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Three Essays on the Empowerment Role of Information Technology in Healthcare Services

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THREE ESSAYS ON THE EMPOWERMENT ROLE OF INFORMATION TECHNOLOGY IN HEALTHCARE SERVICES

BY

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ACCEPTANCE

This dissertation was prepared under the direction of the LIWEI CHEN's Dissertation Committee. It has been approved and accepted by all members of that committee, and it has been accepted in partial fulfillment of the requirements for the degree of Doctor of Philosophy in Business Administration in the J. Mack Robinson College of Business of Georgia State University.

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ABSTRACT

THREE ESSAYS ON THE EMPOWERMENT ROLE OF INFORMATION TECHNOLOGY IN HEALTHCARE SERVICES

BY

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7/12/2016

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Information technology (IT) is empowering consumers, service providers, and inventor teams with superior services. Various IT innovations are enabling diverse groups of people to search, exchange, and learn from information. In healthcare services, the context of the three essays of this dissertation, information resources are often not equally accessible to consumers, not transparent between patients and physicians, and hard to locate across technological domains that may be relevant to the development of breakthrough innovations. Focusing on empowering roles of IT in healthcare services, I develop a three-essay dissertation to study how IT can enable information access to (i) address health inequalities in developing regions of the world, (ii) strengthen the physician-patient relationship where patient trust in the physician has atrophied, and (iii) energize inventor teams in the development of medical device innovations.

Essay 1 examines consumers' awareness and use of mobile health that can empower consumers to access health advice information. Essay 2 investigates how online health consultation communities can empower physicians to build trust with patients, and gain social and economic advantages in competitive healthcare services. Essay 3 studies the role of digital capabilities to empower inventor teams in medical device companies by converting expertise of inventor teams into broad and deep knowledge capital and expanding knowledge production regarding medical device innovations.

I adopt a pluralistic approach to collect data (surveys administered in multiple languages for Essay 1, scraping web data from online communities for Essay 2, and constructing a multisource archival panel dataset for Essay 3) and analyze data (multivariate analysis for Essay 1, multilevel modeling and econometrics for Essay 2 and Essay 3). The essays contribute to our understanding about the acceptance of empowering IT innovations, the empowering role of user-generated content in online communities for providers of credence services, and the empowering role of IT for inventor teams of healthcare innovations.

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Chapter 1

Introduction

Information technology (IT) can empower consumers, service providers, and inventor teams with superior access to information resources. A fundamental principle underlying the empowerment concept is to give the powerless power by providing access to critical resources. Since information is such a key resource in today's economy, providing access and control to information gives people the power to make informed decisions and take actions to change behaviors. From mobile computing to social media to organizational digital applications, IT innovations are enabling diverse groups of people to search, exchange, and learn from information.

In healthcare services, the context of this dissertation, information resources are often not equally accessible to patients, not transparent between patients and physicians, and hard to locate across technological domains that may be relevant to the development of breakthrough innovations. With various functions to access, process, and communicate health information (Fichman et al. 2011), IT plays an empowerment role in supporting multiple stakeholders in the healthcare industry to make informed decisions and solve problems in a strategic and intelligent manner. Under this vein, there is increasing need to understand IT-enabled empowerment for patients, physicians, and inventor teams who develop technological innovations such as medical devices.

Conceptually, empowerment has been viewed from two perspectives: structural empowerment and psychological empowerment. While structural empowerment focuses on the actions of more powerful parties to delegate authority to the less powerful parties (Burke 1986), psychological empowerment focuses on the motivational responses of less powerful parties to reflect the extent to which psychological needs for power are fulfilled (Conger and Kanungo 1988). With the first essay informed by the psychological empowerment perspective and the other two essays informed by the structural empowerment perspective, this dissertation provides a complementary understanding on various empowering roles of IT in healthcare services. Specifically, I study how IT can enable information access to (i) address health inequalities in developing regions of the world, (ii) strengthen the physician-patient relationship in a context where the trust between these parties has atrophied, and (iii) energize inventor teams in their development of medical device innovations. Table 1.1 summarizes the research context, informing theoretical perspectives, and methodology of each essay. An overview of each of the essays is discussed below.

1.1 Essay 1

We adopt the psychological empowerment perspective and examine the role of mobile services to drive consumers in rural and urban areas of India to cultivate intrinsic motivation and ultimately develop awareness and use of mobile health (mHealth). The high penetration of mobile services in India makes it possible to leverage the mobile platform to deliver cost-effective services to alleviate the existing health inequalities (Kahn et al. 2010). In spite of the promising picture, the current state of mHealth acceptance in urban and rural India remains a recognized obstacle (Or and Karsh 2009). We also have limited understanding on how empowerment perceptions toward mobile services lead to the awareness and use of mHealth, and how such influence differs across consumers with different health needs in different socioeconomic groups.

