telemedicine includes a growing variety of applications and services using two-way video imaging, wireless tools, Internet, email, telephones, mobile applications, and other forms of telecommunications technology. The use of telemedicine has expanded rapidly in recent years in certain instances , including primary care/specialist referral, teleradiology, remote patient monitoring, medical education, and others (American Telemedicine Association 2015, Weinstein et al. 2014). It has a potential future role to increase access to quality health care (Sinha and Kohnke 2009), reduce health disparities (Gibbons and Casale 2010) and improve health care overall (Anker et al. 2011). Yet, the telemedicine utilization rate is still fairly low and limited to specific care situations (Weinstein et al. 2014, Anker et al. 2011, Nicolini 2011, Paul 2006).

Rapid adoption and use of Electronic Health Record (EHR) systems and Clinical Decision Support (CDS) systems in recent years presents an opportunity to foster more extensive use of telemedicine. To clearly understand the interaction among the technology components, we focus on the relationship between telemedicine and CDS, one critical component in EHR systems. CDS systems encompass a variety of tools and approaches to “enhance decision-making in the clinical workflow” (Department of Health and Human Services 2013), and the systems aim for “delivering clinical knowledge and intelligently filtered patient information to clinicians and/or patients for the purpose of improving healthcare processes and outcomes” (Osheroff 2009, p. 9). Also, the use of CDS systems closely reflects the adoption rate of EHR (MDH 2014c, Minnesota Department of Health 2014). The information and communication technologies that constitute an EHR system are available and can potentially support both telemedicine and CDS systems (American Telemedicine Association 2015, Nicolini 2011, Gibbons and Casale 2010).

3.2.2. TOE Framework for Telemedicine

A theoretical framework for technology adoption needs to consider general technological, organizational, and environmental contextual factors that influence organizational decisions on telemedicine adoption and its impact on organizational performance. The technology-organization-environment (TOE) framework proposed by Tornatzky and Fleischer in the seminal book of "The Process of Technological Innovation," is appropriate for our study (Tornatzky and Fleischer 1990). The TOE framework describes the entire process of development, adoption, and implementation of technological innovation in a firm. There are three elements in the framework — technological context, organizational context, and environmental context. *Technological context* includes all technologies relevant to the organization, including the existing ones in use and those that are new in the marketplace but the organization is not yet using. *Organizational context* includes the characteristics and resources of the organization, like scope, size, communication processes, and managerial structure. *Environmental context* refers to an organization’s business environment — industry, competitors, technology providers, and regulations.

The TOE framework has been used widely in the literature, particularly in the information system adoption research (Teo et al. 2009, Mishra et al. 2007, Zhu et al. 2004, 2006, Chwelos et al. 2001, Chau and Tam 1997). Zhu et al. (2004) study how TOE factors may influence e-business impacts on firm performance in the financial service industry. Studying the assimilation of Internet-based e-business innovations, Zhu, Kraemer and Xu (2006) explore how the three contexts of TOE determine firm e-business initiation, adoption, and routinization. TOE is also applied in the analysis of decision-making methodologies and satisfaction in IT-induced business transformations (Bernroider and Schmöllerl 2013). Similarly, research has explored the factors from technological, organizational, and inter-organizational levels on the adoption of electronic data interchange (EDI) (Chwelos et al. 2001). In studying firms' adoption of open systems technology, the TOE framework is applied to explore firms' "ability to adopt" and "reactive" attitude during the process (Chau and Tam 1997). In addition, Mishra, Konana, and Barua (2007) summarize the TOE framework and empirically investigate antecedents and consequences of internet use in procurement in U.S. manufacturing firms.

The TOE framework is consistent with our research goal of understanding which contextual factors determine the integration between IT adoption/utilization and practices in an organization, which further affects the operational effectiveness (Nair et al. 2013, Valdmanis et al. 2010, Li et al. 2002). The uniqueness of the health care industry also requires researchers to look at telemedicine adoption from a broader perspective. Health care delivery involves management of goods, services, and experiences, which can be viewed as a bundle of care (Sinha and Kohnke 2009). Quality health care should take into account not only patient's disease condition but also "patient's psychological, sociological, and economic conditions, as well as geographical location" (Sinha and

Kohnke 2009, p. 206). From a supply chain management perspective, care delivery requires all stakeholders to function accordingly (Nicolini 2011, Bui 2000) and bridge the gap between demand and supply of care (Sinha and Kohnke 2009).

Technological context can impact IT adoption and its consequences for care effectiveness. For example, research has identified the role of stages of electronic medical record systems (Dey et al. 2013), and the outcome of implementation and integration sequence of various medical technologies (Angst et al. 2011). IT infrastructure is found to substitute for use of computerized physician order entry (CPOE) in its effect on patient satisfaction (Queenan et al. 2011). These studies align with research on e-business assimilation, where technology readiness and integration can facilitate new technology adoption (Zhu et al. 2006). During the rapid adoption of her systems, various components may interact to affect organizational performance. Thus, telemedicine adoption should be examined in the context of existing technology use, rather than as an isolated project. In this study, we focus on the technological context of CDS system use in clinics. CDS is an important component in EHR systems, has high adoption rates, and is intended for improved patient care quality, safety, and medication error reduction in clinics and hospitals.

Organizational context can play an important role for telemedicine practices. For example, studies identified that telemedicine requires unique organizational practices, routines, and knowledge management practices during the collaborative activities with various parties, some at a geographic distance (Nicolini 2011, Paul 2006). New perspectives on the relationship between "practice" and "knowing," and "knowing" manifests by activities distributed among a variety of people, things and practices (Nicolini 2011). Such knowing requires care providers to acquire a different set of skills and knowledge that are embedded in the specific context. To achieve success in telemedicine, practitioners need to change in terms of "doings and sayings, tempos, material mediators, and interactional orders" (Nicolini 2011, p. 613). During the collaboration with various parties in telemedicine, management of various knowledge-related activities (i.e., knowledge transfer, knowledge discovery, and knowledge creation), and the associated interactions are critical for positive outcomes (Paul 2006). Telemedicine may increase knowledge creation and tacit knowledge discovery, which can lead to positive organizational outcomes.

Environmental context can have implications for care delivery. One important factor is the geographic location of an organization. Studying the relationship between quality/flexibility and cardiology unit performance, Nair, Nicolae and Narasimhan (2013) identify that state and county differences contribute to 57% of cost variation, and county differences constitute 31% of variation in length of stay. Similar, location may also imply a unique requirement of health care delivery responsibility in a specific region, like the emergency preparedness for a hurricane event in Florida (Valdmanis et al. 2010). Studying hospital capability decisions, Li et al. (2002) report that capital and hospital location, size and the service mix play a significant role. In addition, Li and Benton (2006) identify a difference between rural and urban hospitals on staff development, and small rural hospitals tend to emphasize staff development more than urban ones. Thus, disparities in the environmental context may influence the access to and the outcome of health care in non-trivial ways (Nair et al. 2013).

Another dimension of the environmental context for health IT adoption and implementation is socio-economic development status. Local economic development status is not isolated from health care delivery because cost and access to quality care provision are important factors for organizational capability decisions (Anchala et al. 2015, Dey et al. 2013, Valdmanis et al. 2010, Sinha and Kohnke 2009, Li and Benton

2003, 2006). Generally, organizations need to balance cost and innovative change in their business process, product, or service (Craighead et al. 2009). Excess capacity in technology maintained by hospitals may increase costs, lower efficiencies and cause facility closures (Valdmanis et al. 2010, Maiga and Jacobs 2009), when it doesn't match the local environment. Economic factors may be especially important to telemedicine adoption because setting up relatively new and unfamiliar practices with telemedicine traditionally requires sizeable investment allocation (Weinstein et al. 2014, Anker et al. 2011, Paul 2006), although the technology is getting cheaper over time.

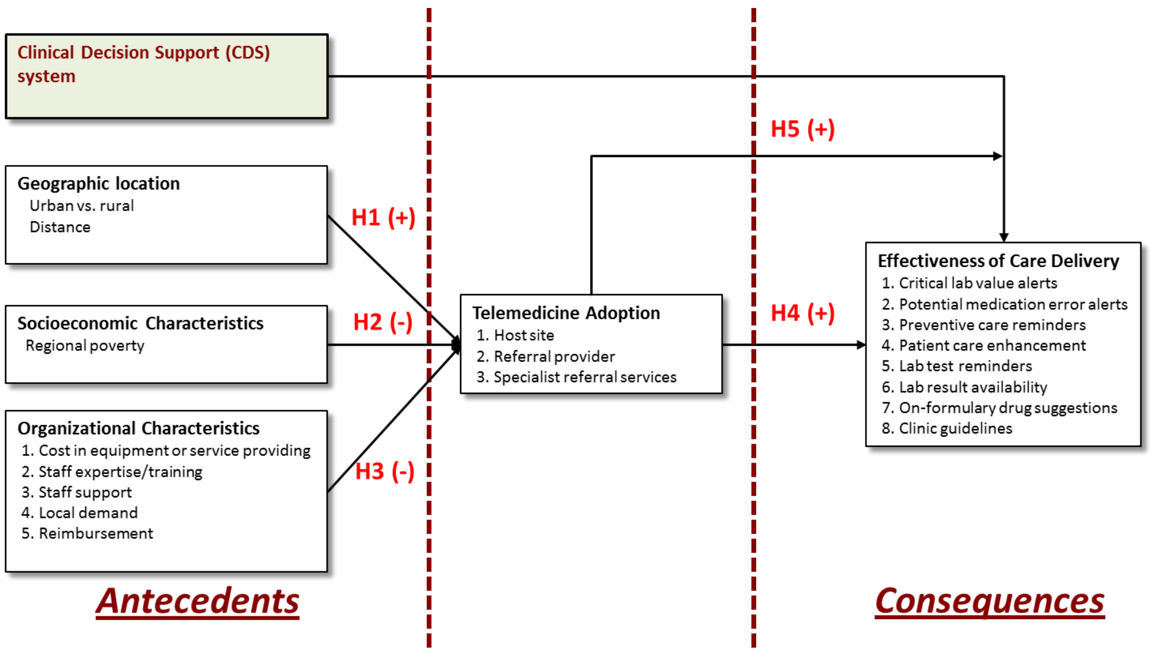
With the rapid adoption of EHR and CDS in clinics and hospitals recently, telemedicine may increase affordability and access of quality care by increasing health care resource utilization in the supply chain (Sinha and Kohnke 2009). With technology support, a patient may locally access a diagnosis from physician specialists with limited travel expenditure (both time and money). However, there is little empirical evidence regarding telemedicine adoption in the new setting of rapidly increasing use of other health IT systems.

3.2.3. The Conceptual Model

Considering the technological, organizational, and environmental characteristics, we develop an integrated model of the antecedents and consequences of telemedicine in the setting of CDS adoption, as shown in Figure 3-1. Drawing upon the TOE framework, we posit that telemedicine adoption depends on the antecedents from organizational and environmental factors, and that it has positive consequences on care delivery effectiveness in clinics. We further posit that telemedicine adoption has a positive interaction effect with CDS.

To construct the model, we first investigate the impact of environmental context, which includes geographical location and socioeconomic characteristics for a clinic. We then explore the role of organizational context, which includes specific challenges or barriers an organization faces in the adoption of telemedicine. We expect that differences in these organizational and environmental contexts can lead to variation in telemedicine adoption levels.

Figure 3-1. Research Model for Telemedicine Adoption



For the consequences of telemedicine adoption, we focus on care delivery effectiveness in the technological context of CDS systems. We focus on organizational performance during technology adoption, rather than direct health care outcome for patients. We argue that care delivery effectiveness is a strategic goal that organizations seek to achieve during adoption of CDS and telemedicine. In our model, telemedicine adoption is expected to increase care delivery effectiveness, and to have a positive interaction with CDS systems. We expect that a higher level of telemedicine adoption may reinforce the positive effects from the use of CDS systems on care delivery effectiveness.

3.2.4. Hypothesis Development on Causes and Consequences of Telemedicine Adoption

3.2.4.1. Antecedents of Telemedicine Adoption

In our integrated model, we consider two types of antecedents that can influence the adoption of telemedicine in an organization: 1) environmental context of geographical location and socioeconomic characteristics, and 2) organizational context of organizational characteristics.

Geographical location

Geographical location is a critical factor in economic geography, knowledge spillover and management, industry and regional growth management (Natividad 2014, Singh and Marx 2013, Zhang et al. 2009), and health care management (Sinha and Kohnke 2009, Singh and Wachter 2008). Geographical location impacts disparities in quality health care, which is evident in underdeveloped, developing and developed countries (Millery and Kukafka 2010, Sinha and Kohnke 2009).

Geographical location is a multidimensional concept, and we focus on characteristics of clinic location that capture the market and relationship with other clinics. This includes rural or urban areas, distance to the closest metropolitan (economic) center, and the density of neighboring clinics. First, research has found that geographic location in rural vs. urban areas can be an important factor in decisions by health care organizations (Li and Benton 2006, Goldstein et al. 2002, Li et al. 2002). A rural clinic may face a variety of demands for care from patients, but low volume for each unique skill and service. Strategically, a rural clinic can choose to rely on other clinics to remotely provide certain types of low volume clinical services to the rural clinic. In contrast, for an urban clinic, such demand for telemedicine use may be low, as patients have options to switch to different clinics that can provide these specific services. Thus, clinics and hospitals in rural areas are expected to have higher incentives to adopt telemedicine.

The second dimension of geographical location is the remoteness of the clinics. Remoteness is the distance between a clinic and the metropolitan center in the study region. In our study dataset, a larger proportion of clinics and hospitals are located in the Twin Cities (Minneapolis-St. Paul), and they may enjoy a larger pool of clinical resources, faster communication on regulations, and easier access to research capabilities. The physical distance in our study differs from the service distance, or variation in quality care access, and some communities in cities still lack quality care. The remoteness of a clinic and hospital is expected to be positively related to the adoption of telemedicine. Remote clinics need to provide a variety of services to local patients (Li and Benton 2006), because patient choice of clinics is limited by long travel distances to the metropolitan or resource-rich center. The dependence of patients in remote areas on a specific clinic may be higher, while remote clinics may not have capacity and capabilities to treat all patient demand due to the limited resource support. Similarly, remote clinics may lack workforce capacity when the local population is relatively small. We expect that such disparity in capacity and service availability may encourage remote clinics to borrow capacity and expertise from other clinics and hospitals through telemedicine.

Geographical location can also include the density of neighboring clinics. Studying how firms respond to rivals when entering new markets, Koçak and Özcan (2013) argue that density of local competitors may affect the focal firm's likelihood of entering the market. In our study, competition and collaboration in a localized cluster of clinics may force a clinic to select a specific set of services to improve both their probability of survival as well as their performance. Ideally, co-location and competition may encourage a clinic to develop special competence in health care delivery and provide complementary services to other clinics in the same area. Jointly, these clinics should provide comprehensive care, and patients may choose among them. Compared to those in a dense cluster, a clinic in a less dense cluster may need to provide a more comprehensive set of services because of patient needs. Following this logic, a clinic in a less dense region is expected to have a higher rate of telemedicine adoption. Therefore, we have the following hypotheses,

H1a: Clinics in rural areas have a higher level of telemedicine adoption compared to those in urban areas, ceteris paribus.

H1b: Clinics further from the metropolitan center have a higher level of telemedicine adoption compared to those closer to the metropolitan center, ceteris paribus.

H1c: Clinics with less density of neighboring clinics have a higher level of telemedicine adoption compared to those in higher density areas, ceteris paribus.

Socioeconomic Characteristics

Socioeconomic characteristics, another factor of environment context, refers to the regional economic development status where a clinic is located. The social determinants, or the interaction between organizations and the community and society, can largely affect clinic specific decisions in health care. For example, socioeconomic characteristics in rural areas can change the community's livelihood and manager's decision-making in the adoption of energy technology (Henao et al. 2012). The adoption of telemedicine may be "socially constructed," or closely related to people and communities (Bernroider and Schmöllerl 2013). One critical perspective of socioeconomic characteristics is poverty, which is highly related to health care disparities (Anker et al. 2011, Millery and Kukafka 2010, Sinha and Kohnke 2009). The telemedicine adoption decision may reflects clinics' intention and efforts to address health care disparities in the community and society (Singh and Wachter 2008, Mitka 2003, Field and Grigsby 2002).

A growing number of management scholars are beginning to explore the opportunities for business and organization in the context of poverty (Ault and Spicer 2014, Mair et al. 2012, Pearce 2005), including research on selecting the poor as suppliers or distributors in the supply chain (Sodhi and Tang 2014), providing products and services to high poverty regions (Kistruck et al. 2013), managing low wage employees in organizations (Leana et al. 2012), supplying sustainable energy for the poor (Henao et al. 2012), managing social entrepreneurship and social innovation (Dacin et al. 2011), and reducing health care disparities between the poor and wealthy (Sinha and Kohnke 2009, Griffin et al. 2008). Practitioners in health care also have the responsibility to reduce health care disparities and improve community health (Sinha and Kohnke 2009, Griffin et al. 2008). In short, the context of regional economic characteristics can affect not only local populations but also organizations, in terms of organizational attitudes, behaviors, and decision-making processes (Henao et al. 2012, Leana et al. 2012).

When clinics in high poverty regions consider telemedicine adoption, the cost of this capability may become a relatively large burden. The cost comes from equipment purchases, data transmission fees, service providing fees, and also from the replacement of such systems, which becomes unavoidable due to the rapid development of technology and equipment (Mitka 2003, Field and Grigsby 2002). Similarly, the cost can further increase because of the requirement for a distinct set of worker skills and experiences in providing telemedicine practices (Nicolini 2011). Increased costs are generally encountered for new and complex technology adoption in organizations (Gollakota and Doshi 2011). Clinics may need to hire new staff with experience with telemedicine and establish new routines in their practices. Or they may need to train staff to build the new capability internally. In all, clinics in high poverty regions may have a lower likelihood of investing in telemedicine technology.

Measuring the regional economic characteristics from the poverty level of a county, we classify regions as either high or low poverty. The poverty statistics are based on the U.S. Census Bureau, 2009–2013 5-year American Community Survey[1]. Compared to clinics in low poverty counties, clinics in high poverty counties may be less likely to invest in telemedicine. The cost and complexity of telemedicine may be barriers to telemedicine adoption. Therefore, we expect that,

> *H2: Clinics in low poverty regions have a higher level of telemedicine adoption compared to those in high poverty regions, ceteris paribus.*

Organizational Characteristics

Organizational context is another important dimension of technology adoption (Bernroider and Schmöllerl 2013, Zhu et al. 2006, Klein and Sorra 1996, Tornatzky and Fleischer 1990). Interaction among managers, staff, routines, and the environment is critical for technology implementation, which may influence decision-making on the level of technology use. The literature reports this role of organizational context in ERP

[1] http://factfinder.census.gov/faces/nav/jsf/pages/searchresults.xhtml?refresh=t

systems (Park et al. 2007) and e-business technology diffusion (Zhu et al. 2006). We investigate four relevant dimensions of organizational context related to telemedicine: cost, staff competence and support, patient demand, and reimbursement availability.

When an organization faces challenges related to the cost of telemedicine equipment or the provision of service, they may question the usefulness of telemedicine and consider it only when available alternatives outweigh these costs. Instances of using telemedicine for heart failure (Anker et al. 2011), teleradiology (Weinstein et al. 2014), and telestroke (Weinstein et al. 2014, Mitka 2009) illustrate that its benefits can be significantly greater than its cost. For example, meta-analyses show that telemedical monitoring for chronic heart failure can reduce total mortality at a follow-up of 6–12 months, and can reduce the number and duration of hospital admissions for worsening heart failure (Anker et al. 2011). These effects lead to a total cost reduction of care delivery in hospitals.

Meanwhile, staff expertise and staff support are critical for implementation of telemedicine. The literature suggests there is a complementary effect between skills and technology, which is critical for technology adoption and improved performance (Aral et al. 2012, Aral and Weill 2007, Manz and Stewart 1997). In the case of limited expertise or experience using telemedicine, or resistance from staff, implementation of telemedicine may be delayed.

Matching supply to demand in the health care supply chain is one priority for efficient and successful health care delivery (Sinha and Kohnke 2009). We further argue that organizations make decisions on telemedicine adoption while incorporating patient demand for such technology. To build excess capacity while ignoring local market demand is generally considered a waste of scarce health care resources (Valdmanis et al. 2010). Given that health care providers need to achieve meaningful use of health care technology (Centers for Medicare & Medicaid Services 2014, Lin et al. 2014), we expect the adoption of telemedicine will be low when organizations do not observe demand for it within their local community.

In addition, reimbursement by insurers to cover the cost of telemedicine services is a regulatory issue in the health care industry (Weinstein et al. 2014, Field and Grigsby 2002). The incentive to use telemedicine may decrease when organizations are challenged to obtain reimbursement for telemedicine services. Overall, when a clinic or hospital faces these problems, they might postpone adoption of telemedicine, even though they might recognize its benefits. We hypothesize that,

> *H3: Organizational characteristics related to challenges in telemedicine adoption, i.e. cost, staff competence and support, community demand and reimbursement, are negatively related to the level of telemedicine adoption, ceteris paribus.*

3.2.4.2. Consequences

Reviewing the IT literature, we find that a higher level of technology adoption is generally associated with better organizational performance, although the technological and organizational contexts can influence this relationship. For example, technology can be an important strategic resource to meet the organization's goals (Aral et al. 2012, Aral and Weill 2007, Zhu et al. 2006). Although the up-front implementation cost in infrastructure investment is high, organizations benefit from technology adoption in terms of long term survival and competence through creating new applications and capabilities. More importantly, the skills and practices developed during the implementation process support technology assimilation, production, and cross-functional integration, resulting in better organizational performance (Aral et al. 2012, Aral and Weill 2007, Zhu et al. 2006).

IT adoption and implementation is also beneficial to medical organizations (Bhargava and Mishra 2014, Dey et al. 2013, Angst et al. 2011, Queenan et al. 2011, Anton et al. 2009, Osheroff 2009). Examining the interaction between physicians and Electronic Medical Record systems , there may be long term benefits in terms of productivity gains for organizations and health care improvement for patients, when physicians can better review synthesized medical information to make decisions (Bhargava and Mishra 2014). For example, Computerized Physician Order Entry systems are shown to have a positive effect on patient satisfaction (Queenan et al. 2011). Studies suggest a positive relationship between higher level IT implementation and health care performance, although we need to account for technological and organizational contexts (Dey et al. 2013, Angst et al. 2011). Additionally, the use of clinical decision support tools can improve practices of health care delivery, including guideline adherence, clinical reminders and alerts, lab tests suggestions and others (Anton et al. 2009, Osheroff 2009). In summary, the literature indicates that there is a positive relationship between IT adoption and health care delivery outcomes.

Telemedicine is a specific set of health IT equipment and capabilities. In alignment with the general and health IT literature, we investigate telemedicine's impact on healthcare delivery effectiveness to provide an organizational perspective. With access to remote and multiple clinical resources and expertise, telemedicine should help to reduce medical errors during decision-making related to disease monitoring (Weinstein et al. 2014). Real-time interaction through a telemedicine systems enables patients and physicians to better communicate about disease conditions and specific expectations (Anker et al. 2011). With the timely support of the telemedicine systems, health care providers can reduce duplicate lab tests and meet standard treatment guidelines for patients, because the information is available system-wide and critical for process improvement (McKinstry et al. 2009). Better disease management, then, is expected. Similar to other health IT, alerts and reminders from a telemedicine system can enhance the interaction between the system and the providers and patients, increasing the efficiency of using health IT in treating patients. Increased use of telemedicine may equip organizations to better conduct medication and clinical management through the integration of telemedicine and other organization capabilities. Thus, telemedicine can help organizations to improve internal quality management. Overall, we hypothesize that,

> *H4: The adoption of telemedicine is positively related to care delivery effectiveness at clinics, ceteris paribus.*

Interaction effect between telemedicine and CDS

The literature on technology adoption emphasizes interaction among various technology components on organizational performance (Gardner et al. 2014, Bertrand and Mol 2013, Angst et al. 2011, Queenan et al. 2011, Aral and Weill 2007). Different combinations and integration among various information technologies reflect organizational and operational choices and practices on the application of those technologies in organizational tasks (Gardner et al. 2014). Knowledge and learning acquired and accumulated from one system can diffuse to new systems, due to the increased organizational learning ability (Angst et al. 2011, Queenan et al. 2011). More extensive learning is achieved by integrating and absorbing diverse knowledge or related knowledge (Bertrand and Mol 2013, Cohen and Levinthal 1990). Studying the joint effects of IT infrastructure and two information processing mechanisms, error processing and strategic processing of data, Gardner, Boyer and Gray (2014) find that both interactions have implications on health care quality improvement and patient satisfaction. Similarly, Queenan et al. (2011)

propose that the use of Computerized Physician Order Entry systems and IT infrastructures are complementary for higher organizational performance. Thus, organizations may experience positive interaction among various technology adoptions when they simultaneously adopt multiple systems.