To address these questions, we synthesized psychological empowerment theory and risk theory to inform hypotheses, collaborated with Apollo Hospitals Group to execute survey in eight locations in India. Using mediation analyses and moderated mediation analyses, we find consumers' appraisals of mobile service enabled empowerment affect their awareness and use of mHealth through innovativeness toward mobile services. We also find that the mediation mechanisms are moderated by current and expected health needs to a different extent between rural and urban consumers.

Essay 1 contributes to the IS literature by identifying the role of mobile service in promoting the awareness and use of mHealth from the psychological empowerment perspective. This work provides an in-depth understanding of the spillover effect that empowerment feelings derived from prior mobile service experience could help motivate consumers to seek for and explore new mobile services. More importantly, this research provides a nuanced understanding on how the impacts of empowerment perceptions vary across individuals with different health characteristics in rural and urban areas.

1.2 Essay 2

Essay 2 takes the structural empowerment perspective and is concerned with how online health consultation communities (OHCC) can empower physicians to transmit signals of service quality, build trust with patients, and deliver effective health consultation services. Health consultation services represent a typical type of credence services that professional knowledge is unequally distributed between physicians and patients and patients heavily rely on their trust in physicians to infer the quality of services. OHCC provides a new platform structure to facilitate the transmission of information to infer quality of credence services and help build trust between physicians and patients when knowledge asymmetry is well acknowledged by both parties. This essay examines the mechanisms through which OHCC help physicians to earn patients' trust by signaling their professional competency and compassionate care, and thus increase online patient base and achieve price premium for health consultation services.

Based on signaling theory and the word-of-mouth literature, we developed a multi-level model to test how online patient feedback moderated the effectiveness of physician's signaling efforts. We used web crawling techniques to collect 12-months weekly data from the Good Doctor website (wwww.haodf.com), the largest OHCC in China. Using mixed effects modeling and panel regression techniques, we find that collective features of online patient feedback may reinforce or compensate the impacts of trustworthiness signals to affect the online patient base increase and price premium for health consultation services.

Essay 2 integrates the signaling mechanism with the online feedback mechanism, and demonstrates the role of OHCC in empowering physicians to build trust with patients given the presence of collective online feedback shared among patients. In a more general sense, our results surface how online credence service communities facilitates effective presentation and transmission of expert knowledge and wisdom of crowds, contributes to effective trust-building between service providers and consumers, and achieve desirable outcomes of credence services.

1.3 Essay 3

The third essay also takes the structural empowerment perspective and is concerned with the role of digital capabilities to empower inventor teams in medical device companies by converting inventors' expertise into broad and deep knowledge capital and expanding knowledge production in terms of medical innovations. Effective innovations in medical devices increasingly need medical teams that not only have deep specialization but also are diverse in multiple knowledge domains. What is unclear, however, is how IT can empower inventor teams to access and recombine information, and to solve the dilemma between broadening knowledge capital via diverse inventor expertise and deepening knowledge capital via specialized inventor expertise.

We conceptualized three dimensions of digital capabilities for *Reach*, *Richness*, and *Protection* respectively, and synthesized literatures on IT-enabled innovation and IT strategy to inform hypotheses. We collected archival data from multiple sources, including the UC Berkeley Patent Database, and Computer Intelligence Technology Databases. After matching across databases, we obtained *8757 medical device patents granted to 15 medical device companies from 2010 to 2013*. We formulated the problem and research questions using a multi-level lens (patents by firms) with the patent as the unit of analysis, and constructed a multilevel panel dataset using multiple archival data sources. Our results reveal that firms need to achieve both the broadening and the deepening of knowledge capital in order to develop high quality medical device innovations. Conceptualizing a three-dimensional *Innovation Development Digital Capability*, we find that digital capabilities exhibit great potential in addressing the tension underlying the conversion of inventor team expertise into knowledge capital. The detrimental effects of expertise specialization on knowledge broadening and of expertise diversity on knowledge deepening are mitigated; while the positive effect of expertise specialization on knowledge deepening is amplified. In addition, digital capabilities may also substitute expertise diversity for knowledge broadening.

Table 1.1. Summary of Research Context, Theoretical Perspectives, and Method				
		Essay 1	**Essay 2**	**Essay 3**
Context	Social context	Rural and urban India	China	The United States
	Technological context	Mobile services	Online health consultation communities	Innovation development digital capabilities
	Empowered stakeholder	Mobile service consumers	Physicians	Medical device inventor teams
	Interested Outcome	Awareness and use of mobile health services	Physician's online reputation and price premium	Patent innovation quality
Theory	Informing Theoretical Perspectives	Empowerment theory; risk theory	Signaling theory; word-of-mouth literature.	Strategic management of innovation; IT-enabled innovation.
Method	Data Sources	Collaborate with Apollo Hospitals Group, the largest hospital systems in Asia, to execute the survey in 8 locations in India.	Online data collected from Haodf.com, the largest Chinese online health consultation community with 77 thousand physician users and more than one million patient users across the nation.	1) UC Berkeley Patent Database, 2) Computer Intelligence Technology Database, 3) COMPUSTAT 4) CRSP
	Sample	Study 1 (Measurement Validation): 300 consumers from rural and urban India Study 2 (Hypotheses Testing): 1844 consumers from 8 locations in rural and urban India	One year bi-weekly data for 3178 physicians who provided online consultations and are specialized in obstetrics and gynecology or cardiology.	8757 medical device patent granted to 15 medical device companies from 2010 to 2013.
	Level of Analysis	Individual level	Multi-level: - Individual level - Individual time-varying level	Multi-level: - Innovation activity level - Firm context level
	Analysis Approach	Mediation analysis and moderated mediation analyses	Mixed effects modeling	Hierarchical linear modeling
Implications	Empowerment Perspective	Psychological empowerment	Structural empowerment	Structural empowerment
	Empowerment Role of IT	Fulfill consumers' values in relation to autonomy and making an impact.	Trust building through visible involvement and transparent two-way communications between patients and physicians	Foster an empowering climate to create structural changes in organizational innovation environments

1.4 General Insights

The three essays expand our understanding about the empowerment role of IT in healthcare services. From both the structural and motivational perspectives, we elaborate the empowerment concept with a focus on the role of IT in different social and technological contexts.

Collectively, the findings uncover how various IT artifacts can be deployed to empower stakeholders including healthcare service consumers, physicians, and medical device inventor teams; and address significant societal and business problems: healthcare access disparity among citizens in rural and urban India; trust breakdowns between patients and physicians in online health consultation communities in China; and tensions in designing inventor teams for the discovery of impactful technological innovations in the medical device industry in the U.S.

In a broader sense, the advancements in IT are radically changing the nature of healthcare series by enabling easier and expanded information access. Psychologically, IT can be used as an innovative digital platform that may fulfill people's values in relation to access, autonomy, self-efficacy, and making an impact (Deng et al. 2016). Thus, IT-enabled platforms provide people with a sense of control and freedom. Structurally, IT can be used to break the monopoly of information or knowledge expertise, and allow the decisional power to flow to less powerful stakeholders through the transformed structure (Bowen and Lawler 1992; Jasperson et al. 2002). Accordingly, IT plays a role of strategic enabler by establishing a transparent, collaborative, and secured platform, and allowing for reconfiguration of interdependencies, diffusion of knowledge, openness to participation, and role repositioning (Leong et al. 2016).

Chapter 2

Consumer Awareness and Use of Mobile Health Services in India: An Urban-Rural Comparison Study

Abstract

Mobile health (mHealth) are touted to have huge potential to broaden access, at low cost, to quality healthcare. We examine how awareness and use of mHealth develops among consumers in urban and rural India through a combination of individual traits related to mobile services and individual health characteristics. We conducted a survey in several parts of urban and rural India to develop a diversified sample that approximates the 2011 Indian Census. We find consumers' appraisals of mobile service-enabled psychological empowerment, affects mHealth awareness/use through innovativeness toward mobile services. We also find that this mediation mechanism is stronger for rural consumers who perceive themselves less vulnerable to chronic diseases or less healthy. Our study has implications on how mHealth awareness and use can be developed among consumers in urban and rural areas and in developing country contexts.

Keywords: Mobile health services, empowerment, innovativeness, awareness and use, urban-rural comparison.

2.1 Mobile Health in India

Mobile health (mHealth) refers to various clinical healthcare services that individuals can access through mobile devices (Lester et al. 2011; Källander et al. 2013). Key services include obtaining health advice through mobile devices and exchanging clinical information with healthcare providers through mobile devices. Mobile technology is rapidly increasing its flexibility and popularity in developing countries, including both rural and urban regions. Among the 868 million wireless subscribers in India in 2013, 60% are from urban and 40% from rural areas (Telecom Regulatory Authority of India 2013). This penetration of mobile services across urban and rural India makes it possible to leverage the mobile platform for the delivery of healthcare services to unserved or underserved populations (Kahn et al. 2010) and to bridge the health disparity between urban and rural India. The potential for mHealth to cost-effectively broaden access to quality healthcare in developing countries, which now have high mobile phone density, motivates us to situate our study of mHealth acceptance in India. Given the fact that health services are often concentrated in urban areas, how mobile services empower consumers, especially those in rural areas who are in a more desperate position with limited resources and disadvantaged social status, to access health services becomes highly important.