We argue that adoption of telemedicine and CDS have a positive interaction effect on care delivery effectiveness in clinics. Previous studies identified evidence of a positive impact of CDS use on various health care outcomes (Kong et al. 2012, Anton et al. 2009, Osheroff 2009). For example, use and development of CDS tools enable clinicians to analyze and work with patient data in real-time, which leads to better decisions and improved patient care outcomes (Anton et al. 2009). With the support of rule-based decision support from CDS, clinicians can provide better risk assessment of cardiac chest pain (Kong et al. 2012). Similarly, when practitioners accurately and clearly understand system recommendations and alerts, CDS intervention can be highly effective for desired clinical objectives (Osheroff 2009). We expect that a CDS system will have a similar positive impact on care delivery effectiveness. When combined with telemedicine adoption and practices, we expect that the impact of CDS systems will be further strengthened.

Knowledge obtained from telemedicine routines and practices can improve CDS use, based on the concept of knowledge spillover inside the organization. Absorptive capability of various functions and practices can be increased when health providers use telemedicine (Bertrand and Mol 2013, Cohen and Levinthal 1990), which can generate new health care delivery knowledge in practices for organization (Nicolini 2011). Additionally, more extensive telemedicine implementation can enable an organization increase coordination among diverse stakeholders and reduce duplicate tasks. This coordination effect is documented for Computerized Physician Order Entry systems in terms of redundant basic patient information and lab tests (Queenan et al. 2011). Additionally, economies of scale can result from extended use of health IT in multiple activities on a similar platform, and the inputs from these activities may enable organizations to substantially expand knowledge generation and innovation creation (Bertrand and Mol 2013, Nelson and Winter 1982). Thus, clinics which adopt more extensive use of both CDS and telemedicine will see a greater impact on outcome than separate adoptions.

> *H5: The adoption of telemedicine positively interacts with CDS use on care delivery effectiveness at clinics, ceteris paribus.*

3.3. Method

3.3.1. Data

We combine data from several sources to exam our research framework. First, we obtain clinic and medical group level telemedicine activity measures from the Minnesota e-Health Initiative survey. This survey measures progress in how Minnesota clinics adopt, utilize and exchange information among Electronic Health Record (EHR) systems in order to deliver better patient care (Soderberg 2014). This data is appropriate for our analysis because we focus on telemedicine activities in the setting of EHR and CDS adoption, and the interrelationship among various health IT systems. To increase data reliability, we combine survey data from 2013 and 2014. Across the two survey years, 1286 of 1623 Minnesota clinics responded, for a response rate of 79% (Minnesota Department of Health 2013). From the survey data, 87% (1114) of clinics reported having an EHR system installed and in use, of which 88% used at least one clinical decision support (CDS) tool while 57% used three or more.

We retrieve data for clinic location through a geocoding process. Geocoding is the process of converting an address to calculated latitude/longitude coordinates (U.S. Census Bureau 2014b). The literature includes an increasing number of studies incorporating a geocoding technique or geographic information systems (GIS) into analysis (Natividad 2014, Singh and Marx 2013, García and Norli 2012, Lahiri 2010). The two main data sources for this study are Nokia's Here map and Google's Map Application Programming Interface (API) (Nissen 2014, Kahle and Wickham 2013). To validate our geocoding results, we also use the U.S. Census Bureau's geocoding API to retrieve separate latitude/longitude coordinates (U.S. Census Bureau 2014b). There is no significant difference among these approaches in terms of accuracy.

The third data source is the U.S. Census Bureau website (U.S. Census Bureau 2014a), which relies on the American Community Survey (ACS) for the poverty level for each county (U.S. Census Bureau 2014c). ACS is an ongoing survey that collects data every year to monitor economic development and guide decision making for communities and governments. The Census Bureau uses a set of income thresholds, which include earnings, compensation, social security, benefits, and assistance before taxes, to determine who is living in poverty, taking into account family size and composition. A family and its members are in poverty if their total income is less than the family threshold (U.S. Census Bureau 2014a). Then, the percentage of families in poverty is constructed for each county. The poverty measure represents local socio-economic status, which may reflect government support for community improvements.

3.3.2. Dependent Variables

In studying the antecedents and consequences of telemedicine adoption, we have two dependent variables. Analyzing the antecedents of telemedicine, the adoption level of telemedicine in clinics is the first dependent variable. There are three dimensions of telemedicine adoption: 1) telemedicine activities at host site via telecommunication systems; 2) providers at another site who may provide telehealth services; 3) specialist referral services that typically involve a specialist assisting a general practitioner in rendering a diagnosis. Clinics respond to these questions with yes (1) or no (0). We construct a total score (0-3) by summing these dimensions to reflect the level of telemedicine adoption in that organization.

The second dependent variable, used to assess the consequences of telemedicine adoption, is care delivery effectiveness. This gauges the extent to which the system helps providers in reporting, improving delivery quality and patient safety. The survey asks clinics whether their EHR contributes to the care delivery effectiveness in the following: 1) critical lab alerts, 2) medication error alerts, 3) preventive care reminders, 4) patient care improvement, 5) needed lab alerts, 6) lab result availability, 7) on-formulary drug order; and 8) guidelines. Each item is measures as yes (1) or no (0), and we sum the items (0-8) for the care delivery effectiveness measure.

3.3.3. Independent Variables

Geographical location.

Rural. To capture the difference in geographical locations of clinics, we dummy code clinics as urban or rural. This classification is based on Rural-Urban Commuting Areas (RUCAs) from 2010 Census Tracts in Minnesota (MN Office of Rural Health and

Primary Care 2011). Zero (0) indicates a clinic is located in a metropolitan, urban, or micropolitan region, and one (1) indicates a clinic is located in a small town or isolated rural region.

Distance. Based on the geocoding results, which include longitude and latitude coordinates for clinics, we estimate the distance from each organization to the economic reference center in the capital of Minnesota, which is the population center in the state. Specifically, we apply the method of great circle (geographic) distance in miles between two locations, or the distance between two points on the surface of the earth sphere (Nychka et al. 2014).

Density. Considering neighboring organizations in the same region around one clinic, the density may also affect telemedicine activities and care delivery effectiveness. We follow a GIS strategy to compute the density of all clinics from our sample to construct a density plot. One critical factor that determines the shape and coverage of map density is the bandwidth parameter. Following previous literature on the average distance a patient travels to a clinic for a general appointment, we use 15 miles as the bandwidth parameter (Arcury et al. 2005, Welch et al. 1993). Based on the density generated on the map, we classify the density of organizations into five quantile categories. To evaluate the robustness of our approach, we also test bandwidth parameters of 10 and 30 miles. The results are largely the same, as the agreement between classification with 15 and 10 miles (30 miles) is 96.7% (91.9%). Based on the consistency of results, we use 15 mile as the bandwidth parameter in our analysis. We are most interested in the lowest density organizations, so we use a dummy variable to indicate whether an organization belongs to the lowest density category.

Socioeconomic characteristics

Regional Poverty. We divide our sample into two groups based on whether clinics are located in high poverty counties or not. The poverty threshold is the overall poverty percentage in Minnesota. We assign dummy code 1 to indicate clinics located in counties with poverty levels higher than the state average poverty level, and 0 for clinics located in non-poverty counties.

Organizational characteristics

In this study, we focus on organizational characteristics specific to the challenges of telemedicine adoption. The challenges include five dimensions, and we dummy code each variable. The specific items are whether an organization faces: 1) high *cost* in telemedicine equipment and services provision; 2) *low staff expertise* or training in using telemedicine; 3) *low staff support*; 4) *low demand* for telemedicine service in the community; 5) *reimbursement issues*.

Telemedicine adoption for care delivery effectiveness

Telemedicine adoption level is the dependent variable for antecedents of telemedicine adoption, and it becomes the independent variable for the analysis of care delivery effectiveness. To avoid endogeneity issues, we construct a new variable for the analysis on consequences. First, we predict telemedicine level based on the variables in the first antecedents model. Then we construct a new variable as the difference between a clinic's raw survey level and the predicted one. In this way, we consider the extra contribution of telemedicine in the consequences model, and avoid the correlation among the telemedicine level and other predictors in the same model.

Clinical Decision Support (CDS) Systems

We measure the use of Clinical Decision Support (CDS) systems that are one component of Electronic Health Record (EHR) systems to support enhanced patient care (MDH 2014b). Investment and implementation of CDS systems produce real value only after they are used effectively to support efficient workflow and effective clinical decisions during the delivery of health care services (Minnesota Department of Health 2013). CDS systems provide clinicians and patients with clinical knowledge and patient-related information at appropriate times for real-time decision making. CDS is measured by whether an organization uses the following dimensions: 1) automated reminders for missing labs and tests; 2) chronic disease care plans and flow sheets; 3) clinical guidelines based on patient problem lists, gender, and age; 4) medication guides/alerts; 5) patient specific or condition specific reminders; 6) preventive care services due. We sum the number of CDS dimensions used (0-6). To avoid a multi-collinearity issue in the analysis with the interaction effect, we normalize the summed score for the CDS measure.

3.3.4. Control Variables

We include several control variables that might affect telemedicine adoption and care delivery effectiveness at clinics. We control for the logarithm of the total number of providers as the indicator of *clinic size*. A health care provider generally refers to a doctor of medicine or osteopathy, podiatrist, dentist, chiropractor, clinical psychologist, optometrist, nurse practitioner, nurse-midwife, or a clinical social worker who is authorized to practice by the State and performing within the scope of their practice. We also control for medical group size (i.e., the number of clinics affiliated with a medical group), using a dummy variable, with *small medical group* indicating five or fewer clinics. The focal activities in clinics may also determine the number of CDS systems and consequent care delivery effectiveness, and we use a dummy variable to indicate whether the clinic focuses on specialty care or primary care. We control for Health Professional Shortage Areas (HPSA), the designation for medically underserved areas or populations, which can interact with government job policies and physician payments (Health Resources and Services Administration 2015, MDH 2014a). We obtain shortage designation data from the Health Resources and Services Administration[2], and create a dummy variable to measure whether a clinic is located in a HPSA region after 2010. EHR system vendors might introduce specific requirements for skills and capabilities which can result in differing care delivery effectiveness. Therefore we use a dummy variable to indicate if a clinic uses an EPIC system, to control for the dominate vendor. Since there are two years of survey data, we control for the year effect. The stage of EHR systems or other health IT may also determine the outcome in health care delivery (Dey et al. 2013). We control for four related dimensions: 1) use of Office of the National Coordinator (ONC)-certified EHR systems; 2) application for meaningful use incentive; 3) E-prescribing of non-controlled substances (i.e., over 80% of clinic's prescriptions are electronic); 4) paperless documentation for patient information. We code each dimension as a dummy variable, yes (1) or no (1).

Needs for workforce skills. Human capital may play an important role during technology adoption and use (Kong et al. 2012, Nag and Gioia 2012, Osheroff 2009, Aral and Weill 2007). The estimated results of technology's impact on organizational performance might be biased by omitted variables related to human capital. Employee skills at both clinic and medical group levels determine organizational knowledge

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[2] http://datawarehouse.hrsa.gov/data/datadownload/hpsadownload.aspx

competence. Provider skills relating to EHR systems may be complementary factors that enable CDS adoption and use for better outcomes. We operationalize workforce skills in clinics based on their indicated needs for staff who have skills in facilitating EHR system preparation and use, information technology, informatics, and/or training. We include a normalized scale of variables indicating whether clinics have *EHR system/IT staff needs*. We also include two dummy variables for *informatics staff needs* (i.e., need for informatics nurses, clinicians, or other staff) and *trainer needs.*

3.3.5. Statistical Analysis Approach

To model the hierarchical levels of clinics and medical groups, we conduct Hierarchical Linear Modeling (HLM) to analyze the data. HLM is widely used to study multilevel data (Nair et al. 2013, Chandrasekaran et al. 2012, Raudenbush and Bryk 2002, 2002). Most of the sample clinics are affiliated with a medical group, and clinics in the same group may be more homogenous than those across different groups. For example, it is possible that a medical group makes decisions regarding telemedicine and CDS adoption for all of its clinics. HLM is an appropriate method for data with this structure. For the two outcome variables -- the adoption level of telemedicine and care delivery effectiveness -- we conduct Likelihood Ratio (LR) tests on random effects to justify the choice of HLM (Nair et al. 2013). The HLM analysis approach is similar for both outcome variables. We focus on the average medical group level effects on clinic outcomes. Therefore, we investigate the independent variables at the medical group level, and we include medical group average measures as well as the hypothesized interaction term into the second level, as well as other control variables.

We specify the statistical model for the two outcome variables as following:

Level 1 - Clinics: $Y_{ij} = \beta_{0j} + \epsilon_{ij}$

Level 2 – Medical Groups: $\beta_{0j} = \gamma_{00} + \gamma_{1j}X_1 + \gamma_{2j}X_2 + \gamma_{3j}X_1 \times X_2 + \delta C_j + \mu_{0j}$

Where:

X – Independent variables,
C – Control variables at medical level,
j – Medical group j,
i – Clinic i.

3.4. Results

3.4.1. Descriptive Analysis

Table 3-1 reports the descriptive statistics and correlations among the key variables. The mean distance from clinics to the Twin Cities is 53.15 miles and the median is 18.26 miles. This indicates that a majority of clinics are close to the population center of the state, while some remote clinics positively skew the data. The proportion of clinics located in rural areas is 17% on average across medical groups. Two-thirds of clinics provide services in regions where the poverty level is above the median state level, while one-third of clinics are located in Health Professional Shortage Areas.

The correlation between telemedicine adoption level and overall care delivery effectiveness is 0.19, while the correlation between CDS adoption level and effectiveness is 0.65. As a robustness check, we develop several alternative measures of care delivery effectiveness. Among correlations between each of them and our main measure of care delivery effectiveness, we find that correlations are all above 0.54. Among the independent variables, we find that there are generally no strong correlations, except between the two geographic location variables, distance and urban vs. rural. In our analysis, we apply orthogonal polynomial transformation of distance to reduce potential collinarity issues.

Table 3-1. Descriptive Statistics for Variables

	mean	median	sd	min	max	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22
1.Care delivery effectiveness	4.44	5.00	2.79	0.00	8.00																						
2. Medical, clinical, and lab alerts and reminders	2.86	3.00	1.79	0.00	5.00	0.97																					
3. Patient care enhancement	0.66	1.00	0.47	0.00	1.00	0.74	0.66																				
4. Lab result availability	0.37	0.00	0.48	0.00	1.00	0.70	0.60	0.35																			
5. Clinic guidelines	0.55	1.00	0.50	0.00	1.00	0.75	0.62	0.54	0.50																		
6. Internal quality improvement	3.00	3.00	1.18	0.00	4.00	0.54	0.53	0.48	0.24	0.45																	
7. Telemedicine activity types	0.80	0.00	1.18	0.00	3.00	0.19	0.19	0.16	0.04	0.19	0.17																
8. Number of clinic decision support (CDS) systems [a]	3.45	3.95	2.13	0.00	6.00	0.65	0.66	0.41	0.40	0.50	0.43	0.25															
9. Small Medical Group	0.30	0.00	0.46	0.00	1.00	-0.31	-0.29	-0.21	-0.21	-0.29	-0.21	-0.17	-0.38														
10. Use of ONC-certified EHR system [a]	0.88	1.00	0.30	0.00	1.00	0.25	0.25	0.23	0.20	0.13	0.27	0.04	0.24	-0.15													
11. EHR Vendor: Epic	0.40	0.00	0.49	0.00	1.00	0.43	0.43	0.23	0.37	0.32	0.22	0.13	0.52	-0.33	0.19												
12. Number of providers in the clinic (log) [a]	2.04	2.05	0.62	-0.69	4.36	0.25	0.25	0.16	0.17	0.18	0.17	0.02	0.19	-0.16	-0.02	0.26											
13. Rural vs. urban location [a]	0.17	0.00	0.29	0.00	1.00	-0.01	0.04	-0.03	-0.12	-0.06	0.03	0.32	0.01	0.13	-0.10	-0.03	-0.20										
14. Full use of electronic documentation [a]	0.74	1.00	0.42	0.00	1.00	0.21	0.16	0.18	0.21	0.21	0.17	0.05	0.25	-0.10	0.28	0.36	0.16	-0.13									
15. E-prescribing of non-controlled substances [a]	0.73	1.00	0.42	0.00	1.00	0.24	0.26	0.14	0.20	0.12	0.14	-0.12	0.25	-0.11	0.08	0.22	0.11	0.14	0.13								
16. Application for meaningful use incentive [a]	0.80	1.00	0.37	0.00	1.00	0.25	0.24	0.19	0.13	0.22	0.22	0.13	0.35	-0.22	0.32	0.18	0.08	-0.14	0.15	0.10							
17. Specialty vs. primary care [a]	0.35	0.12	0.40	0.00	1.00	-0.39	-0.42	-0.22	-0.17	-0.27	-0.29	-0.29	-0.35	0.14	-0.11	-0.32	-0.27	-0.28	-0.13	-0.22	-0.07						
18. High poverty region vs. low [a]	0.67	0.73	0.29	0.00	1.00	0.03	0.00	-0.02	0.11	0.04	0.03	-0.04	0.06	-0.03	0.05	0.21	0.01	0.00	0.19	0.09	-0.02	-0.02					
19. Health professional shortage areas - primary care (after 2010) [a]	0.33	0.20	0.31	0.00	1.00	0.07	0.06	0.04	0.12	0.02	-0.07	0.08	0.05	-0.03	-0.07	0.20	0.11	0.14	0.11	0.01	0.01	0.01	0.48				
20. EHR/IT staff needs [a,b]	0.00	0.31	0.96	-0.92	2.77	-0.22	-0.18	-0.13	-0.28	-0.20	-0.07	0.03	-0.13	0.10	-0.20	-0.28	-0.06	0.09	-0.20	-0.05	-0.11	0.04	-0.17	-0.07			
21. Informatics staff needs [a]	0.31	0.00	0.44	0.00	1.00	0.09	0.12	-0.08	0.13	0.03	-0.01	-0.01	0.14	-0.07	-0.09	0.15	0.18	0.09	0.02	0.21	-0.05	-0.09	0.17	0.05	0.06		
22 .Trainer needs [a]	0.29	0.00	0.43	0.00	1.00	-0.11	-0.10	-0.06	-0.14	-0.09	0.05	-0.16	-0.07	-0.11	-0.08	-0.17	0.10	-0.08	-0.10	0.08	0.03	-0.01	-0.12	-0.20	0.35	0.10	
23. Distance to Twin Cities [a]	53.15	18.26	58.44	0.31	293.91	-0.02	0.01	0.02	-0.15	-0.01	0.04	0.41	0.02	0.04	0.02	-0.01	-0.24	0.72	-0.07	0.14	-0.05	-0.27	0.17	0.12	0.05	0.08	-0.07

[a] Average measurement of clinics for each medical group. [b] Normalized measurement for the variable across clinics and years.

3.4.2. HLM Results

Justifying the use of HLM is important before we proceed to apply it. First, we specify the clinic and medical group levels in the null models on the two outcome variables, telemedicine adoption level and care delivery effectiveness, without any independent variables. For telemedicine adoption level, the null model in Table 3-2 reports that 61.5% (0.64 / (0.64 +0.40)) of variation is attributed to medical groups. The likelihood ratio test suggests that we reject the null hypothesis that the variance of the random intercepts of medical groups is zero ($\chi^2 = 2285; df = 1; p < 0.001$). For care delivery effectiveness, the null model in Table 3-3 reports that 75.7% (5.61 / (5.61 + 1.81)) of variation can be attributed to medical groups. The likelihood ratio test suggests that we reject the null hypothesis that the variance of the random intercepts of medical groups is zero ($\chi^2 = 2615; df = 1; p < 0.001$). The results justify the use of HLM in the analysis. In fact, analysis would be wrong and misleading if we ignored the organizational levels, because they contribute to substantial variation in the data set.

Applying HLM models to examine how variables are associated with the outcome variables, we incrementally include control variables into the base models, then the main effects of the independent predictors, next the studied interaction effects, and finally all effects in the full model. We rely on bootstrapping methods to obtain the confidence intervals for the estimates, because the diagnostic analysis indicates that the residuals do not confirm the normality assumption.

Table 3-2 reports the effects used to predict telemedicine adoption level. Model comparison using an ANOVA test based on Chi-Square statistics indicates that the final model fits the data better than reduced models. The test against the null model suggests that the base model is better ($\Delta\chi^2 = 496.53\, ; df = 9; p < 0.001$). Similarly, the test is significant between the final model and the base model ($\Delta\chi^2 = 237.45; df = 10; p < 0.001$). In the final model, medical groups with more clinics in rural areas have a higher level of telemedicine adoption ($\hat{\beta} = 0.87; p < 0.05$). Those in high poverty regions have less telemedicine adoption ($\hat{\beta} = -0.50; p < 0.05$). After controlling for other factors, we do not find evidence that distance or density of neighboring clinics are significant factors for telemedicine adoption. As for the organizational factors, we find that cost ($\hat{\beta} = -0.20; p < 0.05$) and patient demand ($\hat{\beta} = -0.19; p < 0.05$) are negatively associated with telemedicine adoption. Challenges in lack of staff expertise and training ($\hat{\beta} = 0.59; p < 0.05$), and reimbursement issues ($\hat{\beta} = 0.25; p < 0.05$) are positively associated with telemedicine adoption.

Table 3-3 reports the effects associated with care delivery effectiveness. Similar to the model predicting telemedicine adoption level, we find that the final model fits the data better than other reduced models. The test between the main effects and base models suggests the main model is better ($\Delta\chi^2 = 15.85; df = 1; p < 0.001$). Similarly, the test is also significant between the final model and the main effects model ($\Delta\chi^2 = 6.31; df = 1; p < 0.05$). The full model shows positive main effects for both main variables -- CDS and telemedicine adoption level -- controlling for other variables. As the number of CDS systems increases for a medical group, the clinics on average have improved care delivery effectiveness ($\hat{\beta} = 0.28; p < 0.05$). Similarly, when medical groups adopt higher levels of telemedicine, a positive effect is observed on clinic care delivery effectiveness ($\hat{\beta} = 0.25; p < 0.05$). Additionally, the interaction between CDS and telemedicine adoption is significantly negative ($\hat{\beta} = -0.08; p < 0.05$). The interaction effect is shown in Figure 3-2. The results show that the two studied health IT systems do not strengthen one another's effect on the outcome.

Table 3-2. Hierarchical Linear Modeling (HLM) on Telemedicine Adoption Level at Medical Group Level

Variable	M1:Null	M2:Base	M3:Full
Intercept	0.49 *	1.13 *	0.60 *
	[0.39; 0.61]	[0.78; 1.48]	[0.21; 1.00]
Small Medical Group		-0.57 *	-0.61 *
		[-0.75; -0.37]	[-0.80; -0.42]
Year: 2014		0.12 *	0.12 *
		[0.06; 0.18]	[0.06; 0.18]
Use of ONC-certified EHR system [a]		-0.41 *	-0.13 *
		[-0.54; -0.27]	[-0.26; -0.00]
EHR Vendor: Epic		0.32 *	0.24 *
		[0.17; 0.47]	[0.09; 0.39]
Number of providers in the clinic (log) [a]		0.30 *	0.38 *
		[0.19; 0.41]	[0.27; 0.49]
Fully use of electronic documentation [a]		0.41 *	0.48 *
		[0.28; 0.54]	[0.35; 0.61]
E-prescribing of non-controlled substances [a]		-0.90 *	-0.77 *
		[-1.01; -0.81]	[-0.89; -0.67]
Application for meaningful use incentive [a]		0.12 *	0.22 *
		[0.01; 0.24]	[0.10; 0.33]
Specialty vs. primary care [a]		-0.73 *	-0.49 *
		[-0.92; -0.55]	[-0.67; -0.31]
Distance to Twin Cities [a]			0.33
			[-6.87; 7.17]
Distance to Twin Cities squared [a]			1.38
			[-2.82; 5.30]
Category with lowest density of neighboring clinics			-0.03
			[-0.13; 0.08]
Rural vs. urban location [a]			0.87 *
			[0.46; 1.31]
High poverty region vs. low [a]			-0.50 *
			[-0.76; -0.21]
Health professional shortage areas - primary care (after 2010) [a]			-0.24
			[-0.53; 0.05]
Cost in equipment or in providing service [a]			-0.20 *
			[-0.28; -0.11]
Staff expertise/training(low) [a]			0.59 *
			[0.46; 0.75]
Staff support(low) [a]			0.20 *
			[0.07; 0.32]
No identified need or demand [a]			-0.19 *
			[-0.31; -0.08]
Reimbursement from payors does not cover cost [a]			0.25 *
			[0.13; 0.36]
AIC	4791.36	4347.05	4152.31
BIC	4808.49	4415.58	4283.66
Log Likelihood	-2392.68	-2161.52	-2053.16
Num. obs.	2232	2232	2232
Num. groups: MedGrp_ID	249	249	249
Variance: MedGrp_ID.(Intercept)	0.64	0.76	0.73
Variance: Residual	0.40	0.31	0.27
Model comparison		2 vs. 1	3 vs. 2
Chi-sqaure test		496.53*** (df=9)	237.45*** (df=10)

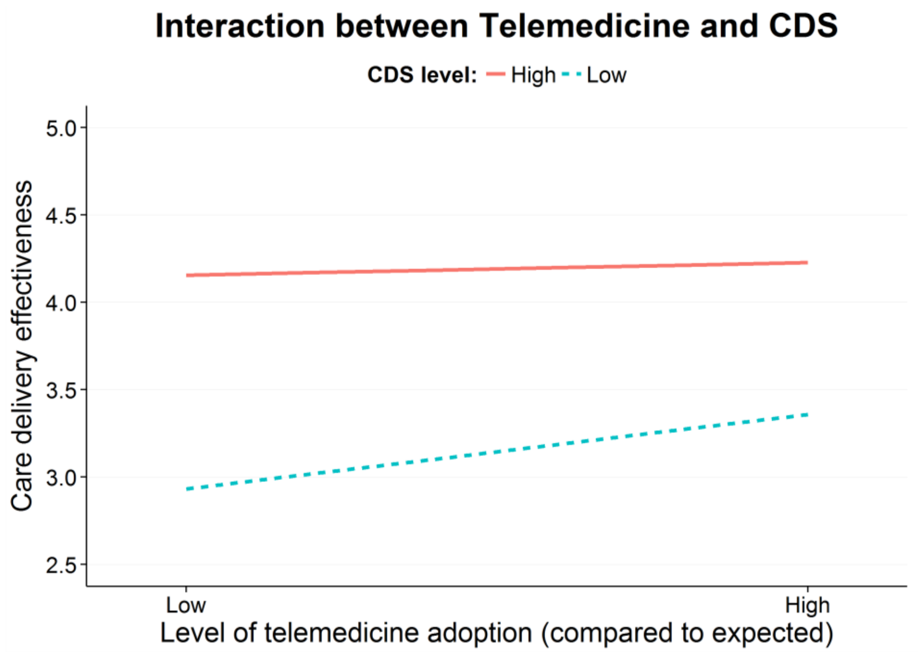
* 0 outside the confidence interval. a Average measurement of clinics for each medical group. b Normalized measurement for the variable across clinics and years. Bootstrapped CIs in brackets.