The extensive discussions on technology acceptance and digital divide have enriched our theoretical understanding on the acceptance of new technologies in developing countries. We know from prior literature that the problem of digital inequality cannot be effectively addressed only by technology access, but instead require a confluence of psychological and social resources to address it effectively (e.g., Venkatesh and Sykes 2012; Hsieh et al. 2008). For example, early studies have identified that socioeconomic characteristics (Hsieh et al. 2008), peer effects (Agarwal et al. 2009), social network factors (Venkatesh and Sykes 2012), and institutional factors (Or and Karsh 2009; Thompson and Brailer 2004) significantly impact the acceptance of new technologies among underprivileged users. Along this line of research, there is a call for more theory-based research into the psychological factors affecting digital inequality (DiMaggio et al. 2001; Jackson et al. 2001). In addition, a recent review of consumer health technology acceptance studies pointed out that many studies have assessed the effects of consumer demographics on health technology acceptance, but the role of context-specific factors, such as individual characteristics related to health technologies and individual health characteristics, is a void in our understanding (Or and Karsh 2009). In response to the knowledge gaps, we integrate the literature on power and risk theory to address the following research questions: 1) how do individual characteristics related to mobile services promote the awareness and use of mHealth services by consumers in urban and rural India? 2) How do consumer needs for health services interact with individual characteristics related to mobile services to influence consumer awareness and use of mHealth in urban and rural India?

First, we adopt the psychological empowerment to identify context-specific constructs with an attempt to understand how consumers develop a psychological sense of power toward mobile services. In detail, we unfold intrinsic motivational mechanisms that mobile services empower consumers to feel meaningful in solving their problems, to believe in their capability in solving problems, to control over the consequences of their problem solving behaviors, and to obtain the autonomy of solving problems on their own. Such sense of empowerment drives consumers to innovate with a variety of mobile services and thus affects their awareness and use of mHealth.

Second, we view the acceptance of mHealth as a decision involving risks and we expect that health needs shape consumers' risk propensities and moderate the strength of empowering mechanisms that promote the acceptance of mHealth. To start with, mHealth is still in its infancy in spite of its promising potential. The mHealth service sector is mostly unregulated, and could present patient safety risks if appropriate precautions are not taken (Lewis and Wyatt 2014). Therefore, we conceive the decision to accept mHealth becomes risky due to such uncertainties and rapid pace of change. Moreover, we argue that consumer needs for health services may shift their proclivity for risk, and may moderate the strength of motivational influence on decision making that involves risk. Accordingly, we are interested in understanding how the strength of empowerment mechanisms promoting the awareness and use of mHealth is contingent upon consumer needs for health services that change risk propensities.

The next section will review the literature on power and risk which provides theoretical foundation for the research model. We discuss two general approaches that the concept of power can be theorized: the structural approach and the psychological approach. Following the second approach, empowerment research develops a core construct of psychological empowerment and validates the nomological network of this construct in workplace context. We then synthesize theoretical arguments and inconsistent findings on the relationship between the possession of power (e.g., sense of power) and risk propensities. Finally, we elaborate our contributions in appropriating psychological empowerment into a non-work context and in justifying consumer needs as potential moderators that reconcile the inconsistent relationship between sense of power and decision-making that involves risk.

2.2 Literature on Power and Risk

The concept of power is defined as the capacity to control valuable resources (Emerson 1962; French and Raven 1959). There are two common approaches to conceptualize power that have been discussed in the literature. The first approach conceives power as a structural construct to reflect the net dependence/interdependence of one party on another (Ng, 1980; Pfeffer 1981). Under this approach, power is often interpreted as hierarchical authority, control over key resources (Conger and Kanungo 1988), and network centrality (Astley and Sachdeva 1984). The second approach views power as a psychological property of individuals (Bugental et al. 1989; Chen et al. 2001; Galinsky et al. 2003). Along this line, psychological empowerment (or the sense of power) is anchored in relational experiences and is a psychological extension of the socio-structural landscape. Individuals may feel empowered when their intrinsic needs for power to influence and control over critical resources are reinforced (McClelland 1975).