Table 3-3. Hierarchical Linear Modeling on Care Delivery Effectiveness at Medical Group Level

Variable	M1:Null	M2:Base	M3:Main	M4:Full	Alerts	Quality	Patient Care	Guidelines
Intercept	3.11 *	2.04 *	2.03 *	2.07 *	0.94 *	2.51 *	-0.83	1.69
	[2.83; 3.44]	[1.16; 2.96]	[1.15; 3.00]	[1.14; 2.98]	[0.35; 1.51]	[2.05; 3.01]	(0.59)	(1.00)
Small Medical Group		-0.30	-0.32	-0.36	0.06	-0.46 *	-1.26 ***	-1.88 ***
		[-0.69; 0.16]	[-0.77; 0.13]	[-0.76; 0.09]	[-0.22; 0.32]	[-0.71; -0.24]	(0.28)	(0.45)
Year: 2014		0.17 *	0.22 *	0.24 *	0.22 *	0.05	0.17	-0.50 **
		[0.04; 0.31]	[0.08; 0.35]	[0.11; 0.38]	[0.13; 0.30]	[-0.02; 0.13]	(0.09)	(0.17)
Use of ONC-certified EHR system [a]		0.70 *	0.63 *	0.51 *	0.52 *	0.39 *	1.96 ***	-1.26 **
		[0.38; 1.03]	[0.32; 0.93]	[0.19; 0.83]	[0.32; 0.72]	[0.22; 0.55]	(0.21)	(0.42)
EHR Vendor: Epic		-0.24	-0.31	-0.22	-0.10	-0.11	0.51 **	0.63
		[-0.57; 0.11]	[-0.66; 0.03]	[-0.58; 0.13]	[-0.31; 0.13]	[-0.29; 0.08]	(0.19)	(0.33)
Number of providers in the clinic (log) [a]		0.27 *	0.24	0.29 *	0.21 *	-0.13	0.39 *	0.63 *
		[0.00; 0.52]	[-0.02; 0.50]	[0.03; 0.55]	[0.05; 0.37]	[-0.26; 0.01]	(0.16)	(0.28)
Rural vs. urban location [a]		1.51 *	1.47 *	1.52 *	1.07 *	0.94 *	0.32	0.93
		[0.50; 2.53]	[0.46; 2.55]	[0.44; 2.57]	[0.41; 1.71]	[0.36; 1.45]	(0.64)	(0.98)
Fully use of electronic documentation [a]		-1.45 *	-1.44 *	-1.46 *	-1.04 *	0.23 *	-1.44 ***	-1.87 ***
		[-1.74; -1.16]	[-1.74; -1.14]	[-1.76; -1.18]	[-1.23; -0.86]	[0.07; 0.38]	(0.18)	(0.36)
E-prescribing of non-controlled substances [a]		1.26 *	1.25 *	1.21 *	0.70 *	-0.40 *	0.82 ***	1.58 ***
		[1.02; 1.47]	[1.02; 1.48]	[1.00; 1.43]	[0.55; 0.83]	[-0.53; -0.27]	(0.18)	(0.37)
Application for meaningful use incentive [a]		0.90 *	0.95 *	0.93 *	0.67 *	0.44 *	0.73 ***	1.50 ***
		[0.64; 1.18]	[0.67; 1.21]	[0.64; 1.21]	[0.51; 0.85]	[0.30; 0.58]	(0.17)	(0.37)
Specialty vs. primary care [a]		-0.65 *	-0.73 *	-0.72 *	-0.55 *	-0.31 *	-1.01 ***	-0.68
		[-1.10; -0.22]	[-1.17; -0.31]	[-1.14; -0.29]	[-0.82; -0.28]	[-0.53; -0.09]	(0.26)	(0.46)
Distance to Twin Cities [a]		-3.95	-2.67	-3.07	-1.42	-8.50	11.36	3.51
		[-21.06; 14.10]	[-20.67; 13.78]	[-21.16; 13.62]	[-12.32; 9.98]	[-17.06; 1.02]	(10.79)	(16.43)
Distance to Twin Cities squared [a]		8.29	7.97	7.12	5.28	1.71	0.03	7.88
		[-2.29; 18.51]	[-2.16; 17.44]	[-3.20; 17.50]	[-1.25; 11.71]	[-3.52; 7.41]	(6.50)	(10.34)
Category with lowest density of neighboring clinics		-0.03	-0.04	-0.03	-0.00	0.06	-0.20	-0.16
		[-0.27; 0.22]	[-0.26; 0.21]	[-0.28; 0.22]	[-0.15; 0.15]	[-0.07; 0.18]	(0.17)	(0.33)
High poverty region vs. low [a]		0.46	0.53	0.55	0.34	0.16	0.38	-0.24
		[-0.30; 1.06]	[-0.12; 1.24]	[-0.17; 1.26]	[-0.08; 0.78]	[-0.21; 0.53]	(0.41)	(0.67)
Health professional shortage areas - primary care (after 2010) [a]		-0.12	-0.15	-0.18	-0.12	0.04	-0.36	-1.74 *
		[-0.81; 0.54]	[-0.84; 0.56]	[-0.85; 0.51]	[-0.53; 0.31]	[-0.32; 0.40]	(0.42)	(0.70)
EHR/IT staff needs [a,b]		-0.46 *	-0.46 *	-0.46 *	-0.28 *	-0.12 *	-0.27 ***	-1.00 ***
		[-0.57; -0.34]	[-0.59; -0.34]	[-0.59; -0.33]	[-0.36; -0.19]	[-0.19; -0.06]	(0.07)	(0.15)
Informatics staff needs [a]		-0.55 *	-0.62 *	-0.64 *	-0.25 *	-0.16 *	-2.03 ***	-1.58 ***
		[-0.81; -0.29]	[-0.89; -0.37]	[-0.91; -0.39]	[-0.41; -0.08]	[-0.29; -0.02]	(0.16)	(0.32)
Trainer needs [a]		-0.61 *	-0.62 *	-0.57 *	-0.09	0.19 *	-0.69 ***	-1.60 ***
		[-0.87; -0.34]	[-0.88; -0.38]	[-0.83; -0.31]	[-0.25; 0.07]	[0.06; 0.32]	(0.17)	(0.28)
Number of clinic decision support (CDS) tools [a]		0.22 *	0.23 *	0.28 *	0.16 *	0.10 *	0.19 ***	0.96 ***
		[0.16; 0.29]	[0.15; 0.29]	[0.20; 0.35]	[0.11; 0.21]	[0.06; 0.14]	(0.06)	(0.11)
Telemedicine (higher than expected)			0.24 *	0.25 *	0.16 *	0.17 *	0.96 ***	0.06
			[0.11; 0.35]	[0.13; 0.37]	[0.09; 0.23]	[0.11; 0.23]	(0.09)	(0.15)
Number of clinic decision support (CDS) tools [a] x Telemedicine (higher than expected)				-0.08 *	-0.02	0.00	0.06	0.04
				[-0.15; -0.02]	[-0.06; 0.03]	[-0.03; 0.04]	(0.04)	(0.09)
AIC	8314.22	7939.45	7929.43	7930.27	5903.35	5168.91		
BIC	8331.35	8065.09	8060.77	8067.32	6040.41	5305.96		
Log Likelihood	-4154.11	-3947.73	-3941.71	-3941.13	-2927.68	-2560.45		
Num. obs.	2232	2232	2232	2232	2232	2232	2232	2232
Num. groups: MedGrp_ID	249	249	249	249	249	249	249	249
Variance: MedGrp_ID.(Intercept)	5.61	4.35	4.43	4.38	1.78	1.24		
Variance: Residual	1.81	1.51	1.49	1.49	0.60	0.43		
Model comparison		2 vs. 1	3 vs. 2	4 vs.3				
Chi-sqaure test		438*** (df=19)	15.85*** (df=1)	6.31* (df=1)				

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$ (or 0 outside the confidence interval).. [a] Average measurement of clinics for each medical group. [b] Normalized measurement for the variable across clinics and years. Bootstrapped CIs in brackets.

Figure 3-2. The Consequence of Telemedicine on Care Delivery Effectiveness



3.4.3. Robustness Analysis

We conduct several additional analyses to ensure that our findings are robust to the choice of outcome measures and analysis approaches. Our analysis focuses on care delivery effectiveness in clinics. We analyze the grouped dimensions of the dependent variable of care delivery effectiveness, and include a quality measure as an additional measure. Specifically, we firstly measure performance on the medication, lab, drug order and prevention alerts and reminders, and obtain the total score. Secondly, we measure quality as the sum of benchmarks/clinical priority development, data sharing with providers, clinical guidelines set up, and professional development support. Thirdly, we conduct analysis using patient care enhancement as the outcome variable. The fourth outcome variable is the adherence to clinic guidelines. For analysis, we apply HLM to test the model on alerts and quality. Since patient care and adherence to clinic guidelines are single-item measures, we use a Generalized Linear Mixed Model (GLMM) with multivariate normal random effects and Penalized Quasi-Likelihood to estimate our model. The results for the four alternative health care delivery performance measurements are reported in Table 3-3.

Significantly positive effects of CDS systems and telemedicine adoption level are supported by all models. This suggests that the main effects are robust regardless the choice of performance measures. However, the interaction effect between CDS systems and telemedicine adoption varies. Similar to the results on care delivery effectiveness, the interaction is significantly negative on alerts and reminders. In contrast, the interaction is significantly positive on clinic guideline adherence. The interaction on quality and patient care enhancement is not significant.

Medical group size varies substantially in our sample data, ranging from 1 to 59. We test whether group size impacts results. We divide the sample into four categories: 1) one clinic, 2) between 1 and 10, 3) between 10 and 30, and 4) more than 30 clinics. We apply ordinary least squares (OLS) regression analysis in the category with one clinic, and HLM in other categories. We show the results in Table 3-4. Overall, we find that the results are qualitatively similar, while differences exist for the interaction effect. CDS systems have a positive effect in categories 1 and 2 with small numbers of clinics, and a positive but not significant effect in category 3. In category 4, medical groups of more than 30 clinics, CDS systems has a significant negative effect. As for telemedicine adoption, its effect is positive but non-significant in categories 2 and 3, and negative but non-significant in the two extreme categories, 1 and 4. The CDS and telemedicine interaction effects are negative in the first three categories and significant in category 2. However, in the last category, the interaction effect becomes significantly positive. The results suggest there might be different mechanisms in different group sizes, which can shift the direction of the telemedicine and CDS effect on care delivery. The variation of the interaction effect across medical group size categories justifies controlling for medical group size in our main model.

The use of the bootstrapping method helps us to relax the assumptions about data distribution, though it becomes less efficient when we conduct inference analysis. For comparison, we re-run our model on care delivery effectiveness, alerts and reminders, and quality improvement, with the assumption of normality in the residuals. Table 3-5 has similar results for main and interaction effects for telemedicine and CDS systems, compared to the results using the bootstrapping method.

3.4.4. Endogeneity Issues

Our HLM estimation for telemedicine adoption following adoption of EHR systems may suffer from endogeneity. The propensity to use telemedicine may not be completely exogenous to organizational practices and performance. A rational organization may strategically choose adoption of technology such as telemedicine to improve outcomes, which violates the assumption of randomness in choice of technologies. Also, the data set may not reveal some critical factors that relate to technology use, due to the limitations in this observational research. For example, clinics which focus on certain types of the care (e.g., stroke care) may see more value from telemedicine and decide to actively apply the new technology in their care delivery. However, it is impossible to obtain full data on every possible relevant factor. Therefore, our estimation based on the observed adoption level of telemedicine may lead to biased results.

Table 3-4. Care Delivery Effectiveness across Medical Group Size at Medical Group Level

Variable	M1: =1	M2: (1,10]	M3: (10,30]	M4: >30
Intercept	2.21 ***	-0.62	-6.10	54.01
	(0.66)	[-2.20; 0.87]	[-28.71; 16.93]	[-18.02; 120.38]
Year: 2014	0.01	0.21 *	-0.21	7.90 *
	(0.31)	[0.03; 0.39]	[-1.06; 0.63]	[2.57; 13.53]
Use of ONC-certified EHR system [a]	0.33	-0.07	0.56	13.53 *
	(0.42)	[-0.46; 0.32]	[-4.97; 6.61]	[1.89; 24.07]
EHR Vendor: Epic	0.93	1.78 *	2.04 *	1.07 *
	(0.47)	[1.00; 2.56]	[1.41; 2.69]	[0.49; 1.68]
Number of providers in the clinic (log) [a]	0.39 *	0.85 *	4.19 *	1.43
	(0.17)	[0.44; 1.28]	[1.00; 7.42]	[-7.61; 10.84]
Rural vs. urban location [a]	-0.14	3.36 *	-6.23	-66.12
	(0.62)	[1.69; 5.08]	[-23.05; 9.01]	[-137.88; 5.63]
Fully use of electronic documentation [a]	-0.27	-0.82 *	-8.14 *	-27.76 *
	(0.34)	[-1.14; -0.49]	[-12.15; -4.35]	[-58.45; -0.05]
E-prescribing of non-controlled substances [a]	0.51	1.50 *	3.10	-1.73
	(0.38)	[1.12; 1.86]	[-6.32; 11.56]	[-7.79; 3.93]
Application for meaningful use incentive [a]	0.42	1.06 *	9.03 *	-17.43
	(0.33)	[0.70; 1.43]	[2.61; 14.89]	[-38.20; 4.06]
Specialty vs. primary care [a]	-1.00 **	-1.43 *	-3.89	-12.93
	(0.35)	[-2.21; -0.62]	[-19.07; 10.79]	[-28.34; 1.60]
Distance to Twin Cities [a]	8.48	-40.52 *	-100.43	532.20
	(11.03)	[-69.92; -11.40]	[-269.42; 84.12]	[-237.24; 1251.31]
Distance to Twin Cities squared [a]	-3.97	29.41 *	-229.88 *	-34.45
	(5.20)	[9.49; 50.40]	[-433.29; -48.60]	[-1171.39; 1052.26]
Category with lowest density of neighboring clinics	0.79	0.15	-0.01	-0.00
	(0.68)	[-0.24; 0.54]	[-0.45; 0.42]	[-0.25; 0.23]
High poverty region vs. low [a]	-0.15	1.81 *	-2.84	-35.18
	(0.35)	[0.62; 2.94]	[-25.18; 16.81]	[-103.58; 33.83]
Health professional shortage areas - primary care (after 2010) [a]	0.01	-1.05	10.76	25.02
	(0.36)	[-2.15; 0.18]	[-7.69; 31.79]	[-27.89; 75.23]
EHR/IT staff needs [a,b]	-0.28	-0.26 *	-0.68	-5.05
	(0.14)	[-0.42; -0.12]	[-3.71; 2.17]	[-12.08; 2.42]
Informatics staff needs [a]	-0.52	-0.24	-6.32 *	1.54
	(0.37)	[-0.55; 0.08]	[-10.99; -1.90]	[-9.58; 12.53]
Trainer needs [a]	0.26	0.15	0.81	-0.84
	(0.42)	[-0.18; 0.47]	[-2.26; 3.82]	[-12.97; 10.70]
Number of clinic decision support (CDS) tools [a]	0.57 ***	0.24 *	0.61	-0.87 *
	(0.12)	[0.12; 0.36]	[-0.12; 1.35]	[-1.73; -0.07]
Telemedicine (hihger than expected)	-0.06	0.06	0.45	-0.24
	(0.37)	[-0.21; 0.32]	[-0.05; 0.94]	[-0.64; 0.18]
Number of clinic decision support (CDS) tools [a] x Telemedicine (hihger than expected)	-0.15	-0.19 *	-0.35	0.71 *
	(0.16)	[-0.29; -0.08]	[-0.71; 0.00]	[0.48; 0.94]
R^2	0.48			
Adj. R^2	0.42			
Num. obs.	187	792	444	809
AIC		2602.41	1475.75	2055.72
BIC		2709.92	1569.96	2163.73
Log Likelihood		-1278.20	-714.88	-1004.86
Num. groups: MedGrp_ID		113	17	12
Variance: MedGrp_ID.(Intercept)		5.08	32.53	46.62
Variance: Residual		0.89	1.33	0.68

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$ (or 0 outside the confidence interval).. [a] Average measurement of clinics for each medical group. [b] Normalized measurement for the variable across clinics and years.

Table 3-5. Hierarchical Linear Modeling on Care Delivery Effectiveness at Medical Group Level

Variable	M1: Effectiveness	M2: Alerts	M3: Quality
Intercept	2.07 ***	0.94 **	2.51 ***
	(0.47)	(0.30)	(0.25)
Small Medical Group	-0.36	0.06	-0.46 ***
	(0.22)	(0.14)	(0.12)
Year: 2014	0.24 ***	0.22 ***	0.05
	(0.07)	(0.04)	(0.04)
Use of ONC-certified EHR system [a]	0.51 **	0.52 ***	0.39 ***
	(0.17)	(0.11)	(0.09)
EHR Vendor: Epic	-0.22	-0.10	-0.11
	(0.17)	(0.11)	(0.09)
Number of providers in the clinic (log) [a]	0.29 *	0.21 *	-0.13
	(0.13)	(0.08)	(0.07)
Rural vs. urban location [a]	1.52 **	1.07 **	0.94 ***
	(0.53)	(0.34)	(0.28)
Fully use of electronic documentation [a]	-1.46 ***	-1.04 ***	0.23 **
	(0.15)	(0.10)	(0.08)
E-prescribing of non-controlled substances [a]	1.21 ***	0.70 ***	-0.40 ***
	(0.11)	(0.07)	(0.06)
Application for meaningful use incentive [a]	0.93 ***	0.67 ***	0.44 ***
	(0.14)	(0.09)	(0.07)
Specialty vs. primary care [a]	-0.72 ***	-0.55 ***	-0.31 **
	(0.21)	(0.14)	(0.11)
Distance to Twin Cities [a]	-3.07	-1.42	-8.50
	(8.73)	(5.55)	(4.65)
Distance to Twin Cities squared [a]	7.12	5.28	1.71
	(5.16)	(3.28)	(2.75)
Category with lowest density of neighboring clinics	-0.03	-0.00	0.06
	(0.12)	(0.08)	(0.07)
High poverty region vs. low [a]	0.55	0.34	0.16
	(0.35)	(0.22)	(0.19)
Health professional shortage areas - primary care (after 2010) [a]	-0.18	-0.12	0.04
	(0.35)	(0.22)	(0.19)
EHR/IT staff needs [a,b]	-0.46 ***	-0.28 ***	-0.12 ***
	(0.06)	(0.04)	(0.03)
Informatics staff needs [a]	-0.64 ***	-0.25 **	-0.16 *
	(0.13)	(0.08)	(0.07)
Trainer needs [a]	-0.57 ***	-0.09	0.19 **
	(0.13)	(0.08)	(0.07)
Number of clinic decision support (CDS) tools [a]	0.28 ***	0.16 ***	0.10 ***
	(0.04)	(0.02)	(0.02)
Telemedicine (hihger than expected)	0.25 ***	0.16 ***	0.17 ***
	(0.06)	(0.04)	(0.03)
Number of clinic decision support (CDS) tools [a] x Telemedicine (hihger than expected)	-0.08 *	-0.02	0.00
	(0.03)	(0.02)	(0.02)
AIC	7930.27	5903.35	5168.91
BIC	8067.32	6040.41	5305.96
Log Likelihood	-3941.13	-2927.68	-2560.45
Num. obs.	2232	2232	2232
Num. groups: MedGrp_ID	249	249	249
Variance: MedGrp_ID.(Intercept)	4.38	1.78	1.24
Variance: Residual	1.49	0.60	0.43

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$. [a] Average measurement of clinics for each medical group. [b] Normalized measurement for the variable across clinics and years. Significance level is based on p-value.

To address the sample selection effect and other unobserved effects, we apply two methods, propensity score matching and panel data analysis, to check the consistency of our results (McCaffrey et al. 2004, 2013, Wooldridge 2010, Angrist and Pischke 2008). Propensity scores have been used to match, stratify, or weight the samples from treatment and control groups, which can reduce disparities on pretreatment characteristics and selection bias (McCaffrey et al. 2013). Rosenbaum and Rubin (1983) suggest that, conditional on the probability of assignment, adjustment can provide unbiased treatment effects by the equally distributed samples in both groups. In our analysis, it allows us to identify pre-adoption factors that could determine the use of telemedicine, and to match the treated with the untreated group of clinics based on similar characteristics. Such correction of imbalance between groups can lead us to make causal inference on the treatment effect. In the second analysis, panel data analysis is helpful for analysis with observations across time periods, and it is also flexible in specification under different assumptions. Our data set has measurements for each clinic for two years, and we can use the short panel to explore further the nature of antecedents and consequences in telemedicine adoption.

3.4.4.1. Propensity Score Analysis

In the choice model, we investigate the pre-adoption factors that can affect the decision on level of telemedicine adoption. We include variables from potential causes in our model, such as year, specialty, vendor, use of electronic documentation, distance, density of clinics, rural vs urban, poverty, Health Professional Shortage Area, and medical group size. We assume these factors are exogenous to the outcome measure of care delivery effectiveness. We also include organizational variables like cost, staff expertise, support, local demand and reimbursement as predictors.

Depending on the operationalization of telemedicine adoption, we apply three strategies in our propensity score for: 1) any level of adoption, 2) full adoption, 3) three category of adoption: None, Low and High. For the first two strategies, the treatment is defined as 0 (none) or 1 (adoption). And for the third strategy, we have three treatments, 0 (none), 1(low) and 2(high). In the last strategy we follow estimation for multiple treatments using generalized boosted models (McCaffrey et al. 2013). Before we conduct outcome analysis, we carefully check the fitness and balance improvement in the choice model.

We report the results of the choice model for any (strategy 1) and full (strategy 2) adoption of telemedicine in Table 3-6. The results indicate that group size, specialty, vendor, distance, and organizational characteristics are significant determinants of the choice of telemedicine adoption. The results are similar to our main analysis for the antecedents in telemedicine adoption. For example, while poverty and cost are also negative predictors, low demand is a barrier. Distance from population center is positively associated with telemedicine adoption. Staff expertise and reimbursement issues are positively associated with adoption. Clinics in larger medical groups are also more likely to adopt telemedicine.

In the outcome analysis in Table 3-7, we find that the studied effects depend on the level of telemedicine adoption. We find that CDS systems are positively related to care delivery effectiveness in both the average treatment effect (ATE) and average treatment effect on the treated (ATT) models. For the effect of telemedicine adoption, it varies across approaches. We find positive estimation in the ATT model for any adoption, and the interaction with CDS is negative. The results in the full adoption model are quite different, where the main effect for telemedicine is negative, while the interaction effect is positive. This may suggest that clinics with full adoption of telemedicine, in fact, lose care delivery effectiveness, compared to if they adopted a lower level or none. Yet, telemedicine reinforces the benefits from CDS for clinics with full adoption.

When we operationalize telemedicine as treatment of none, low, and high levels (strategy 3), the results are reported in Table 3-8. Again, CDS systems are positively associated with care delivery outcome in all models. The effects of telemedicine adoption and its interaction vary across treatment groups. Comparing pairwise average treatment effects in the three sub-samples (M1:ATE), we find that the outcome measure is significantly lower in the high treatment group than the none treatment group. A similar result is shown in the ATT none treatment model, and clinics with no telemedicine see a significant reduction in outcome score if they choose a high level of telemedicine. A positive effect of telemedicine adoption is found in the group of clinics with low level adoption, compared to if they had chosen no adoption. The interaction effect is only present in the ATT none treatment model, which indicates the potential adoption of a high level of telemedicine may strengthen the effect of CDS.

The results from propensity score analysis confirm that clinics strategically choose their telemedicine adoption level to maximize its benefits. For those with sufficient resources, clinics choose the appropriate level of telemedicine to improve care delivery effectiveness. Such benefits may be obtained directly through telemedicine, or the reinforcement of telemedicine on CDS. For those with limited resources, clinics avoid the adoption of telemedicine because they would suffer a loss in care delivery effectiveness. The results highlight the interplay between organizational contexts and telemedicine adoption. Therefore, telemedicine should be aligned with organizational-specific factors for best performance. And our study on the causes and consequences of telemedicine in the CDS setting makes the first step in understanding these situational nuances in adoption effects.

Table 3-6. Logit Model for Propensity Score Analysis on Telemedicine at Clinic Level

Variable	M1: Any Adoption	M2: Full Adoption
Intercept	-3.89 ***	-8.01 ***
	(0.37)	(0.76)
Group size (b)	1.23 ***	2.28 ***
	(0.31)	(0.60)
Group size (c)	1.98 ***	3.82 ***
	(0.31)	(0.61)
Group size (d)	0.95 **	1.84 **
	(0.31)	(0.58)
Group size (e)	2.06 ***	4.31 ***
	(0.31)	(0.63)
Year: 2014	-0.18	1.43 ***
	(0.12)	(0.17)
Specialty vs. primary care	-0.38 **	-1.06 ***
	(0.14)	(0.23)
EHR Vendor: Epic	0.33 *	0.87 ***
	(0.15)	(0.20)
Number of providers in the clinic (log)	-0.06	0.12
	(0.06)	(0.08)
Fully use of electronic documentation	0.08	0.11
	(0.15)	(0.23)
Distance to Twin Cities	0.02 ***	0.02 ***
	(0.00)	(0.00)
Category with lowest density of neighboring clinics	0.44	0.58
	(0.23)	(0.31)
Rural vs. urban location	-0.01	-0.00
	(0.20)	(0.24)
High poverty region vs. low	-0.18	-0.62 **
	(0.13)	(0.19)
Health professional shortage areas - primary care (after 2010)	0.21	0.47 *
	(0.13)	(0.18)
Cost in equipment or in providing service	-0.16	-0.11
	(0.13)	(0.19)
Staff expertise/training(low)	1.01 ***	1.77 ***
	(0.17)	(0.24)
Staff support(low)	0.60 ***	-0.89 **
	(0.17)	(0.32)
No identified need or demand	-1.18 ***	-4.71 ***
	(0.16)	(0.48)
Reimbursement from payors does not cover cost	1.49 ***	1.31 ***
	(0.14)	(0.20)
AIC	2019.52	1124.16
BIC	2133.74	1238.37
Log Likelihood	-989.76	-542.08
Deviance	1979.52	1084.16
Num. obs.	2232	2232

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.

Table 3-7. Propensity Score Outcome Analysis After Balance on Telemedicine at Clinic Level

	Any Adoption			Full Adoption		
Variable	**M1(unw)**	**M2(ATE)**	**M3(ATT)**	**M1(unw)**	**M2(ATE)**	**M3(ATT)**
Intercept	4.56 ***	3.35 ***	4.11 ***	7.08 ***	7.02 ***	8.41 ***
	(0.28)	(0.26)	(0.28)	(0.54)	(0.67)	(0.60)
Year: 2014	0.16	-0.24 *	0.10	-0.92 ***	-0.74 ***	-1.10 ***
	(0.10)	(0.10)	(0.10)	(0.16)	(0.18)	(0.16)
Specialty vs. primary care	-1.16 ***	-0.93 ***	-1.23 ***	-0.97 ***	-1.07 ***	-0.47
	(0.13)	(0.12)	(0.13)	(0.24)	(0.24)	(0.25)
EHR Vendor: Epic	0.07	0.74 ***	-0.04	-0.33	0.20	-0.09
	(0.13)	(0.13)	(0.13)	(0.21)	(0.23)	(0.20)
Number of providers in the clinic (log)	0.06	0.21 ***	0.11 *	0.02	0.07	0.13
	(0.05)	(0.05)	(0.05)	(0.07)	(0.06)	(0.07)
Fully use of electronic documentation	-0.55 ***	-0.69 ***	-0.79 ***	-1.14 ***	-0.64 **	-1.69 ***
	(0.13)	(0.12)	(0.12)	(0.21)	(0.22)	(0.20)
Distance to Twin Cities	-0.00 *	-0.00	-0.00 **	-0.01 ***	-0.00 *	-0.01 ***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Category with lowest density of neighboring clinics	-0.58 **	-0.69 ***	-0.43 *	-0.55	1.33 ***	-0.51
	(0.19)	(0.20)	(0.18)	(0.29)	(0.31)	(0.29)
Rural vs. urban location	0.10	0.32 *	-0.17	-0.09	0.40	-0.02
	(0.16)	(0.15)	(0.13)	(0.22)	(0.23)	(0.19)
High poverty region vs. low	-0.19	0.05	0.08	0.43 *	-0.03	0.32
	(0.11)	(0.11)	(0.11)	(0.18)	(0.06)	(0.18)
Health professional shortage areas - primary care (after 2010)	0.05	0.09	-0.43 ***	-0.36 *	-0.07 *	-0.03
	(0.12)	(0.11)	(0.11)	(0.17)	(0.03)	(0.17)
Small Medical Group	0.26 *	-0.16	0.61 ***	0.45 *	-1.21 ***	0.78 ***
	(0.13)	(0.10)	(0.12)	(0.22)	(0.20)	(0.20)
E-prescribing of non-controlled substances	0.41 **	0.34 **	0.40 **	-1.21 ***	-1.69 ***	-1.67 ***
	(0.13)	(0.12)	(0.12)	(0.23)	(0.22)	(0.21)
Application for meaningful use incentive	-0.12	-0.57 ***	0.35 *	0.33	0.47	0.83 ***
	(0.15)	(0.14)	(0.14)	(0.26)	(0.26)	(0.24)
Use of ONC-certified EHR system	0.79 ***	1.89 ***	0.91 ***	1.26 **	0.26	0.39
	(0.18)	(0.17)	(0.18)	(0.38)	(0.54)	(0.45)
EHR/IT staff needs [b]	-0.32 ***	-0.07	-0.33 ***	-0.68 ***	-0.58 ***	-0.84 ***
	(0.06)	(0.05)	(0.05)	(0.10)	(0.09)	(0.09)
Informatics staff needs	0.05	-0.26 *	-0.08	0.22	0.39 *	-0.17
	(0.12)	(0.12)	(0.11)	(0.18)	(0.19)	(0.17)
Trainer needs	-0.48 ***	-0.21	-0.29 *	-0.05	-1.27 ***	-0.28
	(0.13)	(0.12)	(0.13)	(0.20)	(0.20)	(0.22)
Treatment	0.35 **	0.09	0.41 ***	-0.06	-0.63 **	-0.54 ***
	(0.11)	(0.10)	(0.10)	(0.17)	(0.20)	(0.16)
Number of clinic decision support (CDS) tools	0.73 ***	0.62 ***	0.69 ***	0.65 ***	0.42 ***	0.47 ***
	(0.04)	(0.04)	(0.04)	(0.06)	(0.07)	(0.05)
Treatment x Number of clinic decision support (CDS) tools	-0.11 *	0.05	-0.06	0.07	0.24 **	0.24 **
	(0.05)	(0.05)	(0.05)	(0.08)	(0.09)	(0.07)
R^2	0.50	0.54	0.55	0.52	0.85	0.52
Adj. R^2	0.49	0.54	0.54	0.51	0.85	0.51
Num. obs.	1554	1554	1554	648	648	648

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$. Analysis at clinic level.

Table 3-8. Propensity Score Outcome Analysis after Balancing (Multiple Treatments in Telemedicine) at Clinic Level

Variable	M1: ATE	M2: ATT(None)	M3: ATT(Low)	M4: ATT(High)
Intercept	4.33 ***	3.97 ***	3.70 ***	6.71 ***
	(0.31)	(0.36)	(0.28)	(0.50)
Year: 2014	0.09	0.07	0.35 *	-0.81 ***
	(0.14)	(0.14)	(0.14)	(0.18)
Specialty vs. primary care	-1.20 ***	-1.02 ***	-1.40 ***	-0.91 ***
	(0.15)	(0.16)	(0.15)	(0.20)
EHR Vendor: Epic	0.67 ***	0.99 ***	0.53 **	-0.18
	(0.15)	(0.15)	(0.17)	(0.19)
Number of providers in the clinic (log)	0.10	0.08	0.12 *	0.11
	(0.06)	(0.07)	(0.06)	(0.06)
Fully use of electronic documentation	-0.70 ***	-0.50 ***	-0.65 ***	-1.41 ***
	(0.13)	(0.13)	(0.15)	(0.18)
Distance to Twin Cities	0.00	0.00	0.00 **	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)
Category with lowest density of neighboring clinics	-0.27	-0.30	-0.31	-0.77 **
	(0.25)	(0.26)	(0.24)	(0.28)
Rural vs. urban location	0.28	0.52	0.02	0.05
	(0.23)	(0.28)	(0.19)	(0.22)
High poverty region vs. low	-0.03	-0.06	-0.14	-0.05
	(0.15)	(0.15)	(0.15)	(0.17)
Health professional shortage areas - primary care (after 2010)	-0.01	0.13	-0.16	-0.27
	(0.15)	(0.16)	(0.14)	(0.18)
Small Medical Group	-0.48 ***	-0.58 ***	-0.25	0.41
	(0.14)	(0.14)	(0.15)	(0.21)
E-prescribing of non-controlled substances	0.06	0.21	0.44 **	-1.26 ***
	(0.15)	(0.16)	(0.15)	(0.22)
Application for meaningful use incentive	-0.11	-0.12	-0.03	0.02
	(0.20)	(0.19)	(0.20)	(0.26)
Use of ONC-certified EHR system	0.89 ***	0.97 ***	0.67 **	0.84 **
	(0.20)	(0.25)	(0.22)	(0.27)
EHR/IT staff needs [b]	-0.43 ***	-0.37 ***	-0.46 ***	-0.76 ***
	(0.06)	(0.06)	(0.06)	(0.09)
Informatics staff needs	-0.11	-0.30 *	-0.10	0.40 *
	(0.13)	(0.14)	(0.13)	(0.17)
Trainer needs	-0.33 *	-0.35 *	-0.21	-0.07
	(0.14)	(0.14)	(0.15)	(0.20)
Treatment (low)	-0.12	-0.06	0.25 *	-0.08
	(0.13)	(0.17)	(0.12)	(0.21)
Treatment (high)	-0.43 *	-0.81 ***	-0.10	0.28
	(0.22)	(0.23)	(0.21)	(0.22)
Number of clinic decision support (CDS) tools	0.63 ***	0.61 ***	0.54 ***	0.77 ***
	(0.04)	(0.04)	(0.04)	(0.07)
Treatment (low) x Number of clinic decision support (CDS) tools	-0.03	0.05	-0.04	-0.10
	(0.05)	(0.06)	(0.05)	(0.10)
Treatment (high) x Number of clinic decision support (CDS) tools	0.07	0.26 **	-0.06	0.03
	(0.08)	(0.09)	(0.10)	(0.09)
Deviance	8482.06	7572.54	7696.81	8528.19
Dispersion	3.80	3.39	3.45	3.82
Num. obs.	2232	2232	2232	2232

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$. Analysis at clinic level.

3.4.4.2. Panel Data Analysis for Endogeneity

To address the concern of unobserved individual effects (i.e., effects specific to a clinic) in our main analysis, we explore the short panel nature of our data. We fit pooling effects, random effects, and first difference effects models. Since we have only two years of data (T=2), the fixed-effects model and first difference models are identical.

We report robustness analysis with a White adjustment in the standard error estimation due to the nature of the medical group clusters. Tests comparing the pooling effects, random effects, and first difference models suggest that the first difference model in most reliable. We report the analysis results in Table 3-9. The results show that CDS and telemedicine are beneficial to care delivery effectiveness, and the interaction of high level of telemedicine and CDS are significantly negative. However, the interaction for low level of telemedicine is significantly positive.

Comparing post-hoc analysis methods with our main HLM analysis, we find that our results are generally robust to propensity score analysis and panel data analysis. HLM and panel data analysis have similar specification on the individual effect, especially between HLM and the random effects model. Propensity score analysis allows us to examine the pre-adoption clinic factors and their role on the adoption choice, which supports the logic of our HLM analysis and its factors in adoption.

We rely on the HLM analysis to draw conclusions because the HLM model is more appropriate for our data and research focus. First, panel data analysis is not as flexible as HLM f because the majority of variation in our data comes from the medical group level. HLM allows us to examine how medical group level impacts lower level outcome in clinics. Such limitations become critical for the first difference model, which relies solely on variation within clinics and ignores the broader context in medical groups and environments. Second, for propensity score analysis, the same problems exist. The propensity to adopt various levels of telemedicine is based on clinic characteristics. We may aggregate the data to medical groups, for both analysis methods. In that case, we lose a large proportion of observations and the medical group structure. Since we focus on care delivery at the clinic level and investigate the role of technology adoption with more detailed data, we rely on HLM for the analysis with necessary adjustments.

3.5. Discussion

In this section, we discuss the findings from our analysis. Generally, the results support our proposed model based on the TOE framework for the antecedents and consequences of telemedicine adoption in clinics.

3.5.1. The Causes of Telemedicine Adoption

The results of this study on the antecedents of telemedicine adoption suggest that geographical location, socioeconomic characteristics, and organizational characteristics are significant predictors of telemedicine adoption level. First, adoption is higher for clinics in rural areas. This aligns with evidence that rural organizations provide more versatile care than urban organizations (Li and Benton 2006, Li et al. 2002). Second, regional poverty level, a socioeconomic characteristic, has a significant effect on telemedicine adoption. Our results show that when the poverty level increases, telemedicine adoption decreases. This result adds to the current literature on organizational management on poverty (Ault and Spicer 2014, Mair et al. 2012, Pearce 2005), and supply chain management on poverty and health care disparities (Sodhi and Tang 2014, Sinha and Kohnke 2009, Griffin et al. 2008). It also echoes the call for

Table 3-9. Panel Data Analysis

Variable	M1: Pooling	M2: Random Effect	M3: Fixed Effect	M4: First Difference
Intercept	1.40 ***	1.71 ***		-0.02
	(0.23)	(0.24)		(0.08)
Small Medical Group	-0.19	-0.29 *	0.39	0.39
	(0.10)	(0.12)	(0.33)	(0.33)
Use of ONC-certified EHR system	0.83 ***	0.64 ***	0.32	0.32
	(0.14)	(0.14)	(0.18)	(0.18)
EHR Vendor: Epic	0.35 **	0.25 *	-1.63 ***	-1.63 ***
	(0.11)	(0.12)	(0.23)	(0.23)
Number of providers in the clinic (log)	0.06	0.03	0.06	0.06
	(0.04)	(0.05)	(0.10)	(0.10)
Fully use of electronic documentation	-0.15	-0.46 ***	-1.51 ***	-1.51 ***
	(0.10)	(0.11)	(0.16)	(0.16)
E-prescribing of non-controlled substances	0.47 ***	0.78 ***	1.79 ***	1.78 ***
	(0.11)	(0.11)	(0.15)	(0.16)
Application for meaningful use incentive	-0.13	0.23 *	0.75 ***	0.76 ***
	(0.12)	(0.11)	(0.13)	(0.14)
Specialty vs. primary care	-0.73 ***	-0.73 ***	0.03	0.04
	(0.10)	(0.10)	(0.16)	(0.17)
Rural vs. urban location	0.10	0.18		
	(0.15)	(0.19)		
High poverty region vs. low	-0.16	-0.15		
	(0.10)	(0.12)		
Health professional shortage areas - primary care (after 2010)	0.12	0.16		
	(0.10)	(0.12)		
Distance to Twin Cities	-0.00 *	-0.00 **		
	(0.00)	(0.00)		
Category with lowest density of neighboring clinics	-0.33	-0.27		
	(0.18)	(0.22)		
Cost in equipment or in providing service	-0.06	-0.16	-0.45 ***	-0.45 ***
	(0.10)	(0.09)	(0.12)	(0.12)
Staff expertise/training(low)	0.98 ***	0.78 ***	0.15	0.15
	(0.13)	(0.14)	(0.19)	(0.20)
Staff support(low)	-0.83 ***	-1.18 ***	-1.54 ***	-1.55 ***
	(0.14)	(0.13)	(0.16)	(0.17)
No identified need or demand	-0.05	0.03	-0.02	-0.03
	(0.11)	(0.11)	(0.15)	(0.15)
Reimbursement from payors does not cover cost	-0.23 *	0.10	0.60 ***	0.60 ***
	(0.10)	(0.11)	(0.16)	(0.16)
EHR/IT staff needs [b]	-0.28 ***	-0.39 ***	-0.56 ***	-0.56 ***
	(0.05)	(0.05)	(0.07)	(0.07)
Informatics staff needs	0.14	0.04	-0.41 **	-0.41 **
	(0.10)	(0.10)	(0.15)	(0.15)
Trainer needs	-0.20	-0.21 *	-0.15	-0.14
	(0.10)	(0.10)	(0.13)	(0.14)
Telemedicine level(low)	0.52 *	0.58 **	0.26	0.26
	(0.21)	(0.21)	(0.28)	(0.28)
Telemedicine level(high)	1.19 ***	1.78 ***	2.02 ***	2.01 ***
	(0.33)	(0.33)	(0.42)	(0.42)
Number of clinic decision support (CDS) tools	0.69 ***	0.60 ***	0.14 **	0.14 **
	(0.03)	(0.03)	(0.05)	(0.05)
Telemedicine level(low) x Number of clinic decision support (CDS) tools	-0.11 *	-0.09	0.16 *	0.16 *
	(0.05)	(0.05)	(0.07)	(0.07)
Telemedicine level(high) x Number of clinic decision support (CDS) tools	-0.20 **	-0.30 ***	-0.30 **	-0.30 **
	(0.07)	(0.07)	(0.09)	(0.09)
R^2	0.53	0.42	0.40	0.40
Adj. R^2	0.52	0.41	0.16	0.39
Num. obs.	2232	2232	2232	912

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$. Analysis at clinic level.

inclusion of poverty during decision-making on technology adoption (Bernroider and Schmöllerl 2013, Henao et al. 2012, Gollakota and Doshi 2011, Field and Grigsby 2002). Surprisingly, we do not find evidence that distance from the state population center or density of neighboring clinics are related to telemedicine adoption. One explanation could be that the initial clinic location choice has already accounted for the distance to the population center and the distance to the neighboring organizations. Considering the stages and priorities of technology adoption in health care organizations, it might be that remote clinics set higher priorities on telemedicine adoption. Our cross-sectional analysis cannot portray the historic trend of telemedicine for each clinic.

Our results provide evidence of the critical role of organizational context in technology acquisition decisions. The negative association between the cost of telemedicine/service provision and adoption indicates that cost is still a challenge to organizations, even though organizations have largely adopted EHR systems. This helps to provide an explanation for why telemedicine is successful in limited circumstances (Weinstein et al. 2014, Mitka 2009). Similarly, we find that low demand within the local community also reduces propensity to adopt telemedicine, suggesting that resources are still scarce and organizations make strategic choices on telemedicine adoption to avoid building excess capabilities beyond local demand (Valdmanis et al. 2010). To our surprise, low staff expertise/training and reimbursement obstacles are positively associated with telemedicine adoption. This may reflect that when organizations achieve a higher adoption level, they recognize the need for a higher level of staff expertise and training skills to enable the system to perform to its maximum potential. The reimbursement issue reflects the complicated interaction among financial incentives, strategic goals, and health care quality during telemedicine adoption (Andritsos and Tang

2014, Ata et al. 2013, Rauner et al. 2008, So and Tang 2000). Clinics may choose different approaches to fulfill multiple goals for higher care delivery effectiveness.

3.5.2. The Consequences of Telemedicine Adoption

The results of this study on the consequences of telemedicine adoption show that telemedicine has a positive effect on care delivery effectiveness. This provides evidence that telemedicine adoption can contribute to the strategic resources in an organization and increase organizational competency in health care delivery (Dey et al. 2013, Aral et al. 2012, Angst et al. 2011, Zhu et al. 2006). First, the productivity and access to expertise in real time obtained from telemedicine practices enable organizations and physicians to more efficiently manage information and knowledge on patient care (Bhargava and Mishra 2014, Nicolini 2011, Paul 2006). Second, learning and experience in the adoption process can help organizations better align capabilities, managerial governance, and human resources with the local community. The synthesis introduces broader benefits to the whole system (Bhargava and Mishra 2014). Therefore, our study supports that increased technology adoption can generally benefit health care organizations (Bhargava and Mishra 2014, Dey et al. 2013, Angst et al. 2011, Queenan et al. 2011, Anton et al. 2009, Osheroff 2009), although such benefit may vary across contexts.

Our results show that telemedicine adoption negatively interacts with CDS systems on care delivery effectiveness in clinics. This result contradicts the literature on the complementary effects among concurrent technology adoptions (Bingham et al. 2015, Aral et al. 2012, Aral and Weill 2007, Zhu et al. 2006), and supports the substitution effect on care delivery (Bingham et al. 2015, Queenan et al. 2011). Generally, we can interpret the results as clinics with lower CDS benefitting more from telemedicine adoption, compared to those with higher CDS. One explanation could be that the overlapping functions from different IT systems may help organizations achieve similar goals, thus total benefits are not simply the sum of separate systems (Queenan et al. 2011). From a knowledge transfer perspective, the negative interaction among concurrent technology adoptions can occur when organizations overly rely on common knowledge to implement different systems, while failing to recognize the idiosyncrasies of individual technologies (Bingham et al. 2015). Such uniqueness requires extra attention and resources. However, organizations may lack sufficient capabilities or resources, or fail to adjust to the specific system needs. In addition, to realize the maximum potential from both telemedicine and CDS systems in terms of operational performance benefits, organizations may need to build novel and commensurate technological, organizational, and environmental characteristics (Dey et al. 2013). Thus, one general solution may not work in the setting of concurrent technology adoptions, although organizations do enjoy the improved care delivery effectiveness when adopting either systems compared to non-adoption.

Our results additionally suggest that the medical group and clinical levels matter in technology adoption in clinics. The substantial variation in telemedicine adoption and care delivery effectiveness across medical groups, compared to within groups, highlights that we need to carefully specify appropriate models to accommodate such issues (Nair et al. 2013). This may indicate that in terms of the management of technology, medical groups may benefit from making group decisions and using similar guidelines and resources to help all group members achieve similar outcomes. Thus, the large proportion of knowledge management may occur at the medical group level (Pisano 1994, Beard and Dess 1981).

3.6. Conclusion

This study develops an integrated model of the antecedents and consequences of telemedicine adoption in the period of rapid adoption of CDS and EHR systems. These technologies individually and collectively impact outcomes, and are impacted by their technological, organizational, and environmental contexts (Tornatzky and Fleischer 1990). We find that differences in geographical location, socioeconomic characteristics, and organizational characteristics lead to variation in the telemedicine adoption levels. More importantly, telemedicine adoption has significant implications for care delivery effectiveness. Telemedicine appears to substitute for other health information technologies with its impact on care delivery performance, and telemedicine itself is related to improved organizational performance.

Theoretical contribution. Our findings support our model on the antecedents and consequences of telemedicine, and provide insights into the management of technology. First, this study supports the theory on the technological, organizational, and environmental contexts in technology management, i.e., the TOE framework (Bernroider and Schmöllerl 2013, Aral et al. 2012, Aral and Weill 2007, Park et al. 2007, Zhu et al. 2006, Klein and Sorra 1996, Tornatzky and Fleischer 1990). Our findings provide evidence on the significant role of geographical location (i.e., rural vs. urban areas), socioeconomic characteristics (i.e., regional poverty) and organizational context (i.e., cost and demand). Our study also complements the extant literature on the management of technology in health care settings (Dey et al. 2013, Nair et al. 2013, Angst et al. 2011, Queenan et al. 2011, Osheroff 2009). We explore the interaction among the adoptions of IT systems in an organization (Aral et al. 2012, Queenan et al. 2011, Aral and Weill 2007). Different from the notion that telemedicine and CDS are complementary systems that can increase an organization's absorptive capability (Bertrand and Mol 2013, Cohen and Levinthal 1990), our study suggests these two ITs may act as substitutes (Queenan et al. 2011). Telemedicine adoption may require novel processes and practices, or involve different knowledge creation and management skills (Nicolini 2011, Paul 2006).