The possession of power, either as a structural construct or as a psychological construct, has been shown to affect diverse psychological processes including decision -making processes under conditions of risk (Galinsky et al. 2003). We observe discussions on the relationship between power and risk propensities in two major theories. First, prospect theory proposes that individuals are more risk-seeking in the domain of losses and more risk averse in the domain of gains (Kahneman and Tversky 1979). Therefore, powerless individuals focus more on threats and negative outcomes (Keltner et al. 2003), thus are cognitively operating in the domain of losses and are expected to be more risk seeking. By contrast, powerful individuals focus more on rewards and positive outcomes, thus are cognitively operating in the domain of gains and are expected to be more risk averse (Tversky and Kahneman 1981).

As opposed to prospect theory, approach/inhibition theory proposes that possessing power increases, rather than decreases, individual proclivity for risk (Anderson and Galinsky 2006; Keltner et al. 2003). The sense of possessing power triggers the behavioral approach system to a greater extent than the behavioral inhibition system (Carver and White 1994; Sutton and Davidson 1997). Hence, powerful people tend to pay more attention to positive and rewarding information, and attend less the potential negative outcomes inherent in the risk (Anderson and Berdahl 2002). Focusing on rewards and being less aware of dangers, people who possess power have shown more optimistic when perceiving risks, resulting in increased propensity of risk-taking than those who do not.

Our study aims to enrich the discussion on the relationship between power and risk from two aspects. First, although often conceived as a structural variable (Ng 1980), power as a psychological property merits more attention and theory-driven measures for this construct need to be developed. The psychological oriented conceptualization of power indicates that individuals can form internal representations of their power in specific contexts (Conger and Kanungo 1988). Such sense of power may be activated by external cues, intrinsically motivate individuals to pursue for their desires, and consequently influence their behaviors in meaningful ways (Chen et al. 2001; Galinsky et al. 2003). Prior research has operationalized power as a psychological construct using two methods: (1) measured individual differences in subjects' sense of power (Bargh et al. 1995), (2) primed subjects with a high-power mind-set by either recalling a time in which one possessed power (Galinsky et al. 2003) or using word completion tasks (e.g., Anderson and Galinsky 2006) . While these methods provide complementary evidence on the link between power and risk, we lack a solid theoretical foundation to explain the nature of sense of power. Drawing upon empowerment theory (Conger and Kanungo 1988), we adopt a theory-driven approach and appropriate the construct of psychological empowerment to the context of mobile services. We develop a context-specific construct of *Mobile Service Enabled Empowerment* to directly capture consumers' sense of power in using mobile services to solve problems, and to evaluate the mechanisms through which psychological sense of power results in the acceptance of mHealth, a decision-making process that involves risks.

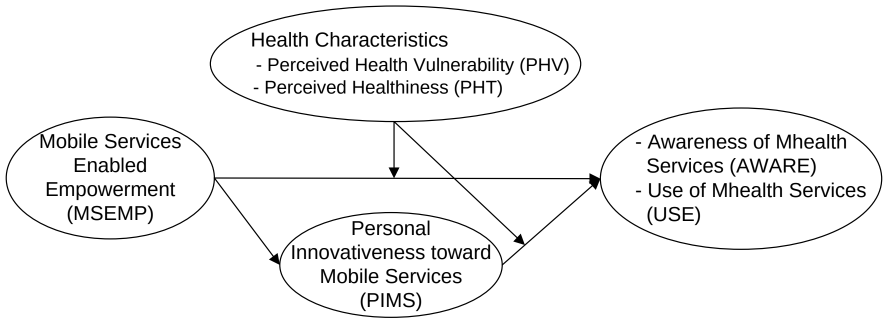
Second, we reconcile the contradictory argument on the relationship between power and risk propensities by examining the moderating roles of consumer needs, specifically consumers' health needs in our context of mHealth services. In more detail, we take the dynamic properties of health needs into consideration, and make a distinction between current health needs and future health needs. Accordingly, we investigate how the moderating effects of current and future health needs differ between consumers in rural and urban areas. This work extends the existing discussion by showing when the effects of power on risk-taking will be exaggerated or mitigated.

2.3 Research Model and Hypotheses

According to empowerment theory (Conger and Kanungo 1988), psychological empowerment is developed as a construct of cognitive-based intrinsic motivation in the workplace. It refers to the extent to which *one's job in general* satisfies his or her psychological needs for *meaningfulness*, *competence*, *self-determination,* and *impact*. Specifically, *meaningfulness* concerns the value of job goals judged in relation to the employee's own values or standards (Hackman and Oldham 1980), *competence* reflects an employee's beliefs in his or her own capabilities to perform work activities with skill (Gist 1987), *self-determination* reflects an employee's sense of having a choice in initiating and regulating actions (Deci et al. 1989), and *impact* denotes the degree to which an employee can make a difference in organizational outcomes (Ashforth 1989).