Managerial contribution. Our study can provide insights for practitioners on managing technology adoption. First, organizations need to incorporate geographical location and socioeconomic characteristics into their decision-making process and align the adoption of technology with the environment. We find that there is higher adoption of telemedicine in rural areas and in non-poverty regions. This may suggest that certain geographical locations may determine the use of telemedicine. Second, organizations need to evaluate organizational challenges in technology adoption. High costs of equipment and service provision, together with low demand for such technology in the local community, may suggest difficulty for organizations to increase their level of telemedicine. Third, organizations should not isolate the adoption of health IT systems from one another and need to consider their combined effects on organizational performance. We observe that organizations can improve their performance from adopting either telemedicine or CDS. However, the magnitude of improvement in CDS adoption decreases when the telemedicine level increases. Thus, organizations should be cautious about the substitution effect. Clinics with lower CDS might see the opportunity to achieve higher care delivery effectiveness through telemedicine adoption. These results also have implications for policy makers when they try to motivate the adoption of specific health IT systems to address access to quality care. Our study suggests policy incentives can be aligned with the antecedents and consequences of one technology, and encourage its adoption.

Limitation and future study. One limitation of this study is the empirical data. Future research can extend this study to a larger context and with longitudinal data.

Additional research is needed to provide a more complete view of antecedents and consequences of technology adoption across clinics and medical groups in domestic and international settings. Second, investigating how telemedicine adoption evolves as related ITs change rapidly is another avenue for future inquiry. Although our study examines telemedicine adoption in the context of EHR and CDS systems, we do not account for many other technologies with potential use. For example, smart phones, mobile devices and personal gadgets may further promote information communication between patients and health providers. Third, multiple perspectives of performance, such as patient satisfaction and affordability, are necessary for fully understanding management of technology in health care settings. Although our study focuses on organizational management and measures care delivery effectiveness in clinics, patient perception would provide an alternative perspective. Moreover, future research can extend this study to examine how upstream health care supply chains affect technology adoption and integration among technologies. Health care is a bundle of care with goods, services, and experiences (Sinha and Kohnke 2009), and involves many stakeholders across the supply chain. More research is required to further uncover the interaction among technology development, adoption, and implementation, together with health care professorial knowledge in the supply chain. Such effort is necessary due to social interactions among all stakeholders in health care settings, where we need to explore how health IT adoption and practices across the supply chain enables clinics, hospitals, communities, and the population to achieve significant health care improvement.

Chapter 4

Evaluating Working Conditions in Supplier Factories: An Empirical Analysis of Global Sourcing from Developing Countries

4.1. Introduction

> *Companies have compelling reasons to expand their supply chains across the globe…With these benefits, however, there are potential complications in relying on outsourced, global suppliers. As TNCs [transnational corporations) look to developing countries to manufacture goods, they risk that suppliers will violate international or local labor standards and, with that, negative exposure when working conditions are brought into the public consciousness. (Miller 2015, p. 432)*

Supply chains of goods and services are increasingly spanning the globe (Pigors and Rockenbach 2016, Bartley 2007). Concurrently, work involved with the production of goods and services, too, is increasingly distributed across firm and country boundaries (Sinha and Van de Ven 2005). The global distribution of work to developing countries is largely driven by the lower costs of labor and materials coupled with the availability of skilled labor necessary to perform relevant work in such countries (Miller 2015, Locke et al. 2009). Notwithstanding these benefits, designing and managing global supply chains whose reach extends into supplier factories in developing countries often involves the stark reality of substandard working conditions in such factories, often referred to as "sweatshops." Recent illustrative examples include the widely publicized building collapse and fires due to poor maintenance in Bangladesh ready-made garment (RMG) factories (Greenhouse 2013), routine overwork in Chinese electronic manufacturing units (Svensson 2012), and inadequate worker safety procedures in Samsung's manufacturing unit in Brazil (Pearson 2013).

In Bangladesh garment factories, the empirical setting for this study, retailers from North America and Europe, who are the buyers from the factories, have adopted an innovative approach towards improving the working conditions in these supplier factories by forming consortiums. The consortium of North American retailers is the Alliance for Bangladesh Worker Safety (Alliance). The consortium of European retailers is the Accord on Fire and Building Safety in Bangladesh (Accord). Alliance was formed in 2013 by a group of 26 large North American clothing retailers who developed and launched the Bangladesh Worker Safety Initiative, a binding, five-year agreement intended to be transparent, results-oriented, measurable and verifiable with the intent of improving safety in Bangladesh's garment factories. Similarly, the Accord was formed in 2013 by 72 large mostly European clothing retailers to monitor supply chains and improve working conditions in Bangladesh's RMG factories (Evans 2015, The Economist 2013).

The formation of Alliance and Accord represents an innovative approach to addressing the social challenge of poor working conditions in supplier factories in three ways. *First*, compared to existing approaches that focus largely on self-monitoring by supplier factories or third-party audits (Distelhorst et al. 2016, Porteous et al. 2015, Gillai et al. 2013, Locke et al. 2007), the objectives of Alliance and Accord are to establish working conditions standards and best practices in Bangladesh RMG industry. They do so by educating supplier factories through inspections and training efforts, and by providing financial support to the factories for carrying out corrective actions (Short et al.

2015, World Bank 2015). *Second*, unlike existing approaches, Alliance and Accord involve all stakeholders in the garment value chain – i.e., from supplier factories and buyer firms to consumers, government agencies, policymakers, and NGOs. The resulting eco-system increases the transfer of ideas, standards and best practices among the stakeholders making improvement efforts "more effective, efficient, sustainable, or just" than existing solutions (Phills et al. 2008, p. 36). *Third*, the increased transparency and public disclosure of working condition risks in supplier factories not only reduce heterogeneity in standards and best practices across factories, but also promote greater awareness and learning among the factories. Since their formation in 2013, the two consortiums, Alliance and Accord, have inspected the majority of supplier factories in the Bangladesh RMG industry and have released detailed safety and inspection reports on the working condition risks.

This study investigates the effect buyers have on factory working conditions for work that is distributed in a global supply chain. Toward this end, scholars have begun exploring the management of corporate social responsibility beyond temporal profit maximization (Distelhorst et al. 2016, Besiou and Van Wassenhove 2015, Briscoe et al. 2015, Carroll et al. 2012, King 2008) in settings where business transactions transcend firm and country boundaries (Short et al. 2015, Porter and Kramer 2011, Freeman 2010). Corporate social responsibility encompasses the notion that buyers need to conduct business "*to do good, to do well, to do the right thing in the right way*" (Carroll et al. 2012, p. 9). That is, buyers not only need to manage their internal business practices, but also the business practices in supplier factories (Short et al. 2015, Sinha and Van de Ven 2005). Such a focus has significant implications for ensuring consumer confidence in the buyers' products, and subsequently their profitability. While concerns about product quality have exposed buyers that source from supplier factories in developing economies to reputation harm — e.g., in the toy industry (Marucheck et al. 2011) and pharmaceutical industry (Gray et al. 2011), buyers are also subject to such harm when "dangerous, illegal, or otherwise problematic" working conditions in supplier factories are revealed (Short et al. 2015, p. 1). Therefore, the importance for a buyer to demonstrate corporate social responsibility through a focus on working conditions in supplier factories in developing countries cannot be overstated.

At the same time, with increasing globalization of supply chains and heterogeneity in working conditions across geographical locations, managing *trust* in the supplier's ability to safely and reliably deliver on its contractual obligations is a matter of fundamental importance to buyers (Wang et al. 2014, Zaheer et al. 1998). During the economic exchange, a buyer's trust in a supplier can not only reduce transaction costs and the complexity of formal contract design (Williamson 1985), but more importantly, it can also reduce the risk of adverse supplier selection (Hoetker et al. 2007). A relevant question then arises as to whether the knowledge of working conditions in a supplier factory has implications for a buyer's trust in a supplier. More specifically, *how do working conditions in a supplier factory impact buyer trust in the supplier?* This is the central question addressed in this study.

As indicated earlier, we focus on factories in the Bangladesh RMG industry that serve as suppliers for major retailers in North America and Europe. Bangladesh plays a critical role in the RMG industry — it is the third largest exporter to the U.S., after China and Vietnam (Anner 2015), and the second largest overall exporter in the world after China (Evans 2015). In a recent McKinsey survey, nearly 90% of chief purchasing officers projected Bangladesh as the No. 1 sourcing "hot spot" over the next 5 years (Berg et al. 2011). Currently, Bangladesh's RMG industry sector employs nearly 4 million mostly female workers (Mahr and Habib 2013), and clothing accounts for 80% of total exports, at $22 billion (Evans 2015). In terms of employment, contribution to reducing poverty levels, and overall GDP growth, Bangladesh's RMG industry sector continues to be the foremost industry sector within the country. The data for this study were collected from more than 1600 garment (supplier) factories located in Bangladesh through the Alliance and Accord consortiums.

Using data from Alliance and Accord, we characterize risks related to working conditions in supplier factories in terms of three types, namely, structural risk, fire risk, and electrical risk. Next, departing from subjective measures of trust in prior literature (e.g., Brinkhoff et al. 2015, Fang et al. 2014), we evaluate the impact of working conditions risks on a fine-grained measure of buyer trust that captures the number of retailers (buyers) that have contracted with each supplier factory.

The empirical analysis is carried out using a fixed-effects negative binomial regression with robust standard errors. Controlling for unobserved heterogeneity in factory inspections across the two consortiums as well as observed heterogeneity in factory characteristics, the results lend support to the contention that buyers are sensitive to working condition risks in a supplier factory. That is, as working condition risk in a supplier factory increases, buyer trust in the factory decreases. However, such a relationship varies with the type of the risk. Specifically, among the three types of working condition risks, fire and electrical risks are significant in reducing buyer trust, while structural risk has a marginal effect. We also find that the negative relationship between working condition risks in a supplier factory and buyer trust is moderated by the size of the supplier factory such that the negative relationship is reduced in large supplier factories as compared to small supplier factories. This suggests that buyers tend to trust large supplier factories more, and expect such factories to improve their working conditions and reduce the relevant working condition risks to a greater extent than small supplier factories. The above findings, taken together, provide nuanced insights into the marketplace implications of working condition risks in supplier factories, and highlight not only the sensitivity of the buyer's trust to such risks but also provide actionable guidance to supplier factories on how to manage working conditions risks.

The remainder of the paper is organized as follows. In section 2, we review the prior literature on corporate social responsibility and working conditions, identify gaps in the literature and discuss how our study addresses these gaps. In section 3, we develop hypotheses that link working condition risks to buyer trust in the supply chain. In section 4, we discuss the data collection procedure. In section 5, we discuss the model specification and report the results of the empirical analysis to test the hypotheses. Finally, in section 6, we conclude the study with a discussion of the theoretical and practical contributions, limitations and directions for future research.

4.2. Corporate Social Responsibility and Working Conditions

The concept of corporate social responsibility is rooted in the idea that firms are responsible for managing economic and non-economic practices, and for creating shareholder value by meeting the needs of non-shareholding stakeholders (Pigors and Rockenbach 2016, Guo et al. 2015, Holt and Littlewood 2015, Eccles et al. 2014, Porter and Kramer 2011, Freeman 2010, Donaldson and Preston 1995). The concept further emphasizes that firms exist within a society with rights and responsibilities as society members to conduct their business in a responsible manner (Carroll et al. 2012). Our review of the extensive literature on corporate social responsibility highlights the following five dimensions across which such responsibility can be exercised by a firm: (i) environmental dimension, (ii) social dimension, (iii) economic dimension, (iv) stakeholder dimension, and (v) voluntariness dimension (Carroll et al. 2012, p. 7–8). Among these five dimensions, the stakeholder dimension is the focus of our study. Generally speaking, besides shareholders, a firm's stakeholders may include employees, customers, suppliers, local communities, regulators, and the general public (Besiou and Van Wassenhove 2015, Madsen and Rodgers 2015). In the context of global supply chains, firms often interact with suppliers who may be located across country boundaries (Short et al. 2015, Surroca et al. 2013, Porter and Kramer 2011). Therefore, working conditions in a supplier factory belong to the domain of corporate social responsibility management for firms.

The concept of working conditions can be categorized into wages (e.g., fairness , minimum standards) and non-wage working conditions (e.g., worker safety, hours, security, union environment) (Jayasuriya 2008). Consistent with this view, Toffel et al. (2015, p. 7) highlight the importance of studying working condition issues in developing countries that include "*child labor, forced or compulsory labor, working hours, occupational health and safety, minimum wage, disciplinary practices, treatment of foreign workers, and illegal subcontracting.*" These issues fall into three general sub-categories: labor selection (child, forced or compulsory), management practices (working hours, minimum wage, discipline, treatment of foreign workers, and illegal subcontracting), and facilities (occupational health and safety). This study focuses on the third category, specifically the physical structure as it relates to the welfare of workers in supplier-owned and managed production facilities. In this study, we conceptualize working conditions in terms of *worker safety in operational settings such as a supplier factory*.

Worker safety in factories has become a topic of much attention in the popular press since the 2013 Rana Plaza building collapse tragedy in Bangladesh in which 1100 factory workers died and more than 2500 workers were injured. However, the operations and supply chain management literature, despite its origins and rich history in the study of factory operations and performance (Hopp and Spearman 1996, Hayes and Wheelwright 1984, Skinner 1974), has provided limited attention to this topic with emerging studies focusing mainly on theoretical and anecdotal explorations of worker safety issues in supply chains (e.g., Besiou and Van Wassenhove 2015, Guo et al. 2015, Plambeck and Taylor 2015, Sodhi and Tang 2008, 2012, Brown 1996). As Pagell et al. (2014, p. 1161) note, "*One would expect that an issue of this magnitude would attract significant attention from operations management researchers. Yet, 20 years after Brown's* (1996) *seminal call [for study on workplace safety], operations management research that considers safety remains very sparse.*" One possible explanation for the paucity of research on worker safety in the operations and supply chain management literature could be that such a concept is often perceived as distant and disconnected from traditional operational performance metrics of efficiency and effectiveness (Das et al. 2008). Second, with the rapid servitization of North American and European economies over the last two decades and significant offshoring of manufacturing jobs from these economies, concerns relating to worker safety in offshore supplier factories have often remained peripheral to the interests of the business community in these economies. Organizations continue to pursue the prior practices in supplier evaluation and selection without deliberating much about the particular circumstances surrounding the newly added stakeholders, like substandard worker safety in an international factory (Briscoe et al. 2015, King 2008). Third, from an empirical research standpoint, the availability of reliable objective data on worker safety issues in supplier factories has been scarce; while few factories conduct regular audits of working conditions and worker safety issues on their own, even fewer are willing to reveal such information for outside scrutiny (Short et al. 2015).

A limited number of empirical studies in the operations and supply chain management literature that have focused on worker safety issues have used primary data sources — e.g., surveys, interviews (Pagell et al. 2014, 2015, de Koster et al. 2011, Das et al. 2008). These studies have focused on the linkage between: (i) safety in working conditions within a firm and the quality of firm outputs (e.g., Das et al. 2008), (ii) safety and operational effectiveness (Pagell et al. 2015), and (iii) organizational culture and worker safety within a firm (Pagell et al. 2014). Some exceptions to the above lines of inquiries include Levine et al.'s (2012) study that uses archival data on random Occupational Health and Safety Assessment (OSHA) inspections to examine their impact on injury rates and firm performance (measured using data on sales, payroll, employment, creditworthiness, and firm survival), and Lo et al.'s (2014) study that uses archival data on firms' safety certification, consistent with OHSA guidelines, on safety incidents and operational performance (measured using data on sales growth, labor productivity, and profitability). Taken together, these studies provide broad support for the notion that improvement in working conditions positively contributes to operational and financial performance of a firm (Pagell et al. 2014). Emphasizing this point further, the Vice President of Research at Health Enhancement Research Organization (HERO) notes, "*there is much to be learned about the connection between workplace health and corporate performance, but the pieces of the puzzle are coming together and we're seeing that investing in employee health and wellness is a common thread between well-respected, high-performing organizations*" (HERO 2016, p. 2).

It is worth noting that the above empirical studies have examined the implications of working conditions from an intra-firm perspective, and do not take into consideration the notions that (i) a significant volume of firms today operate within the context of a global supply chain, with buyer and supplier firms often located across country boundaries, and

(ii) working conditions in supplier firms (e.g., factories) may have implications for the buyer-supplier relationship. Our study contributes to the emerging research on worker safety in the operations and supply chain management literature by examining whether buyers exercise corporate social responsibility in their transactions with suppliers by taking into consideration the working conditions in supplier factories (Short et al. 2015, Sinha and Van de Ven 2005). More specifically, we seek to understand how working conditions in a supplier's factory influences a buyer's trust in a supplier. In the following section, we identify and discuss the types of working condition risks examined in our study, highlight the concept of *buyer trust* in global supply chains, and develop hypotheses that link working condition risks to buyer trust.

4.3. Hypotheses Development

4.3.1. Working Condition Risks in Supplier Factories

Our study focuses on working conditions in supplier factories. We consider three types of risks related to working conditions in Bangladesh's RMG industry. These risks present potential threats to worker safety and are the focus of factory inspections by Alliance (Alliance 2015) and Accord (Accord 2015) – namely, structural risk, fire risk, and electrical risk. These three types of risks are consistent with risks related to health and safety in a workplace as identified by the Fair Labor Association (FLA 2015), and are characterized as follows:

- **Structural Risk**. The operations of a supplier factory should be conducted in buildings with structural integrity and protection from danger to life from building collapse. The buildings should have logical vertical/lateral load carrying systems, satisfactory structural elements/additions, no visible distress, satisfactory strength, and performance.

- **Fire Risk**. The factory should be compliant with fire safety requirements, and have protection from danger to life from effects of fire including smoke, heat, and toxic gasses created during a fire. The structural systems should be properly protected in the event of a fire, and have fire resistance. There should be sufficient means of escape, in a manner that protects occupants. Fire protection systems should be installed, operated, and maintained in accordance with standards, and building occupants should be properly trained and aware of emergency evacuation procedures.

- **Electrical Risk**. The factory should be compliant with electrical safety requirements, and have protection from danger to life from electrical hazards. The electrical system should be designed and installed in a way that protects the building occupants' health and safety. It should be maintained in a manner that is safe and ensures the system remains operational. Those responsible for operating and maintain the system should be properly licensed and trained.

4.3.2. Implications of Working Conditions Risks on Buyer Trust

At an inter-organizational level, trust between partnering firms in a dyadic relationship represents the extent to which each firm believes that its partner is honest and/or benevolent (Li et al. 2010, Dyer and Chu 2003, Zaheer et al. 1998). A firm's trust in its partner firm (and vice-versa) includes two elements: (i) confidence in the partner firm's behavior, and (ii) confidence in the partner firm's goodwill (Zaheer et al. 1998, Ring and van de Ven 1992). During an economic exchange, trust between partnering firms can reduce contract complexity and lower transaction costs (Williamson 1985). More importantly, with increasing globalization of supply chains (Berry and Kaul 2015, Sinha and Van de Ven 2005), trust becomes critical for ensuring effective information exchange between partnering firms and for reducing the risk of moral hazard (Voigt and Inderfurth 2012, Hoetker et al. 2007, Dyer and Chu 2003, Zaheer et al. 1998). Furthermore, trust can enhance the acquisition and exchange of both explicit and tacit knowledge between buyers and suppliers in the supply chain (Li et al. 2010).

Noting the importance of trust in global supply chains, the extant literature has explored its determinants in the context of supply chains, focusing on factors such as culture and country differences among partners (Özer et al. 2014), knowledge of a partner's unethical behavior (Hill et al. 2009), asymmetric dependence between partners (Brinkhoff et al. 2015) and perceptions of organizational justice (Wang et al. 2014). Additionally, a number of studies have investigated trust from a supplier perspective and find evidence that it is impacted by buyers' strategic communication, professional knowledge, and ability to reach compromises (Zhang et al. 2011). That is, perceived unethical buyer behaviors can break suppliers' trust (Hill et al. 2009). However, the extant literature is largely silent on factors on the supply-side and characteristics of the supplier environment that may influence buyer trust. We propose that buyers perceive working conditions in supplier factories not only as an important dimension of corporate social responsibility, but also a factor critical to the operational performance of the supply chain. As a result, the presence of working condition risks in a supplier factory may *negatively* affect buyer trust in the supplier. Such a relationship can manifest due to increased buyer apprehension regarding the potential for: (i) supply chain disruptions, and (ii) reputation loss.

First, increasing levels of working condition risks can increase the potential for supply chain disruptions and affect a supplier's ability to reliably fulfill their production orders. Toward this end, recent studies (e.g., Pagell et al. 2015, Das et al. 2008) have noted that working condition risks are often associated with workplace accidents, machine failures and worker absenteeism, all of which can reduce the operational performance of the supply chain. With increasing focus on worker safety in factories in recent years and its potential benefits for operational performance, these findings suggest that buyers should be more likely to offer contracts to suppliers perceived as capable of fulfilling contractual obligations, thus reducing the likelihood of supply chain disruption (Wang et al. 2014, Hill et al. 2009, Zaheer et al. 1998). As a result, knowledge of working condition risks in a supplier factory is likely to reduce buyer trust in a supplier and thereby reduce the likelihood of the supplier being selected by the buyer.

In addition, the presence of working condition risks can increase the potential that a buyer may incur significant loss in reputation when information relating to poor working conditions in supplier factories is revealed to the public. Reputation is a key strategic concern for most buyers (Short et al. 2015). Buyers seek to avoid reputational spillovers and liabilities arising from dangerous, illegal, and unethical behavior at supply chain factories (Distelhorst et al. 2016, Toffel et al. 2015). In recent years, buyers are increasingly volunteering to monitor working conditions in supplier factories, and requiring suppliers to meet globally recognized standards of conduct (Distelhorst et al. 2016, Guo et al. 2015, Plambeck and Taylor 2015, Porteous et al. 2015, Locke 2009, Locke and Romis 2007). For example, third-party non-governmental organizations (NGOs) (e.g., Fair Labor Association) are monitoring supplier compliance with buyers' "code of conduct" for many buyer firms (Briscoe et al. 2015), including Apple Inc. (Reisinger 2012). Such moral obligations toward the workers in supplier factories represent an important facet of the corporate social responsibility for buyers.

Taken together, the above arguments suggest that working condition risks in a supplier factory have the potential to reduce buyer trust in the supplier factory. This is due to the anticipated effects of risk on operational performance as well as the potential reputation hazards associated with adverse supplier selection. Therefore, we propose the following set of hypotheses.

Hypothesis 1a*: Structural risk in a supplier factory is negatively associated with buyer trust in the supplier, ceteris paribus.*

Hypothesis 1b*: Fire risk in a supplier factory is negatively associated with buyer trust in the supplier, ceteris paribus.*

Hypothesis 1c*: Electrical risk in a supplier factory is negatively associated with buyer trust in the supplier, ceteris paribus.*

4.3.3. Moderating Effect of Supplier Factory Size

We argue that the relationship between working condition risks and buyer trust in a supplier factory can depend upon the size of the supplier factory. This argument is consistent with past studies where firm size has been used as a moderator in investigating the impact of trust on knowledge acquisition (Li et al. 2010), the effect of organizational constraints on trust in the partner organization in a buyer-supplier context (Perrone et al. 2003), and trust damage (Wang et al. 2014).

All else remaining constant, a larger supplier factory is more likely to signal to buyers about a supplier's focus on corporate social responsibility. Since a large supplier is, typically, likely to be a significant player in the local community as well as in the supply chain, the supplier is more likely to take into account the stakeholders, including its employees, during the manufacturing process. Further, since larger factories are likely to have more comprehensive organizational structure and hierarchical controls, larger factories are likely to encourage suppliers to take proactive steps toward addressing working conditions (Audia and Greve 2006). Therefore, operational uncertainty (Zaheer et al. 1998) is relatively lower in larger factories than in smaller factories. In addition to greater production capacity, larger suppliers may have a greater likelihood of survival, compared to smaller ones (Dawar and Frost 1999). Also, larger suppliers are more likely to fulfill their contractual commitments with buyers. In sum, buyers are more likely to enter into contractual relationships with larger suppliers (Wang et al. 2014).

Beyond its direct effect on buyer trust, we argue that supplier factory size can moderate the negative impact of working conditions risk on buyer trust. That is, the effect of working condition risks on buyer trust is likely to be contingent on differences in the factory context, some of which may be driven by factory size. This moderation effect can manifest in three ways. First, larger suppliers tend to have more resources to address working condition risks and may devote greater investment toward maintaining long-term supply chain relationships (Besiou and Van Wassenhove 2015, Pagell et al. 2015), whereas smaller suppliers may have limited resources, and, therefore, focus more on short-term returns. Further, with higher existing levels of resources, larger factories may be able to acquire and leverage additional resources from financial institutions more easily for addressing working condition risks, whereas small factories may have limited leverage for acquiring resources from external sources (Sarkar et al. 2001). At the same time, larger factories, given their scale and complexity, would have more formalized structures and organizational systems in place compared to their small-factory counterparts (Distelhorst et al. 2016, Sila 2007, Dalton et al. 1998), and therefore would be more likely correct deviations from working conditions standards. For instance, larger factories are likely to have higher role specialization (Sørensen 2007) and dedicated human resource specialists, which may enable the efficient tracking and remediation of working condition risks than smaller factories. Second, with increasing size, the negative publicity of working conditions risks in supplier factories may not easily transfer to buyers. This is because, with increasing supplier size, status differences between buyers and suppliers decrease and responsibilities toward ensuring safe working conditions are more equitably distributed between the contracting parties (World Bank 2015, Boyd et al.

2007). That is, a buyer is less likely to have sole obligation for corporate social responsibility toward improving working conditions in a large supplier factory, as the supplier is expected to contribute toward this effort. Finally, given that larger factories tend to have higher reputation capital and benefit from existing reputational advantages during supplier selection (Dineen and Allen 2016), this may dilute the negative signaling effects of the working condition risks on buyers. In such a case, a buyer has a lower perception of working condition risks in a larger supplier factory. Therefore, we propose the following hypothesis.

> ***Hypothesis 2**: The negative association between each of the three risk types — structural, fire, and electrical — on buyer trust in a supplier is moderated by the supplier's factory size, ceteris paribus. That is, as the supplier's factory size increases, the strength of the negative association decreases.*

4.4. Method

4.4.1. Data

To empirically test the proposed hypotheses, we analyze data on working conditions and buyer trust in the Bangladesh RMG industry from safety inspection reports released by the Alliance and Accord consortiums. These safety inspections are the first steps toward addressing such issues in Bangladesh garment factories (Saini 2014, The Economist 2013). Following the inspections, the two consortiums attempt to provide meaningful advice on remediation and improvement of the working conditions in the supplier factories through training efforts in the supplier factories, and by providing financial support, wherever necessary, to the factories for carrying out corrective actions. Between them, the two consortiums inspect and provide remediation advice to nearly 40% of the factories in the Bangladesh's RMG industry (Labowitz and Baumann-Pauly 2014). All inspections are conducted for the consortiums by third-party auditors based on uniform standards with respect to three types of risks related to factory working conditions: fire risk, structural risk, and electrical risk (Accord 2015, Alliance 2015). Alliance inspected sourcing factories for its retailer members from September 2013 to July 2014, and Accord inspected sourcing factories from January to September in 2014 (Al-Mahmood 2013). Each consortium released the inspection reports on its websites independently.

We downloaded all available inspection reports from each consortium website in July 2015— specifically, inspection reports on 621 factories from the Alliance website and 1005 factories from the Accord website, resulting in 1626 unique factories in our sample. We note here that the analyzed sample is smaller than the number of unique factories due to: (i) partial (incomplete) inspections, and (iii) missing values for many variables. In addition to providing information on working condition risks, the consortium websites provide additional information on factory characteristics such as inspection date, location (i.e., city, whether located in special commercial zones), and building characteristics (whether housed in multi-factory/multi-purpose building) etc. We also retrieved information on factory age and detailed factory addresses from Bangladesh Garment Manufacturers and Exporters Association (BGMEA) and Bangladesh Knitwear Manufacturers & Exporters Association (BKMEA). Coupled with the zip code list from Bangladesh Post Office (http://www.bangladeshpost.gov.bd/postcode.asp) and location information from Google Maps, we were able to identify additional important location characteristics for each factory (e.g., whether the factory is located in a specific industrial area or economic zone) that may impact a buyer's decision to contract with a supplier factory.[3]

4.4.2. Dependent Variable

Buyer Trust. Consistent with our theoretical arguments that buyer-supplier relationships are likely influenced by buyers' consideration of corporate social responsibility, we employ buyer trust in suppliers from Bangladesh as the key dependent variable in our study. Measures of trust vary substantially across domains such as psychology, political science, social science, marketing and economics, depending on the context of investigation (Özer et al. 2014). At the organizational level, trust has widely been measured using multi-item survey measures (e.g., Brinkhoff et al. 2015, Fang et al. 2014, Pavlou and Gefen 2004, Gefen et al. 2003, Zaheer et al. 1998). Such subjective measures, however, tend to be more closely related to inter-personal trust rather than organizational trust, or at most, an individual's perception of organizational trust (Fang et al. 2008, Zaheer et al. 1998).

In our study, we measure buyer trust in a supplier as the *number of buyers that are contracted with the supplier's factory*.[4] That is, the greater the number of buyers that have contracted with a supplier factory, the greater the buyer trust in the supplier. This

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[3] Zip codes are not widely used in Bangladesh. Therefore, we took three approaches to obtain the zip code for each factory address: 1) Use Accord or Alliance address zip code (56.1% factory zip codes obtained). 2) Search Accord and Alliance databases for similar street/areas and use zip codes from those factories. Obtain factory address information from BGMEA (cumulatively, 91.3% zip codes obtained). 3) Search address and factory name in google, google map, and other map sites to obtain the zip code. (Cumulatively, 99.9% zip codes obtained.)

[4] Our measure of trust is different from customer loyalty. The measure emphasizes the number of buyers that a factory would be able to influence, while customer loyalty may indicate the repeated purchasing activities for a customer with one seller.

measure of trust is used in the online auctions literature where trust in a seller is reflected in the number transactions successfully executed by the seller (e.g., Huck et al. 2012, Hergert 2007). This stream of literature focuses on the role of trust in online shopping and/or purchasing with product uncertainty (Kim and Krishnan 2015, Gefen et al. 2008, Kim and Benbasat 2006, Pavlou and Gefen 2004). These studies support that trust represents reduction of perceived risk. Such a measure of trust is particularly relevant in the context of a global supply chain and has a number of advantages over existing perceptual measures. Our measure focuses on the link between the propensity to trust a supplier (i.e., trust propensity is formed through the socialization and contracting experience in the garment industry, which is invariant across situations) and buyers' consequent trust behaviors (Pavlou and Gefen 2004). *First*, our measure of trust signals a buyer's willingness to depend upon the ability of a geographically distant supplier to produce goods in a safe, reliable and responsible manner. *Second*, our measure is objective, eliminating respondent biases typically observed in perceptual measures of trust in the extant literature. In our study context, buyers are from North America and Europe. The use of a perceptual measure of trust may introduce biases into the analysis because the understanding of trust is likely to vary substantially across countries and/or regions. Our approach allows other researchers to replicate and reproduce our research across different industries. *Third*, our measure is supported by studies on the consequences of trust. The literature reports that a buyer's trust can increase repurchasing intentions in online marketplaces (Fang et al. 2014, Gefen et al. 2003), increase resource investments in supplier firms (Fang et al. 2008), and increase buyers' likelihood of purchasing from a supplier firm (Doney and Cannon 1997). To that end, we measure the consequence of buyer trust which directly reflects buyer risk-taking behavior through the contract with a supplier (Mayer et al. 1995).

All supplier factories in our sample have a contract with *at least* one buyer. Additionally, the number of buyers per factory ranges from 1 to 19, with a mean of 3.21 and standard deviation of 2.71.

4.4.3. Independent Variables

We construct measures for the three types of working condition risks in a supplier factory based on the inspection reports from Alliance and Accord. A factory needs to meet a common set of minimum safety requirements established by Alliance and Accord with respect to the three types of risks to continue its operations. We also include the measure of factory size as a moderator of the relationship between working conditions risk and buyer trust.

Structural Risk. The inspection reports from both Alliance and Accord specify the potential safety issues associated with the physical structure of a factory as well as the integrity and performance of the structural factory components (e.g., walls, concrete elements, load carrying beams). Examples of comments reported by inspectors as indicators of structural risk in a factory include the following: *"cracks in concrete elements" "reinforcing steel does not meet 415MPa (60 ksi) for those installed after 2004, based on the requirement of minimum construction material properties."* We measure structural risk as the count of structural issues reported in the inspection report for the factory.

Fire Risk. To measure fire risk, we count the number of identified fire-related issues in the inspection report for each factory. Examples of inspection items for evaluating fire risk include *"whether appropriate fire detection and alarm system are provided for the factory in accordance with the standard, whether all new installations and design* *requirements of water supply meet requirements of NFPA 20 standard (fire pumps), NFPA 22 standard (water tanks), and NFPA 24 standard (underground water mains), and whether separation of floors, occupancies, hazards, exit enclosures are provided with fire-resistive rated construction fire barriers".*

Electrical Risk. Similar to the measures of structural and fire risks, the measure of electrical risk is the number of electrical issues in the inspection reports for each factory. Examples of inspection items for evaluating electrical risk include determining: "*(i) whether visual assessment will confirm details of the service entrance, generators, switchboards, distribution, lighting, grounding, emergency/standby power systems, and lightning protection, (ii) whether separate branch circuits are provided from miniature circuit breaker (MCB) or fuse distribution boards (FDB) for general lighting automatic and fixed appliances with a load of 500 watt or more and plug receptacles, and (iii) whether banks of high-voltage switchgears are segregated from each other by means of fire resistant barriers in order to prevent the risk of damage by fire or explosion arising from switch failure."*

To reduce skewness in the distribution of the data on individual working condition risks per factory, we apply a log transformation to the measure of each risk. Further, we normalize the log-transformed measure to a common scale for ease of interpretation.

Factory Size. We measure factory size as the number of employees in each factory. To reduce skewness, we apply a log transformation to the data. Further, given that factory size is used as a moderator in our analysis, we center the measure to minimize multi-collinearity concerns. The median of number of employees is 1188, and the largest factory has 11,968 employees.

4.4.4. Control Variables

In addition to the independent variables above, we include a number of additional controls related to factory characteristics.

Multi-building. Factories in the Bangladesh garment industry often occupy two or more buildings. This distribution is reflected in our sample where approximately 41% of the factories are located across two or more buildings. To account for this heterogeneity across factories, we created a dummy variable that is coded as '1' if a factory has more than one building or '0' otherwise.

Multi-factory/Multi-purpose Building. Housing multiple factories in one building may affect the extent to which working conditions in given factory are under the control of the factory manager; often, working conditions within a factory may depend upon conditions in another factory within the same building. Additionally, a building that is characterized as a multi-purpose building (e.g., a building including residence units as well as a garment factory) may indicate the possibility that it was not designed for manufacturing work. This, in turn, may create heterogeneity in safety focus among occupants of the building. For instance, the Rana Plaza building that collapsed in 2013 contained multiple garment factories, a bank, apartments and several commercial shops (Than 2013). To control for these differences across factories, we created a dummy variable that is coded as '1' if a factory is housed in a multi-factory building and/or a multi-purpose building or '0' otherwise.

Joint Factory. Combining the inspection reports from Alliance and Accord, we find that some factories (about 30% of the sample) allow inspections by both consortiums. These factories may garner higher trust from the two groups. To control for such heterogeneity across factories, we created a dummy variable that is coded as ‘1’ for a joint factory or ‘0’ otherwise.

Factory Age. The age of a factory may indicate its level of production maturity and capabilities in garment production, i.e., older factories may have a proven record in garment manufacturing. On the other hand, newer factories may be more likely to use modern infrastructure and machinery, and may be housed in newer buildings. As a result, the age of a factory may have implications for buyer trust. Therefore, we control for this variable in our analysis (based on the year a factory was established). The descriptive statistics show the average age of factories to be 12.77 years old, with a median age of 11 years. The maximum age of a factory in our sample is 34 years.

Area Division. A majority of the factories in our study sample are located in the two largest cities in Bangladesh: Dhaka (85%), Chittagong (14%), and others (1%). Dhaka is the capital of Bangladesh, while Chittagong is a port city. Differences in geographical location, size, and development progress between cities may create differences in transportation and logistical characteristics and influence the extent to which factories in a given city are considered attractive to buyers. Therefore, we create a dummy variable that is coded as ‘1’ if a factory comes from Dhaka, and ‘0’ otherwise.

BSCIC Region. Bangladesh Small and Cottage Industries Corporation (BSCIC, http://www.bscic.gov.bd/) is a government-supported project that provides medium- and long-term loans to small industries, either directly or through a consortium of commercial banks. BSCIC also provides assistance in other matters related to the development and expansion of small and cottage industries (SCI). Based on the factory address, we use a binary variable to show whether ‘1’ the factory comes from a BSCIC region, and ‘0’ otherwise. Our sample has 105 (11.2%) factories from the BSCIC region.

EPZ Region. Export Processing Zone (EPZ) is another government supported project to promote, attract and facilitate foreign investment in zones of interest. Bangladesh Export Processing Zones Authority (BEPZA, http://www.epzbangladesh.org.bd/) is the authority that performs inspections and supervision related to social and environmental issues, along with safety and security in the workplace in order to maintain labor-management relations in the EPZ. Based on the factory address, we use a binary variable to show whether ('1') the factory is in an EPZ region, and '0' otherwise. We identify 75 (8%) factories in the EPZ region.

Inspection Date. Both Alliance and Accord began safety inspections in response to the widely publicized Rana Plaza building collapse in 2013. It is possible that Alliance and Accord prioritized inspection differently across factories. It is also possible that a later inspection would leave more time for a factory to improve its working conditions, compared to an earlier inspection. To control for these differential effects of inspection date, we measure the number of days since the Rana Plaza building collapse for each factory inspection, and include it in our analysis.

4.5. Model Specification and Results

Table 4-1 presents the summary statistics and pairwise correlations for all variables. Given that the dependent variable, *Buyer Trust*, is a count variable which exhibits over-dispersion (i.e., variance >> mean), we use a negative binomial regression specification to model predictors of buyer trust (Agresti 2013). Since this variable starts from 1 rather than 0, we transform the variable by subtracting 1 from it for our model specification. To control for time-invariant unobserved heterogeneity in factory inspections between the two consortiums, Alliance and Accord, we use a conditional fixed-effects specification with robust standard errors. The estimation results using the negative binomial regression specification with fixed effects are presented in Table 4-2.

To study the effects of working condition risks on the dependent variable, we first include the control variables in the base model (M1). Building upon this model, we include structural, fire, and electrical risk variables and their interactions with factory size in the subsequent models (M2-M4). Finally, in the full model (M5), we include the interactions between all risk variables and factory size. The variance inflation factors (VIFs) for each variable in the above models are less than 2, suggesting that multi-collinearity is not a serious concern. The explanatory power of the full model is assessed by pseudo R^2 values; the Cox and Snell R^2 is 0.50 and the McFadden R^2 is 0.393, suggesting high explanatory power. All hypotheses tests are reported based on the full model. We report one-tailed results for hypotheses tests and two-tailed results for the control variables.

We first focus on the control variables in the full model and interpret the results associated with these variables. We find that factory size has a significant positive effect on the outcome ($\hat{\beta} = 0.43; p < 0.001$) when we control for other variables in the model. This indicates that, on average, larger factories have more buyers compared to smaller ones. Similarly, factories with more than one buildings ($\hat{\beta} = 0.27; p < 0.001$) and joint factories ($\hat{\beta} = 0.31; p < 0.001$) have significant positive effects. These results, respectively, suggest that factory capacity is an important factor in supplier selection, and that factories that open themselves to inspection by both Alliance and Accord are seen favorably by buyers. Interestingly, we find a negative effect of multi-factory or multi-purpose buildings ($\hat{\beta} = -0.36; p < 0.001$). This finding implies that building characteristics can affect buyers' choice of supplier— i.e., when a supplier's factory

Table 4-1. Summary Statistics and Pairwise Correlations

Variable Names	Mean	SD	Min	Max	1	2	3	4	5	6	7	8	9	10	11	12	13
1.Buyer Trust (transformed)	2.21	2.71	0	18													
2.Inspection by Alliance	0.24	0.43	0	1	-0.33												
3.Factory Age	12.77	7.17	2	34	-0.07	0.10											
4.Joint Factory	0.29	0.46	0	1	0.02	0.47	0.00										
5.Inspection Date	362.15	98.83	-74	798	-0.13	-0.05	-0.07	-0.07									
6.Area Division	0.85	0.35	0	1	0.16	-0.28	-0.08	-0.15	-0.08								
7.BSCIC Region	0.11	0.32	0	1	-0.12	0.06	0.11	0.00	0.03	-0.22							
8.EPZ Region	0.08	0.27	0	1	-0.02	0.10	-0.01	0.18	-0.01	-0.30	-0.10						
9.Multi-building	0.41	0.49	0	1	0.28	-0.02	-0.04	0.11	-0.02	0.04	-0.12	0.05					
10.Multi-factory/Multi-purpose Building	0.25	0.43	0	1	-0.19	0.08	0.13	-0.07	-0.12	-0.08	0.04	-0.10	-0.18				
11.Factory Size (log)[b]	0	0.79	-2.89	2.33	0.35	0.11	0.06	0.28	-0.20	0.07	-0.09	0.12	0.35	-0.11			
12.Structural Risk (log)[a]	0	0.96	-3.98	2.31	-0.04	0.05	0.14	0.00	-0.01	-0.12	0.02	-0.04	0.05	0.12	-0.01		
13.Fire Risk (log)[a]	0.02	0.98	-2.84	4.37	0.09	0.04	0.06	0.04	0.22	-0.06	0.01	0.02	0.19	-0.02	0.20	0.13	
14.Electrical Risk (log)[a]	0	1	-3.49	2.55	-0.14	0.06	0.04	-0.04	0.01	-0.06	0.02	0.02	-0.02	0.08	-0.02	0.15	0.16

Note. [a] Normalized score in each type. [b] Centered score.

Table 4-2. Fixed Effects Negative Binomial Regression with Heteroskedasticity Robust Standard Errors

	Dependent Variable: *Buyer Trust*				
Variable	**M1:Base**	**M2:Stuctrual**	**M3:Fire**	**M4:Electrical**	**M5:Full**
Intercept	0.76 (0.31) *	0.87 (0.46) +	0.95 (0.47) *	0.98 (0.47) *	0.95 (0.51) +
Factory Age	-0.01 (0.00) **	-0.01 (0.00)	-0.01 (0.00) +	-0.01 (0.00) +	-0.01 (0.00)
Joint Factory	0.29 (0.07) ***	0.30 (0.09) **	0.30 (0.09) ***	0.26 (0.09) **	0.31 (0.08) ***
Inspection Date	-0.00 (0.00) ***	-0.00 (0.00) **	-0.00 (0.00) **	-0.00 (0.00) **	-0.00 (0.00) **
Area Division	0.26 (0.10) **	0.22 (0.12) +	0.22 (0.12) +	0.18 (0.12)	0.20 (0.12)
BSCIC Region	0.08 (0.09)	-0.08 (0.11)	-0.11 (0.11)	-0.09 (0.11)	-0.14 (0.11)
EPZ Region	-0.02 (0.10)	-0.03 (0.12)	-0.02 (0.12)	-0.03 (0.12)	-0.02 (0.12)
Multi-building	0.32 (0.06) ***	0.31 (0.07) ***	0.24 (0.07) ***	0.26 (0.07) ***	0.27 (0.07) ***
Multi-factory/Multi-purpose Building	-0.23 (0.07) **	-0.34 (0.09) ***	-0.38 (0.09) ***	-0.35 (0.09) ***	-0.36 (0.09) ***
Factory Size (log)[b]	0.41 (0.04) ***	0.40 (0.05) ***	0.44 (0.05) ***	0.45 (0.05) ***	0.43 (0.05) ***
Structural Risk (log)[a]		-0.07 (0.03) *			-0.05 (0.03) +
Factory Size (log)[b] x Structural Risk (log)[a]		0.02 (0.04)			-0.01 (0.04)
Fire Risk (log)[a]			-0.08 (0.03) *		-0.06 (0.04) *
Factory Size (log)[b] x Fire Risk (log)[a]			0.11 (0.03) ***		0.11 (0.03) ***
Electrical Risk (log)[a]				-0.16 (0.03) ***	-0.14 (0.03) ***
Factory Size (log)[b] x Electrical Risk (log)[a]				0.06 (0.03) *	0.07 (0.03) *
AIC	5246.83	3499.41	3427.28	3453.70	3265.94
Log Likelihood	-2613.41	-1737.71	-1701.64	-1714.85	-1616.97
Cox and Snell R^2	0.401	0.456	0.483	0.479	0.500
McFadden R^2	0.325	0.359	0.381	0.377	0.393
Num. obs.	1587	1007	978	986	936

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, + $p < 0.1$. [a] Normalized score in each type. [b] Centered score. For pseudo R^2 calculation, we simplify the model with negative binomial model, and include a dummy variable for Accord or Alliance in the model.

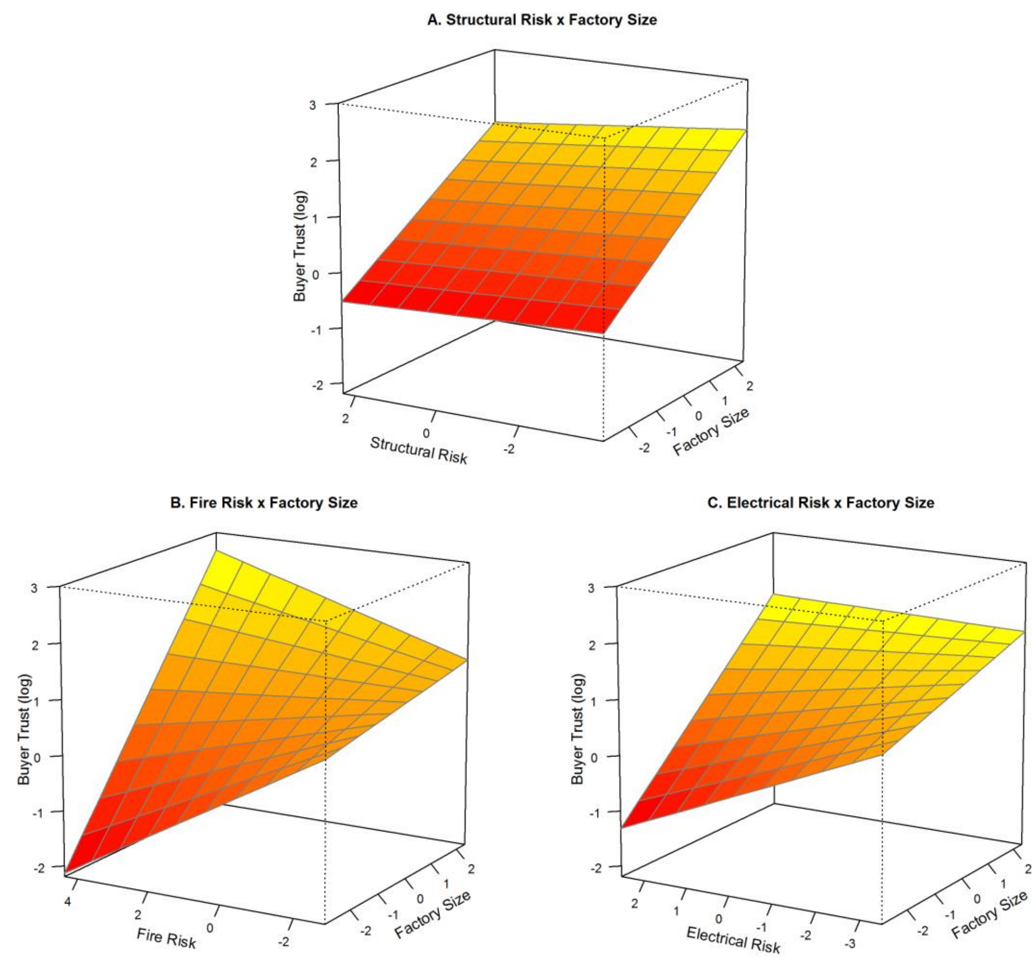
shares the building with other factories or is located in a non-manufacturing purpose building, the propensity for buyers to select that factory is low.

Focusing on the main effects of working condition risks in the full model, we find that fire risk has a significant negative association ($\hat{\beta} = -0.06; p < 0.05$) with buyer trust, holding all other variables constant. Hypothesis 1b is supported. This result suggests that, with a one unit increase in the measure of fire risk, the number of buyers is expected to decline 6%. Further, we find that electrical risk also has a significant negative association ($\hat{\beta} = -0.14; p < 0.001$) with buyer trust, supporting Hypothesis 1c. This result indicates that, with a one unit increase in the measure of electrical risk, the number of buyers associated with a factory will decline by 14%. These main effects are consistent across Models 2-4. The main effect of structural risk is negative and significant in Model 2, but only marginally significant in the full model, thereby suggesting only weak support for Hypothesis 1a.

Regarding interaction effects, we find that factory size has significant positive interaction with fire risk ($\hat{\beta} = 0.11; p < 0.001$) and electrical risk ($\hat{\beta} = 0.07; p < 0.05$). The positive interactions indicate that the negative main effects of the two types of working condition risks are lessened with increasing supplier factory size. In other words, compared to smaller factories, larger factories suffer less loss of trust when they have fire and electrical working condition risks. The interaction between factory size and structural risk is not significant.

To enable an intuitive understanding of the interaction effects, we present interaction plots – see Figure 4-1. We observe that the joint effects of working condition risks and factory size on the dependent variable – buyer-trust – vary across the different risk variables. Specifically, while fire risk and electrical risk have negative associations with the number of buyers for a supplier factory, the negative association is significantly dampened for larger factories. From the plot, we also observe that factory size has a positive effect on the dependent variable, buyer trust.