This study extends the conceptualization of psychological empowerment from a work context to a non-work context. We appropriate a *context-specific* psychological empowerment construct by focusing on a non-work technology use context—namely, the use of mobile services. We propose a new construct—*Mobile Services Enabled Empowerment* (MSEMP) — defined as the extent to which mobile services are perceived to satisfy consumers' psychological needs for power in terms of *meaningfulness*, *competence*, *self-determination*, and *impact*. We suggest that using mobile services enables consumers to meaningfully fulfill their needs, to become confident in solving problems, to obtain a sense of independence and autonomy in solving problems, and to feel that the outcomes and impacts are all under their own control.

Based on the above conceptualization, we propose a moderated mediation model with three hypotheses (Figure 2.1). The definitions of core constructs are summarized in Table 2.1. In general, we expect that mobile services are perceived to generate a sense of power that motivates consumers to become innovative in exploring new services, and such innovativeness allows consumers to be more likely to be aware of and use mHealth services. We expect such mediation effects to work for consumers in both rural and urban areas, but the strength of mediation effects to be contingent upon consumers' current health needs and future health needs.



Control variables: age, gender, education, income, perceived usefulness, perceived ease of use, social norms

Figure 2.1. Research Model

Table 2.1. Definitions of Constructs

Construct	Definition	Origins
Mobile Services Enabled Empowerment (MSEMP)	The extent to which mobile services are perceived to satisfy consumers' psychological needs for power in terms of meaningfulness, competence, self-determination, and impact	Spreitzer (1995)
	Meaning: the value of mobile services to fulfill personal needs, judged in relation to an individual's own ideals or standards.	
	Competence: consumers' belief in their capability to solve problems with the support of mobile services.	
	Self-determination: a consumer's sense of having choice in initiating and regulating action with the support of mobile services.	
	Impact: the degree to which mobile services enable consumers to make a difference in fulfilling particular needs.	
Personal Innovativeness toward Mobile Services (PIMS)	The degree to which a consumer has experienced with different mobile services.	Adapted from Spetz and Maiuro (2004)
Awareness of mHealth Services (AWARE)	Whether a consumer is knowledgeable about, but has not used, mHealth services.	-
Use of mHealth Services (USE)	Whether a consumer who is aware of mHealth has already used mHealth services.	-
Perceived health vulnerability (PHV)	A consumer's subjective probability of becoming the victim of a chronic disease.	Champion (1984)
Perceived healthiness (PHT)	A consumer's beliefs about their current health condition.	Champion (1984)

We expect a positive link between mobile services enabled empowerment (MSEMP) and personal innovativeness toward mobile services (PIMS). In general, intrinsic motivation contributes to innovative behaviors (Redmond et al. 1993). Specifically, empowered consumers believe they have the autonomy and capability to solve problems and make changes to their lives (Çakar and Ertürk 2010). Such empowerment feelings are important for stimulating changes (Conger and Kanungo 1988), encouraging individual flexibility (Thomas and Velthouse 1990), and fostering innovative behaviors. As a result, empowered consumers may feel less constrained than others to take innovative actions to solve problems and fulfill their needs. This positive MSEMP-PIMS relationship confirms the underlying theoretical assumption that psychological empowerment and innovativeness are inseparably linked (Kanter 1983).

Furthermore, we expect that PIMS is positively associated with consumers' awareness and use of mHealth services. Prior literature has suggested that people with greater exploratory behavior tendencies are likely to be more aware of developments in areas of their interest (Lyons and Henderson 2005). More specifically, those with higher innovativeness toward IT are often associated with greater use of innovative technologies such as Internet, e-commerce, and mobile services when they were first introduced (Goldsmith 2002; Citrin et al. 2000; Kuo and Yen 2009; Lu et al. 2005). Given that the delivery of health services on mobile platforms is currently at an early stage of diffusion, it is likely that individuals who are innovative in seeking out the latest innovations are more likely to be initially aware of and use mHealth. In other words, PIMS is expected to enhance the awareness and use of mHealth services.

Synthesizing the above two relationships (i.e., MSEMP→PIMS, PIMS→ AWARE /USE), we anticipate that PIMS mediates the impact of MSEMP on AWARE/ USE. Elaborating, empowered consumers are more innovative to explore various mobile services, including mHealth services. As a consequence, these consumers that have a greater likelihood of exploring mobile services in general are more likely to be aware of and ultimately to use mHealth services. Such mediation mechanisms are expected for consumers in both urban and rural areas. Accordingly, we expect that,

H1: PIMS mediates the influence *of MSEMP on*

(a) AWARE in urban areas;

(b) AWARE in rural areas;

(c) USE in urban areas; and

(d) USE in rural areas.