Figure 4-1. Interaction Plot between Factory Size and Safety Risk



4.5.1. Robustness Checks

We carried out multiple additional analyses using alternative specifications of our estimation model to test the robustness of our results. First, given that the dependent variable is a count and that a number of factories in our sample have only one buyer, it is plausible that the results may be influenced by such distributional characteristics of the dependent variable. To address this concern, we ran the analysis using the zero-inflated negative binomial regression specification. Table 4-3 shows the results on this specification. We find that the results for fire risk, electrical risk, and their interactions with factory size in the full model (Model 4) are consistent with our main analysis, highlighting the robustness of our results to alternative specifications of the dependent variable.

Second, we apply a Generalized Additive Model (GAM) to obtain more descriptive analysis and an in-depth examination of the interaction between working condition risks and factory size. We specify the GAM with a negative binomial model. We report the GAM results in Table 4-4. We find that the smoothed terms between factory size and the three working condition risks are significant on the dependent variable in Models 1-3. In the full model, fire risk and electrical risk demonstrate significant interaction with factory size, while the smoothed term between structural risk and factory size is marginally significant. The full model explains 41% of deviance, reaffirming the significant explanatory power of our predictors in determining buyer trust in a supplier factory.

We identify duplicate inspections by both Alliance and Accord in 23 factories (4.9% of the full sample). Such duplication can help us to examine the inspection coherence between the two groups. We find the measures of risk are quite consistent. For example, the correlation between number of safety issues and inspection group is 0.69 for fire risk,

Table 4-3. Zero-inflated Negative Binomial Regression

	Dependent Variable: *Buyer Trust*			
Variable	**M1:Structural**	**M2:Fire**	**M3:Electrical**	**M4:Full**
Intercept	1.03 (0.19) ***	1.06 (0.20) ***	1.10 (0.20) ***	1.00 (0.21) ***
Inspection by Alliance	-1.56 (0.10) ***	-1.65 (0.11) ***	-1.61 (0.11) ***	-1.66 (0.12) ***
Factory Age	-0.01 (0.00) *	-0.01 (0.00) *	-0.01 (0.00) *	-0.01 (0.00) +
Joint Factory	0.30 (0.08) ***	0.31 (0.08) ***	0.26 (0.08) **	0.31 (0.08) ***
Inspection Date	-0.00 (0.00) *	-0.00 (0.00) *	-0.00 (0.00) *	-0.00 (0.00) *
Area Division	0.19 (0.12)	0.19 (0.12)	0.15 (0.12)	0.17 (0.12)
BSCIC Region	-0.12 (0.12)	-0.14 (0.12)	-0.12 (0.12)	-0.17 (0.12)
EPZ Region	-0.07 (0.12)	-0.05 (0.13)	-0.04 (0.13)	-0.04 (0.13)
Multi-building	0.34 (0.07) ***	0.27 (0.07) ***	0.29 (0.07) ***	0.30 (0.07) ***
Multi-factory/Multi-purpose Building	-0.31 (0.08) ***	-0.35 (0.08) ***	-0.33 (0.08) ***	-0.32 (0.08) ***
Factory Size (log)[b]	0.45 (0.05) ***	0.51 (0.05) ***	0.50 (0.05) ***	0.49 (0.05) ***
Structural Risk (log)[a]	-0.06 (0.03) *			-0.04 (0.03)
Factory Size (log)[b] x Structural Risk (log)[a]	0.02 (0.04)			0.00 (0.05)
Fire Risk (log)[a]		-0.09 (0.04) **		-0.08 (0.04) *
Factory Size (log)[b] x Fire Risk (log)[a]		0.12 (0.04) ***		0.13 (0.04) ***
Electrical Risk (log)[a]			-0.15 (0.03) ***	-0.13 (0.03) ***
Factory Size (log)[b] x Electrical Risk (log)[a]			0.05 (0.04) +	0.05 (0.04)
Log(theta)	0.93 (0.18) ***	0.94 (0.15) ***	0.97 (0.17) ***	0.99 (0.12) ***
Zero model: Intercept	-5.13 (5.13)	-6.81 (20.87)	-5.27 (5.47)	-11.12 (80.01)
AIC	3517.39	3441.94	3472.08	3287.49
Log Likelihood	-1743.70	-1705.97	-1721.04	-1624.75
Num. obs.	1007	978	986	936

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, + $p < 0.1$. [a] Normalized score in each type. [b] Centered score.

Table 4-4. Generalized Additive Model (GAM)

	Dependent Variable: ***Buyer Trust***			
Variable	**M1:Stuctrual**	**M2:Fire**	**M3:Electrical**	**M4:Full**
Intercept	1.02 (0.19) ***	1.06 (0.20) ***	1.11 (0.20) ***	1.00 (0.21) ***
Inspection by Alliance	-1.55 (0.10) ***	-1.66 (0.11) ***	-1.62 (0.11) ***	-1.66 (0.12) ***
Factory Age	-0.01 (0.00) *	-0.01 (0.00) **	-0.01 (0.00) *	-0.01 (0.00) *
Joint Factory	0.30 (0.08) ***	0.31 (0.08) ***	0.26 (0.08) **	0.31 (0.08) ***
Inspection Date	-0.00 (0.00) *	-0.00 (0.00) *	-0.00 (0.00) **	-0.00 (0.00) *
Area Division	0.19 (0.12)	0.20 (0.12)	0.14 (0.12)	0.17 (0.12)
BSCIC Region	-0.11 (0.12)	-0.14 (0.12)	-0.11 (0.12)	-0.15 (0.12)
EPZ Region	-0.07 (0.12)	-0.06 (0.13)	-0.04 (0.13)	-0.04 (0.13)
Multi-building	0.34 (0.07) ***	0.27 (0.07) ***	0.29 (0.07) ***	0.30 (0.07) ***
Multi-factory/Multi-purpose Building	-0.31 (0.08) ***	-0.34 (0.08) ***	-0.33 (0.08) ***	-0.31 (0.08) ***
Smoothed Terms with Factory Size (log)[b], Structural Risk (log)[a]	8.32 (49.00) ***			0.77 (49.00) +
Smoothed Terms with Factory Size (log)[b], Fire Risk (log)[a]		10.33 (49.00) ***		10.58 (49.00) ***
Smoothed Terms with Factory Size (log)[b], Electrical Risk (log)[a]			8.89 (49.00) ***	4.31 (49.00) ***
AIC	3506.99	3438.70	3463.46	3277.28
Log Likelihood	-1733.75	-1697.46	-1711.42	-1609.16
Deviance	1072.73	1032.31	1044.81	979.91
R^2	0.38	0.39	0.38	0.41
GCV score	1770.68	1737.39	1749.16	1656.70
Num. obs.	1007	978	986	936
Num. smooth terms	1	1	1	3

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, + $p < 0.1$. [a] Normalized score in each type. [b] Centered score. In the GAM model, we specify the model with low rank thin plate spline like and penalty in the null space smooth terms.

and 0.70 for electrical risk, although the correlation is only 0.09 for structural risk. As a robustness check to determine if duplicate inspections impact our observed results, we conduct subgroup analysis with data from Alliance only, Accord only, and data without duplicate inspections (i.e., dropping the latter inspection for a factory). The results are shown in the Table 4-5. Overall, the results are consistent with our main analysis, especially the analysis with Accord data and analysis without duplicate inspections. However, in the analysis with Alliance data, we do not find significant results for fire risk and the interaction effect between factory size and electrical risk. Yet their signs are similar to our main analysis. Thus, the duplicate inspections sub-sample does not alter our findings from the main analysis.

4.6. Discussion

4.6.1. Summary of Findings

This study was motivated by the recognition that, notwithstanding the benefits of low cost and skilled labor, designing and managing global supply chains that extend into supplier factories in developing countries often involves contending with unsafe working conditions in such factories. The well-publicized building collapse and fire in Bangladesh ready-made garment (RMG) factories in 2013 are illustrative of the unsafe working conditions. In response, retailers from North America and Europe sourcing from the garment factories in Bangladesh adopted an innovative approach to improve working conditions in the factories by forming two separate consortiums: Alliance (consortium of North American retailers) and Accord (consortium of European retailers). The results of analysis of data from the factory inspection reports of Alliance and Accord indicate that

Table 4-5. Subgroup Analysis and Analysis without Duplicated Inspection Observations

	Dependent Variable: *Buyer Trust*		
Variable	**M1: Alliance Only**	**M2: Accord Only**	**M3: Without duplication**
Intercept	-1.49 (0.59) *	1.03 (0.22) ***	0.94 (0.23) ***
Factory Age	-0.02 (0.01)	-0.01 (0.00) +	-0.01 (0.00)
Joint Factory	0.83 (0.33) *	0.29 (0.09) ***	0.32 (0.07) ***
Inspection Date	0.00 (0.00)	-0.00 (0.00) **	-0.00 (0.00) **
Area Division	-0.29 (0.28)	0.34 (0.14) *	0.24 (0.12) *
BSCIC Region	-0.02 (0.36)	-0.22 (0.13) +	-0.15 (0.12)
EPZ Region	0.06 (0.31)	-0.08 (0.14)	-0.03 (0.12)
Multi-building	0.46 (0.22) *	0.25 (0.07) ***	0.25 (0.07) ***
Multi-factory/Multi-purpose Building	-0.40 (0.26)	-0.32 (0.09) ***	-0.38 (0.09) ***
Factory Size (log)[b]	0.33 (0.15) *	0.50 (0.05) ***	0.42 (0.05) ***
Structural Risk (log)[a]	-0.21 (0.12) *	-0.01 (0.04)	-0.06 (0.03) +
Fire Risk (log)[a]	-0.20 (0.16)	-0.07 (0.04) *	-0.06 (0.04) *
Electrical Risk (log)[a]	-0.24 (0.11) *	-0.11 (0.03) ***	-0.14 (0.03) ***
Factory Size (log)[b] x Structural Risk (log)[a]	-0.05 (0.15)	0.02 (0.05)	-0.01 (0.04)
Factory Size (log)[b] x Fire Risk (log)[a]	0.36 (0.18) *	0.10 (0.04) **	0.11 (0.03) ***
Factory Size (log)[b] x Electrical Risk (log)[a]	0.06 (0.13)	0.06 (0.04) +	0.07 (0.03) *
AIC	433.83	2846.60	3181.74
Log Likelihood	-199.92	-1406.30	-1574.87
Deviance	184.24	807.55	
Cox and Snell R^2	0.311	0.379	0.505
McFadden R^2	0.309	0.296	0.398
Num. obs.	222	714	913

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, + $p < 0.1$. [a] Normalized score in each type. [b] Centered score. Model 1 and Model 2 are negative binomial regression with subgroup analysis. Model 3 is negative binomial regression with fixed effect, after we take the average for each safety risk measure based the score from Alliance and Accord, and then we keep the earlier inspection observation in the analysis.

For pseudo R^2 calculation, we simplify Model 3 with negative binomial model, and include a dummy variable for Accord or Alliance in the model.

working condition risks in supplier factories—namely, structural risks, fire risks and electrical risks, significantly impact buyer trust on a supplier. Specifically, the results indicate that fire and electrical risks play a significant role in reducing buyer trust; however, we do not find support for the impact of structural risk on buyer trust consistently across the models we estimated. The above results, taken together, highlight the differential effects associated with working condition risks and suggest that buyers perceive the potential for supply chain disruptions and reputation loss to be greater from electrical and fire risks, compared to structural risks (Plambeck and Taylor 2015, Short et al. 2015). Beyond this explanation, the lack of consistent support for the effects of structural risk on buyer trust may also suggest that initial inspection and evaluation of working condition risks may not be robust across the different risk types (Short et al. 2015). That is, while fire risk and electrical risk may be more obvious and easily identifiable by auditors, evaluation of structural risk in a supplier factory may be more complex and require greater auditor expertise. Further, it raises the possibility that current inspection practices relating to structural risk by both Accord and Alliance may not be sufficiently detailed or may not be understood by buyers in a way that affects their rationale for selecting a supplier.

Our findings further indicate that the negative consequence of working condition risks on buyer's choice of suppliers can be moderated by an important factory characteristic, namely, factory size. We find a significant negative main effect for fire and electrical risk, and a significant positive main effect for factory size. Both working condition risks have significant positive interaction with factory size. That is, suppliers with large-sized factories appear to garner more buyer trust compared to suppliers with small-sized factories. A potential explanation for this result may be the fact that suppliers with larger factories are perceived to have more resources for addressing working conditions risks. Further, they are perceived to devote greater effort toward exercising corporate social responsibility and maintaining a long-term relationship with buyers (Pagell et al. 2015), compared to smaller suppliers with limited resources and a likely focus on short-term returns. Thus, our hypothesis on the contingent role of factory size is generally supported by the analysis. However, factory size is not significant with respect to the relationship between structural risk and the buyers' choice of a supplier, further reinforcing the point that evaluations of structural risk are less likely to be understood by buyers in a way that affects their perception of a supplier.

4.6.2. Contributions to Theory and Practice

This paper makes significant contributions to research and practice related to supplier-buyer relationship management in a global supply chain that extends into a developing country where working conditions in factories cannot be assumed to be safe. First, our study echoes the call from the extant literature that firms are expected to "*assume important and integral social, psychological, and ecological responsibilities*" (Ødegaard and Roos 2014, p. 2205) and to establish "*socially responsible operations*" (Besiou and Van Wassenhove 2015, p. 1390). Further, firms need to have demonstrated empirical evidence of integrating workplace safety measures into operations practices (Distelhorst et al. 2016, Guo et al. 2015, Plambeck and Taylor 2015, Brown 1996). We identify the effectiveness and limitation of the current corporate social responsibility practices during the initial supplier selection before buyers can manage responsible practices after the relationship is built (Distelhorst et al. 2016, Porteous et al. 2015, Locke 2009, Locke et al. 2009). In sum, firms need to improve their corporate social responsibility (Carroll et al. 2012), evaluate the safety for workers (Pagell et al. 2014, 2015, Lo et al. 2014, Pagell and Gobeli 2009), and develop a responsible sourcing strategy and practices across firm and country boundaries (Distelhorst et al. 2016, Plambeck and Taylor 2015, Toffel et al. 2015, Porter and Kramer 2011, Sinha and Van de Ven 2005).

Second, our study contributes to the supply chain risk management literature which has highlighted that working conditions in supplier factories in developing countries should be an important consideration in global sourcing (Sodhi 2015, Chopra and Sodhi 2004, 2014, Sodhi et al. 2012, Robertson et al. 2009, Jayasuriya 2008). Specifically, our findings indicate that, in the context of the Bangladesh garment industry, buyers from developed countries do value better working conditions in a supplier factory given its potential implications for supply chain disruptions and reputation loss, and that such evaluation of working conditions influences the likelihood that a buyer will contract with a supplier. Therefore, our study highlights the implication of improving working conditions on supply chain management by demonstrating the consequences of working condition risks on buyer trust of the supplier. Our findings are a contribution to the literature on workplace safety management and operational performance that is premised on the notion that safe working conditions are essential to leveraging human capital and potentially contributing to operational performance (Pagell et al. 2014).

Third, our study findings indicate that while buyers (e.g., North American and European retailers) demonstrate corporate social responsibility by accounting for working conditions in supplier factories, specific contingencies in the factory environment may moderate the extent to which buyers exercise corporate social responsibility. Specifically, our results show that perceptions of working condition risks are moderated by factory size, with such perceptions of risks being considerably lower in the context of larger factories compared to smaller factories. This provides support to our arguments that larger factories may be perceived to be more active in remediating working conditions risks due to greater availability of resources and/or the presence of formalized structures and explicit organizational systems (Distelhorst et al. 2016, Sila 2007). In sum, our study findings lend credence to arguments from the literature that the extent to which buyers exercise corporate social responsibility in global supply chains may often be dependent upon the specific characteristics of the supplier factories embedded within the supply chains (Distelhorst et al. 2016, Besiou and Van Wassenhove 2015).

Beyond the theoretical implications, our study findings have actionable implications for both buyers and suppliers in the Bangladesh garment industry. From the buyers perspective, their sustained participation in industry-wide consortiums (such as Alliance and Accord) aimed at improving worker safety in supplier factories sends a clear signal to suppliers about the importance of maintaining acceptable safety standards in their factories. This, in turn, reduces the potential for supply chain disruptions and reputation losses that can occur due to supplier safety events. At the same time, buyers' participation in consortium efforts also establishes a level-playing field where buyers can compete with each other without compromising the safety of workers in supplier factories. From a suppliers' standpoint, our study findings demonstrate that improving working conditions in their factories can reduce buyer concerns about related risks and may translate into greater potential for contracting with buyers. That is, it signals to suppliers that improvement in working conditions can have beneficial financial consequences, and that greater efforts should be expended toward the regular maintenance of factory structures, specifically in areas that minimize fire and electrical risks for workers. Taken together, our findings imply to both buyers and suppliers that "safe" factory operations are not an oxymoron (Pagell et al. 2014), and indeed, such operations present sustainable benefits for both sides.

Finally, findings from our study have the potential to inform policy and decision making at the governmental level in Bangladesh (Besiou and Van Wassenhove 2015), and other developing economies focused on the garment industry (e.g., Vietnam, Cambodia, and Ethiopia). Highlighting the importance of this industry in the economic growth of developing countries, a recent World Bank report (World Bank 2015, p. xiii) notes, "*One of the first steps that many countries have taken in the past hundred years to begin their development process is to produce apparel. The apparel sector is labor-intensive, which makes it an appealing industry for many countries as they seek to create jobs for their citizens…for millions of poor unskilled workers [in developing countries], jobs in apparel manufacturing can be a first step toward escaping poverty.*" In the context of Bangladesh, as noted earlier, the garment industry accounts for nearly 80% of Bangladesh's total exports and contributes significantly to reducing unemployment and poverty. Further, the sample of factories in our full model represent approximately one-fifth of the garment factories in Bangladesh (BGMEA 2016). Therefore, the empirical findings that working condition risks in supplier factories are negatively associated with buyer trust in the garment industry provides strong incentives for the Bangladesh government to support supplier factories in improving working conditions. Remediation efforts for minimizing working condition risks in Bangladesh garment factories are estimated to range between $250,000-$350,000 per factory on average (Alliance 2015), and financial support for such efforts is often necessary. Through provisions of low-interest rates credit and loan schemes aimed at garment factories in Bangladesh, the local government can not only signal their explicit support for the industry, but also encourage supplier factories to proactively engage in carrying out improvements in working conditions. Further, such interventions at the government level can not only help raise the overall standards or working conditions in factories industry-wide, but also attract greater foreign direct investment—as Kucera (2002) notes, all else being equal, countries that comply with global working condition standards are more likely to attract foreign direct investment.

4.6.3. Limitations and Concluding Remarks

Our study has limitations that can also serve as avenues for future research. First, our study focuses solely on the RMG industry in Bangladesh. While the study findings and implications may be extended to factories in different industries (e.g., high-tech manufacturing and garment manufacturing in south-east Asian nations), more research needs to be carried out across a variety of industry and geographical settings. Such an extension would add greater depth to our understanding of the conditions and context for integration between corporate social responsibility and global sourcing. Second, the use of cross-sectional data in our analysis does not allow us to take a closer look at the dynamics of trust-building vis-à-vis improvement in working conditions. While such exploration can be carried out using longitudinal data, the availability of such data can also enable deeper and nuanced insights into: (i) how maturity in working conditions occurs within an industry, and (ii) how such maturity can influence the integration of corporate social responsibility practices in global sourcing strategies of firms. Third, another limitation of the study is that the measure of buyer trust, the dependent variable, is the number of contracts per factory. While this variable serves as a suitable proxy for measuring buyer trust in a supplier factory, it does not take into consideration the scale and scope of the contract associated with each buyer. Future studies would benefit from collecting more nuanced data on buyer trust which accounts for such heterogeneities in contracts across buyers. Finally, in this study, we examine corporate social responsibility from the buyers' perspective. A future line of research would be to examine the role of suppliers and their actions in the working conditions improvement process. Specifically, future studies can explore innovative ways through which suppliers can actively collaborate with buyers to improve working conditions in their factories, or whether a "backfiring condition" is necessary for buyers to motivate suppliers to do so, as suggested by Plambeck and Taylor (2015, p. 1).

Notwithstanding the above limitations, this study provides new, theoretically grounded empirical insights into innovative and impactful approaches to improve working conditions in factories in developing countries. These supplier factories are an integral part of the global supply chains. Their importance to their workers and to global business should motivate scholars to pursue this consequential line of inquiry.

Chapter 5

Conclusion

5.1. Conclusion and Contributions

The dissertation is motivated by the increasing challenge of managing human capital and technology for sustainable and responsible operations in global supply chains. Facing new technologies and the necessity for the appropriate accompanying skills in global supply chains, organizations must manage well both the technology and the human capital, and must do so both internally and externally. This dissertation focuses on integrating technology and human capital in supply chains. The investigation unfolds in the four arenas: 1) technology development; 2) human capital; 3) work design; and 4) working conditions. These areas present critical challenges for operations management in supply chains in the current era. The dissertation echoes the call from the extant literature that organizations are expected to develop technological capabilities to accommodate the technology adoption and have important and integral social, psychological, and ecological responsibilities. Employing data from the health care and garment industries as empirical settings for the analysis, two main research questions guide the three essays embedded in the dissertation. More specifically, *1) how do organizations manage health information technology investment and develop the technological capability of physicians and nurses to provide quality health care to a larger population? 2) how do buyers encompass socially responsible operations and improve working conditions in a supplier factory?*

To address the research questions, the dissertation conducts both exploratory and confirmatory analysis with a mixed-method approach. Overall, the results and findings contribute to the development of supply chain management theory and to the application of these theories to real world industrial practice. The overall contributions of the dissertation are as followings.

First, the dissertation has significant research relevance. The dissertation is rooted in industry practices in the real world, and is motivated "by the thought of gaining and developing truly relevant knowledge that might change the world of organizations" (Toffel 2016, p. 11). The research relevance is established by engaging practitioners (e.g., policy makers, cooperate managers, NGOs) in the projects, and addressing research questions that challenge the supply chains and operations practices in the organizations (Van de Ven 2007).

Second, the investigation is formulated and advanced in the consistent inquiry about the relationship between managing technology and managing human capital (Wachter 2015, Babbage 1832). One aim of the dissertation is to obtain deeper understanding of the role of technology and operations practices on bridging disparities across communities and regions (World Bank 2015, 2016, Sinha and Kohnke 2009).

Third, the dissertation contributes to the literature on organizational interventions for managing and organizing the "social evaluations" (i.e., goodwill, reputation, image, or status) towards employees in supplier factories across country boundaries (Jayasinghe 2016, Wang et al. 2016). Our study extends the breadth and depth of the current literature by dealing with global challenges in supply chains and operations practices.

Below, we summarize the specific findings from this dissertation and their implications for theory and practice. We also discuss the limitations of the dissertation studies, and suggest directions for future research.

5.1.1. Essay I: Evaluating the Implementation Effectiveness of Clinical Decision Support (CDS) Systems: The Enabling Role of Health Care Provider Capability

Essay I investigates how workforce capabilities shape the implementation effectiveness of CDS systems, one critical component of an Electronic Health Record system. Under the knowledge management framework of technology, the dissertation develops a model on the integration between explicit knowledge embedded in the technology system and tacit knowledge from workforce capabilities, and their impact on care delivery effectiveness in clinical organizations (Gaimon 2008, Alavi and Leidner 2001, Nonaka 1994).

Our empirical analysis results show that more extensive CDS system implementation can enhance care delivery effectiveness, while low levels of related workforce capabilities have a significantly negative impact. These results align well with the argument of the critical role of both explicit and tacit knowledge on care delivery in clinics. We further study their joint effect, and investigate how each specific type of workforce capabilities interacts with CDS systems. The findings on the interaction relationships vary across the types of workforce capabilities. Specifically, trainer needs (i.e., low workforce capability in training on information technology use) negatively moderate the relationship between CDS and care delivery effectiveness, suggesting that this type of workforce capability can strengthen the effectiveness of CDS. However, both informatics needs (i.e., low workforce capability in health informatics skills), and EHR/IT staff needs (i.e., low workforce capability in preparing and maintaining EHR/IT systems) have positive moderating effects. Counter-intuitively, we find that these two types of workforce capability, in fact, dampen the effectiveness of CDS. These findings indicate that a complex relationship exists for the integration of explicit and tacit knowledge related to technology implementation.

This study has significant implications for theory and practice. The study extends current research on knowledge creation and transfer for explicit and tacit knowledge as they relate to organizational performance in health care delivery organizations (Dey et al. 2013, Nag and Gioia 2012, Aral and Weill 2007, Preuss 2003, Alavi and Leidner 2001, Nonaka 1994, Pisano 1994). Creation and transfer of explicit knowledge during the process of CDS system implementation can strengthen care delivery effectiveness in clinical organizations. At the same time, creation and transfer of tacit knowledge from workforce capabilities has a similar positive impact. Also, our study illustrates the impact of knowledge creation on outcomes at the medical group level, which supports the proposition that the knowledge creation can occur at certain levels across the organizational structure (Aral et al. 2012, Pisano 1994). In our study, the knowledge generated at the medical group level can affect clinical outcome. More importantly, we identify the heterogeneous roles of the joint effects of knowledge in CDS system implementation and various types of workforce capabilities. This is similar to previous studies that find the direct benefits of adoption and use of health IT in healthcare industry, while these benefits can be contingent on specific workforce skills, management choice/sequence and other infrastructures (Dey et al. 2013, Kong et al. 2012, Angst et al. 2011, Hess and Rothaermel 2011, Queenan et al. 2011). This study therefore contributes to the current understanding of the integration and interaction among knowledge elements in health care delivery settings.

For practitioners in clinical organizations, the findings in this study provide deep insights on how to manage CDS system implementation and related workforce capabilities development. Our results indicate that knowledge in certain workforce capabilities, EHR/IT related skills and informatics may need to be continuously updated, in order to accommodate the increased knowledge requirement in CDS system implementation. Managers need to recognize the complex interactions among the technical system implementation and workforce capability development. The immediate and positive interaction may not be evident for novel workforce capabilities (e.g, informatics skills). These insights can also be applied in similar new technology adoption projects.

5.1.2. Essay II: Evaluating Telemedicine Adoption in Clinics: Accounting for Socioeconomic, Geographical, Organizational and Technological Antecedents

Essay II investigates how geographical, socioeconomic, organizational, and technological contexts affect telemedicine use and its effectiveness. The dissertation employs the technology-organization-environment (TOE) framework as the theoretical underpinning to examine antecedents and consequences of telemedicine adoption in clinics (Tornatzky and Fleischer 1990).

Combining data from multiple sources relevant to clinical organizations, our empirical analysis indicates that differences in geographic location characteristics and organizational barriers have significant impact on telemedicine adoption. Specifically, rural and low poverty regions are positively associated with telemedicine adoption, while cost and low local demand are barriers. We further examine the implication of telemedicine adoption on organizational outcomes. The results suggest that telemedicine adoption is related to the effectiveness of care delivery in clinics. More extensive use of telemedicine is associated with greater care delivery effectiveness. However, examining the interaction among technologies, we find that telemedicine reduces the effectiveness of Clinical Decision Support (CDS) systems – i.e., the benefit of telemedicine is greater in clinics with a lower level of CDS adoption.

The dissertation provides evidence supporting the proposed theoretical model on the antecedents and consequences of telemedicine. First, this study generally supports the theory framework on the technological, organizational, and environmental contexts in technology management, i.e., the TOE framework (Bernroider and Schmöllerl 2013, Aral et al. 2012, Aral and Weill 2007, Park et al. 2007, Zhu et al. 2006, Klein and Sorra 1996, Tornatzky and Fleischer 1990). Our findings provide evidence on the significant role of geographical location (i.e., rural vs. urban areas), socioeconomic characteristics (i.e., regional poverty) and organizational context (i.e., cost and demand). Meanwhile, our study complements the extant literature on the management of technology in health care settings (Dey et al. 2013, Nair et al. 2013, Angst et al. 2011, Queenan et al. 2011, Osheroff 2009), and supports that different IT systems can interact with each other in an organization (Aral et al. 2012, Queenan et al. 2011, Aral and Weill 2007). Contrary to the notion that telemedicine and CDS are complementary systems that can increase an organization's absorptive capability (Bertrand and Mol 2013, Cohen and Levinthal 1990), our study suggests these two ITs may interact in a more complicated way (Queenan et al. 2011). Telemedicine adoption may require novel processes and practices, or involve different knowledge creation and management skills (Nicolini 2011, Paul 2006).

These findings provide insights for practitioners on managing technology adoption. Specially, our findings provide guidance to clinics on carefully choosing adoption levels of telemedicine and CDS to maximize the potential benefits of both technologies on care delivery effectiveness. First, managers need to decide whether telemedicine-enabling investments are appropriate based on the many technological, organizational, and environmental characteristics of their particular clinical organization. Our evidence indicates that, currently, clinics in rural and wealthier communities may benefit more from using telemedicine. Second, when adopting multiple technologies, managers may need to choose appropriate approaches to avoid the potential performance loss when the use of one technology negatively affects the effectiveness of the others.

5.1.3. Essay III: Evaluating Working Conditions in Supplier Factories: An Empirical Analysis of Global Sourcing From Developing Countries

Essay III uses the Bangladesh ready-made garment (RMG) industry, and investigates how buyers in the global garment industry coordinate and collaborate to improve working conditions in supplier factories in Bangladesh. In line with the literature on supply chain trust and risk management, the dissertation explores the implications of three types of working condition risks on buyer sourcing strategy. We characterize these risks as structural risk, fire risk, and electrical risk. We collect data from two large consortiums: North American retailers comprise the Alliance for Bangladesh Worker Safety (Alliance), and European retailers comprise the Accord on Fire and Building Safety in Bangladesh (Accord). We examine the implications of each type of risk for *buyer trust* and buyer sourcing strategy.

The empirical results support the contention that buyers are sensitive to working condition risks in a supplier factory. When working condition risks in a supplier factory increase, buyer trust in the factory decreases. Our analysis, however, shows that this relationship varies with the type of the risk. Specifically, among the three types of studied risks, fire and electrical risks are associated with decreased buyer trust, while structural risk has a marginal negative effect. Further, the negative relationship between working condition risks and buyer trust is contingent on the size of the supplier factory. The results indicate that for a given level of risk, buyers have greater trust in larger factories compared to smaller factories. It may imply that buyers expect large factories to share the responsibility and take corrective actions toward improving working conditions.

This paper makes significant contributions to research and practice related to supplier-buyer relationship management in a global supply chain that extends into supplier factories located in developing countries. The working conditions in these factories cannot be assumed to be safe, but the studied consortiums can be impactful in sharing risk information with distant buyers.

Our study contributes to the literature on the implications of corporate social responsibility on supply chain management(Carroll et al. 2012), evaluate the safety for workers (Pagell et al. 2014, 2015, Lo et al. 2014, Pagell and Gobeli 2009), and develop a responsible sourcing strategy and practices across firm and country boundaries (Distelhorst et al. 2016, Plambeck and Taylor 2015, Toffel et al. 2015, Porter and Kramer 2011, Sinha and Van de Ven 2005). First, our study echoes the call from the extant literature that firms are expected to "*assume important and integral social, psychological, and ecological responsibilities*" (Ødegaard and Roos 2014, p. 2205) and to establish "*socially responsible operations*" (Besiou and Van Wassenhove 2015, p. 1390). This study provides empirical evidence that firms do integrate workplace safety measures into operations practices (Distelhorst et al. 2016, Jayasinghe 2016, Guo et al. 2015, Plambeck and Taylor 2015, Brown 1996). Meanwhile, we identify the effectiveness and limitation of the current evaluation practices of workplace safety during the supplier selection before the contracting relationship is built (Distelhorst et al. 2016, Porteous et al. 2015, Locke 2009, Locke et al. 2009).

Second, our study contributes to the supply chain risk management literature which has highlighted that working conditions in supplier factories in developing countries should be an important consideration in global sourcing (Jayasinghe 2016, Sodhi 2015, Chopra and Sodhi 2004, 2014, Sodhi et al. 2012, Robertson et al. 2009, Jayasuriya 2008). Specifically, our findings indicate that, in the context of the Bangladesh garment industry, buyers from developed countries do value better working conditions in a supplier factory. Given its potential implications for supply chain disruptions and reputation loss, the evaluation of working conditions influences the likelihood that a buyer will contract with a supplier.

Third, our study findings indicate that, while buyers (e.g., North American and European retailers) demonstrate corporate social responsibility by accounting for working conditions in supplier factories, specific contingencies arise from the factory characteristics (e.g., factory size in our study) that may moderate the extent to which buyers exercise corporate social responsibility. The above findings highlight the marketplace implications of working condition risks in supplier factories and suggest that the competitiveness of a supplier factory in a developing country is inversely related to the level of working condition risks in the factory.

These findings provide insights for practitioners from both buyers and suppliers on managing working conditions. First, we show that information on working condition risks impacts buyer decisions. When starting sourcing from developing countries, managers from buyer firms need to treat working condition risks in upstream supplier factories more seriously. They need to work with suppliers that can comply with industry codes of conducts. Otherwise, buyers may not be able to avoid the loss of reputation or supply chain disruption (Short et al. 2015), when they neglect the likelihood of disasters in a supplier factory with poor working conditions. Second, the current practices for buyers have some limitations and the inspection in structural risk may need more attention. Third, managers from supplier factories also need to continuously improve the working conditions. Our results provide significant implication of working conditions, and poor working conditions can lead to loss of trust, which may reduce supplier factories' competitiveness in the market.

5.2. Limitations and Future Studies

The dissertation has some limitations that should be addressed in future studies. First, the key limitation is that the operationalization of our constructs using secondary data is not perfect. For example, in studying CDS and telemedicine in the health care industry, we measure health care delivery effectiveness via an organizational perception on the improvement in several dimensions. Such a measure is neither objective nor comprehensive. Different clinics and medical groups may choose different standards to indicate their success in using the technology. And the data do not provide detailed information on how the care delivery is improved through patient treatment, physician involvement, or learning related to technology use in the care processes used by health care providers. Future studies can extend our aggregate measure of health care delivery effectiveness to provide deeper understanding on the process of technology adoption and use in clinical organizations. Similarly, in studying the buyer-supplier relationship in the global garment industry, we use the number of contracting buyers to indicate buyer trust for each supplier factory. While this variable serves as a suitable proxy for buyer trust in a supplier factory, it does not take into consideration the scale and scope of the contract associated with each buyer. Future studies would benefit from collecting more nuanced data on buyer trust which accounts for such heterogeneities in contracts across buyers.

The second limitation of the dissertation relates to the analysis from the health care and garment industries, and each analysis is constrained to an individual industry sector. While in each industry the data are quite comprehensive in terms of scope and depth, and each study involved the combination of several relevant databases, the analysis and results do not provide implications for across industry scenarios. Therefore, the generalization of our findings to different industry sectors or regions/counties should be cautionary.

The third limitation relates to the role of organizational levels at managing technology and human capital for socially responsible operations. The organizational levels can involve individual employees, teams, units, organizations, networks and industries. Future study can extend the dissertation by exploring the effect of cross-level factors, including workforce capabilities, technology implementation, and management. More effort is needed to provide a complete view of cross level knowledge creation and transfer in the technology management.

One future research opportunity is to extend the scope of our research model. The dissertation is limited to organizations in one industry or one supply chain. For example, studying CDS and telemedicine in the health care industry, the dissertation focuses on clinics and medical groups in the health care industry. Although they provide direct health care equipment and services to patients, we do not include in our sample the organizations in pharmaceuticals, biotechnology and related life science groups, based on the Global Industry Classification Standard (GICS) developed by MSCI and Standard & Poor's (MSCI 2015). The latter group includes companies that produce biotechnology, pharmaceuticals, and miscellaneous scientific services. The dissertation makes an effort to examine more than one type of organization in the health care and global garment industries because the success of one organization may be highly dependent on upstream and downstream partners in the global market. However, the dissertation is not able to collect data for all related organizations in a whole supply chain or industry. Future research can identify some novel datasets or unique industries that enable such valuable enquiry. For example, it would be valuable to incorporate the role of health IT development organizations (e.g. the organizations which develop and produce CDS systems and telemedicine equipment), and to study the impact of their development activities on the effectiveness of technology adoption in clinics. Future research can also explore technological development in the pharmaceutical, biotechnology, and life science industry group, and examine how newly developed new techniques and interventions change the clinical practices. Such change may alter the usefulness and utility of certain types of health IT technologies in clinical organizations.

The presence of inconsistent effects related to the use of different technological components, external factors affecting technology use, and types of working conditions on sourcing strategies open up another new research direction. The dissertation provides substantial evidence of the contingent role of various factors on the technology management and working conditions improvement. For example, we find that workforce capabilities in clinical organizations can affect the effectiveness of CDS systems adoption. Also, the negative impact of working condition risks on buyer sourcing decisions can be mitigated by the supplier factory size. Still, only a small proportion of complexity in the contingencies is covered. Future research needs to investigate further the specific interactions among the main factors around managing technology and human capital in supply chains, study the underlying mechanisms, and explore more on contingencies to understand "why," "how," and "so what."

Notwithstanding the above limitations, the dissertation provides new, theoretically grounded empirical insights into managing human capital and technology for sustainable and responsible operations in global supply chains. More specifically, the study uncovers the critical role of the mix of technology and human capital in organizations, centering on the following dimensions: 1) technology development; 2) human capital; 3) work design; and 4) working conditions. Also we identify some contingencies that have implications for both sustainable and socially responsible operations. Yet, two main gaps exist: 1) how do technology and human capital management relate to other business functions in organizations, such as finance, accounting, marketing and strategy management? 2) how do sustainable and socially responsible operations interact with other business functions for organizational competitiveness in the global market? More research is necessary to fill these gaps, because managing human capital and technology for sustainable and responsible operations play an integral role in global supply chain management. Their importance to global business should motivate scholars to pursue this consequential line of inquiry.

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Appendices

A.1. Appendices Related to Chapter 3

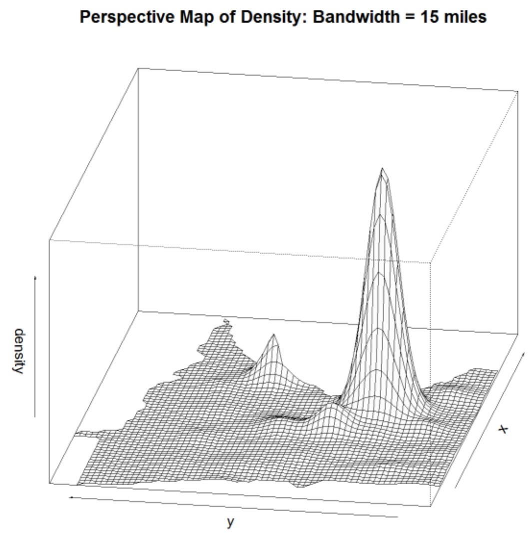
A.1.1. Percent of People below Poverty Level in the Past 12 Months

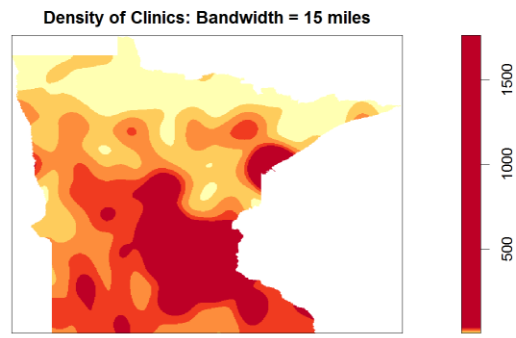
Geographic Area	Percent	Margin of Error
Minnesota	11.5	+/-0.1
Aitkin County	12.1	+/-1.3
Anoka County	7.4	+/-0.4
Becker County	12.9	+/-1.4
Beltrami County	21.9	+/-1.9
Benton County	14.5	+/-1.8
Big Stone County	12.4	+/-2.4
Blue Earth County	19.2	+/-1.2
Brown County	9.4	+/-1.3
Carlton County	12.5	+/-1.5
Carver County	5.0	+/-1.0
Cass County	16.4	+/-1.3
Chippewa County	10.6	+/-2.4
Chisago County	7.5	+/-1.1
Clay County	12.3	+/-1.4
Clearwater County	16.5	+/-1.7
Cook County	8.3	+/-2.4
Cottonwood County	13.7	+/-2.4
Crow Wing County	12.9	+/-1.2
Dakota County	7.6	+/-0.5
Dodge County	7.4	+/-1.3
Douglas County	10.8	+/-1.4
Faribault County	12.8	+/-2.2
Fillmore County	12.1	+/-1.2
Freeborn County	11.0	+/-1.3
Goodhue County	9.9	+/-1.4
Grant County	10.1	+/-1.8
Hennepin County	12.8	+/-0.3
Houston County	10.9	+/-2.1
Hubbard County	13.2	+/-1.5
Isanti County	8.0	+/-1.4
Itasca County	12.5	+/-1.2
Jackson County	11.7	+/-1.9
Kanabec County	13.5	+/-1.9
Kandiyohi County	13.6	+/-1.4
Kittson County	9.8	+/-1.7
Koochiching County	14.1	+/-2.4
Lac qui Parle County	8.0	+/-1.4
Lake County	13.6	+/-3.2

Geographic Area	Percent	Margin of Error
Lake of the Woods County	7.9	+/-3.3
Le Sueur County	8.8	+/-1.3
Lincoln County	8.7	+/-1.2
Lyon County	14.4	+/-2.2
McLeod County	8.5	+/-1.5
Mahnomen County	26.2	+/-2.8
Marshall County	7.9	+/-1.0
Martin County	10.7	+/-1.7
Meeker County	10.2	+/-1.3
Mille Lacs County	13.9	+/-1.5
Morrison County	12.6	+/-1.3
Mower County	16.3	+/-2.2
Murray County	10.6	+/-2.1
Nicollet County	10.6	+/-1.8
Nobles County	16.0	+/-2.7
Norman County	13.1	+/-2.0
Olmsted County	8.0	+/-0.7
Otter Tail County	11.7	+/-0.8
Pennington County	10.9	+/-1.9
Pine County	14.8	+/-1.5
Pipestone County	10.7	+/-1.7
Polk County	12.6	+/-1.3
Pope County	9.2	+/-1.8
Ramsey County	16.9	+/-0.6
Red Lake County	11.9	+/-1.8
Redwood County	10.0	+/-1.4
Renville County	11.6	+/-1.4
Rice County	11.6	+/-1.6
Rock County	13.1	+/-2.8
Roseau County	9.7	+/-1.4
St. Louis County	16.4	+/-0.6
Scott County	5.5	+/-0.7
Sherburne County	7.8	+/-1.2
Sibley County	11.8	+/-1.9
Stearns County	13.1	+/-0.8
Steele County	10.3	+/-1.3
Stevens County	15.4	+/-2.3
Swift County	9.8	+/-1.7
Todd County	15.7	+/-1.6
Traverse County	9.0	+/-2.1
Wabasha County	8.3	+/-1.5
Wadena County	16.9	+/-2.7
Waseca County	9.4	+/-1.7
Washington County	5.7	+/-0.6
Watonwan County	10.8	+/-2.4
Wilkin County	9.2	+/-1.8
Winona County	15.0	+/-1.2
Wright County	6.5	+/-0.8
Yellow Medicine County	12.2	+/-1.8

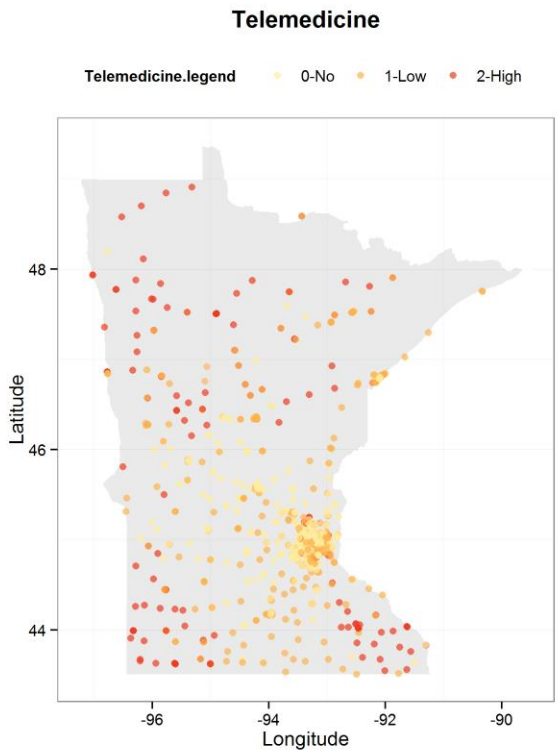
Source: US Census of Bureau. The data is retrieved through “American FactFinder” on the Census Bureau’ website, and the data set is Poverty from “2009-2013 American Community Survey 5-Year Estimates.”
http://factfinder.census.gov/faces/tableservices/jsf/pages/productview.xhtml?src=CF

A.1.2. Density and Contour Plot of Neighboring Clinics in Minnesota





A.1.3. Map of Telemedicine Adoption



A.1.4. Propensity Score Analysis

The propensity score is the probability that a study participant is assigned to the treatment group of interest rather than a control group, based on the observed factors. The propensity score is calculated by the following estimation,

$$t^{*} = X\beta + \epsilon$$

$$t = I(t^{*} > 0)$$

$$p(t = 1|X) = p(t^{*} > 0|X)$$

$$= p(\epsilon > -X\beta|X)$$

$$= 1 - \Phi(-X\beta) = \ \Phi(X\beta)$$

Where t^{*} is the unobserved probability for treatment given the observed characteristics, X. t equals 1 if treatment occurs, and 0 otherwise. ϵ is the error term, which is assumed to follow a normal distribution, and $\Phi(\cdot)$ is the cumulative distribution function, which ranges from 0 to 1. We further define the potential outcome as Y[t] for t =1,0. The difference in the two groups is denoted by $D[t_1, t_0] = Y[t_1] - Y[t_0]$.

We use counterfactuals to define the treatment effects from observational data with treated and control groups. The first is average treatment effect (ATE), which is comparison of outcomes had the entire population received the control, versus had the entire population received the treatment. The ATE effect is $E(D[t_1, t_0]) = E(Y[t_1] - Y[t_0]) = E(Y[t_1]) - E(Y[t_0]) = \mu_{t_1} - \mu_{t_0}$. The second is average treatment effect on the treated (ATT). ATT is comparison of outcomes for those treated with treatment t_1, versus outcomes if they had instead been assigned to the control group. We can write it as $\mu_{t_1,t_0} = E(Y[t_0]|t_1)$, and the ATT is $\mu_{t_1,t_1} - \mu_{t_1,t_0}$. For the outcome analysis, we follow a regression approach with all variables in the model, while use the propensity as weights (McCaffrey et al. 2013).

A.1.5. Panel Data Analysis

In the fixed effects model,

$$y_{it} = X_{it}\beta + a_i + \epsilon_{it}$$

Where i indicates clinic, t indicates year (2013 or 2014), and ϵ_{it} follows a normal distribution. The unit effect a_i captures the unobserved effect in our data.

In the random effects model, a_i is not estimated directly, rather it is assumed to follow a specified distribution. We can assume a_i follows a normal distribution with mean μ_a and variance σ_a^2. Compared to the fixed effects model, a random effects model can incorporate the effect from the individual level.

In the first difference model, we can use the variables from the second period minus the first period to cancel out the specific effect for each clinic, which is not reported in the data set. The estimation for the treatment effect then indicates the difference in the outcome, comparing the treatment and control groups. The model can be written as,

$$\Delta y_{it} = y_{it} - y_{it-1} = \Delta x_{it}\beta + \Delta\epsilon_{it}$$

A.2. Appendices Related to Chapter 4

A.2.1. Data Sources for Sample Development

Source	Note	Access date	Number of factories
1. Accord	1578 active factories	07/23/2015	1005
2. Alliance	662 active factories	07/23/2015	614
3. Bangladesh Garment Manufacturers and Exporters Association (BGMEA)		08/19/2015	4393
4. Bangladesh Knitwear Manufacturers & Exporters Association (BKMEA)		08/26/2015	1830

A.2.2. Safety Inspection Report Examples from Alliance and Accord

Alliance Inspection Report - Example 1

Fire Protection Construction		
Question:	Are exit enclosures provided with fire-resistive rated construction barriers?	 
Priority Level:	High	
Non-Compliance Level:	3	
Description:	Exit enclosures itself are provided with fire resistive construction barriers, but the doors and ventilation near production floor are not fire rated in any stair. Visually some of the exit doors appear to be fire door in stair-3. However, no credible certificate is available and there is an arrangement of collapsible shutters with fire door.	
Source of Findings:	Photograph: Rolling shutter type doors and fire door are available at exits leading to exit enclosure.	
Suggested Plan of Action:	Exit enclosure shall have a minimum fire-resistance rating of 2 hr when connecting four stories or more and a minimum fire-resistance rating of 1 hr when connecting three stories or less. Fit doors that swing in the direction of egress, side-swinging, self-closing, non-lockable fire doors of 1.5 hr rating at 2 hr rated fire barriers and 1 hr rating at 1 hr rated fire barriers. Consult a qualified fire protection engineer to design the required rated construction barriers.	
Suggested Deadline Date:	23 Sep 2014	
Standard:	Reference Alliance Standards Part 4 Section 4.5 Separation	

Accord Inspection Report – Example 2

Item No.	Observation	Recommended Action Plan	Recommended Timeline
1	Stress levels in Columns	Building Engineer to review design, loads and stresses in columns in the area noted.	**6-weeks**
2	Stress levels in Columns	Building Engineer to verify insitu concrete strength by taking 100mm diameter cores from 4 columns.	**6-weeks**
3	Stress levels in Columns	Building Engineer to verify grade of steel reinforcement and no. and diameter of main column bars.	**6-weeks**
4	Stress levels in Columns	Make structural alterations if required as advised by Engineer.	**6-months**
5	Hairline cracking on beams and some slab soffit areas	Monitor cracks on beams. Building Engineer to investigate if cracks are only in the plastering.	**6-months**