We expect that perceived health vulnerability (PHV) moderates the above mediation mechanism for the awareness of mHealth. People who feel more vulnerable to chronic diseases (e.g., diabetes, heart disease, cancer, high blood pressure, and stroke) anticipate their future health needs and may already take preventive actions to reduce the risk that health problems will occur. In addition, people who feel more vulnerable to chronic diseases will become relatively more risk-averse (DeShazo and Cameron 2005). Even people feel empowered by mobile services, they are still less motivated to seek for service options that they are not aware before (Bitner et al. 2000). In other words, perceived health vulnerability suppresses the empowering mechanism and constrains consumers to seek for innovative healthcare solutions among mobile services, thus weakening the effects on the awareness of mHealth services.

Furthermore, we anticipate that the suppressed mediation effect is more salient for rural consumers than for urban consumers. This is because, compared to urban consumers, rural consumers often lack access to resources such as health knowledge and access to public healthcare facilities, and are less able to afford the uncertainty of exploring innovative health prevention activities. Consequently, perceived health vulnerability constrains empowered consumers in rural areas to innovate and acknowledge the existence of mHealth services. By contrast, urban consumers possess richer health knowledge and are exposed to better access to public health facilities, thus they are more tolerant to the uncertainty associated with innovative health solutions. Therefore, the empowering mechanism for urban consumers to be conscious of mhealth services is less likely to be suppressed by consumers' perceived health vulnerability. On the basis of the above reasoning, we hypothesize that,

H2: The moderating effect *of PHV on the mediation relationship MSEMP→ PIMS→ AWARE is stronger for rural consumers than for urban consumers.*

We expect that perceived healthiness (PHT) moderates the above mediation mechanism for the use of mHeath. People who feel less comfortable about their current health conditions demonstrate stronger needs to go beyond awareness and actually use healthcare innovations in order to mitigate negative health consequences (Fox and Duggan 2012). With stronger healthcare needs (i.e., lower level of perceived healthiness), empowered consumers are more motivated to utilize existing solutions to better take care of their own health. In other words, stronger health needs will accentuate the empowering process and motivate consumers to actively utilize innovative healthcare solutions among mobile services, thus strengthening the effects on the use of mHealth services.

Furthermore, we anticipate that the moderated mediation effect is stronger for rural consumers than urban consumers. This is because consumers in rural areas lack public local facilities and other resources to access healthcare services. With fewer alternative solutions to address their health concerns, rural consumers with greater health needs are at a better position to adopt mHealth services. By contrast, consumers in urban areas can take advantage of the greater healthcare facilities and resources and get convenient access to healthcare services. Therefore, urban consumers usually have greater choices to handle their health concerns, and thus are less likely to depend on mHealth services even if they are aware of their existence. On the basis of the above reasoning, we hypothesize that,

H3: The moderating effect of PHT on the mediation relationship MSEMP→ PIMS → USE is stronger for rural consumers than for urban consumers.

2.4 Methodology

Since we are appropriating the psychological empowerment construct to the mobile service context, we first conducted Study 1 to develop and validate the measure of MSEMP. Through this study, we established satisfactory psychometric properties for the MSEMP construct. Study 1 also allows us to use a concise measure of MSEMP in the large-scale survey (Study 2) to test the three hypotheses.

2.4.1 Study 1

Measures

In this study, we appropriated Spreitzer's (1995) measures to the mobile services context, and measured each dimension of MSEMP (i.e., meaning, competence, self-determination, and impact) using three items on a seven-point Likert scale (i.e., 1 =

strongly disagree to 7 = strongly agree). Employees were asked to indicate the extent to which they agreed with each statement based on their perceptions. Example items for each dimension included: "using mobile services is meaningful to me" (meaning), "using mobile services makes me have a large impact on solving my problems" (impact), "using mobile services makes me have significant autonomy in solving my problems" (self-determination), and "using mobile services makes me feel confident about my ability to solve my problems" (competence).

Following the translation-back translation procedure (Brislin 1980), we hired two bilingual research assistants translated the English version of the questionnaire into Tamil, Hindi, Telugu, Bengali and Gujarati languages. The translated questionnaires were then sent to an external team to independently translate back into English.

Research Sites and Sample

We recruited two research assistants in India to help execute the survey in both rural and urban areas. We conducted a pilot test with 20 consumers in India. The pilot test offered preliminary evidence of acceptable construct validity and reliability. We made minor modifications in wording based on the feedback from these participants. The research assistants then sampled 300 Indian consumers of mobile services based on the distribution of age and geographical location in 2011 Indian Census.

2.4.2 Study 2

Measures

We designed a cross-sectional survey to measure consumers' awareness and use of mHealth. Data regarding mobile service access and utilization, perceptions with mobile services, healthcare access and utilization, socio-economic status, and demographics were also collected. Existing instruments were applied whenever possible, and all questions were adapted to our study context (measures listed in Table 2.2). We also provided our definition of mHealth in the questionnaire and enumerated the scope of services of interest to include accessing healthcare advice and exchanging clinical information with providers.

Table 2.2. Construct Measures

Constru	Items	Item Scale	Sour
Mobile Service Enabled Empowerment (MSEMP)	Using mobile services is meaningful to fulfill my needs. Using mobile services makes me have a great deal of control on solving my problems. Using mobile services enables me to independently decide on how to solve my problems. Using mobile services make me feel confident about my ability to solve my problems.	1=Strongly disagree to 5= Strongly agree	Spreitzer (1995)
Personal Innovativeness toward Mobile Services (PIMS)	How frequently are you using mobile phones for the following services: email, internet access, shopping, banking, music, humor, astrology, movies, games, social networking, travel, devotional, work-related advice/ information.	Continuous measure (Saidin Index that reflects the extent to which a consumer is an early adopter across a portfolio of mobile services; Saidin index is cross-validated with a 3-item Likert scale measure)	Spetz and Baker (1999);
Awareness of mHealth Services (AWARE)	Please characterize your level of use of mobile services for healthcare: Not aware; aware but no plan to use; aware but plan to use in the near future; less than once per month; a few times per month; weekly, daily, multiple times per day.	0=Not aware; 1= Aware but no plan to use/ Aware but plan to use in the near future	Self-developed
Use of mHealth Services (USE)	Please characterize your level of use of mobile services for healthcare: Not aware; aware but no plan to use; aware but plan to use in the near future; less than once per month; a few times per month; weekly; daily; multiple times per day.	0= Aware but no plan to use/ Aware but plan to use in the near future; 1= Less than once per month/ A few times per month/ Weekly/Daily/ Multiple times per day	Davis (1993)
Perceived Health Vulnerability (PHV)	I feel vulnerable to severe chronic diseases (i.e., Diabetes/ Heart Disease/ Cancer/ Stroke/ High Blood Pressure) in the next five years.	1=Strongly disagree to 5= Strongly agree	Janz et al. (2002)
Perceived Healthiness (PHT)	I feel I am (very unhealthy/ very healthy).	1=Very Unhealthy to 5=Very Healthy	Janz et al. (2002)

Following the translation-back translation procedure (Brislin 1980), five bilingual research assistants translated the English version of the questionnaire into Tamil, Hindi, Telugu, Bengali and Gujarati languages. The translated questionnaires were then sent to an external team to independently translate back into English. We conducted extensive pre-testing with mHealth providers (physicians and IT professionals) and consumers prior to final administration of the survey. We slightly modified the content and format of the questionnaire given the feedback we received.

Data Collection

To achieve a nationally representative sample across different parts of India, we recruited volunteers to conduct the survey in eight locations, namely Gandhi Nagar (Gujarat), Hyderabad (Andhra Pradesh), Chennai (Tamil Nadu), Aragonda (Andhra Pradesh), Bilaspur (Madhya Pradesh), Madurai (Tamil Nadu), Kolkata (West Bengal), and the Union Territory of New Delhi. These volunteers were students at Apollo Nursing Colleges that are associated with Apollo Hospitals Group, one of the largest hospital systems in Asia. As part of their academic curriculum, the student volunteers had background knowledge on healthcare research and survey administration. In addition, they were computer literate, articulate, and, as part of the community, were more likely to be accepted by the potential respondents.

We developed a protocol to train the volunteers to orally administer the survey so as to elicit meaningful responses across individuals with different backgrounds and literacy rates. We trained the student volunteers from Apollo Nursing Colleges to administer the survey between October 2012 and April 2013. Each volunteer recruited a convenience sample in their respective areas that represents the Indian population in terms of age, gender, education and income, according to the 2011 Indian Census. They were also given guidelines to sample individuals who have a mobile phone and to diversify consumers surveyed based on socio-economic status, literacy and computer literacy so as to attempt to represent the whole country.

In terms of logistics, 2,500 hard copies of questionnaires were printed at Chennai (Apollo Hospitals headquarters) and were distributed in equal numbers to each nursing college in the eight locations. The filled-in hard copies were couriered to Chennai. A trained Project Coordinator, assisted by trained data entry operators, meticulously transferred the data from 1900 filled-in questionnaires to an electronic format for analysis. The authenticity and reliability of the transferred data was re-checked by four research assistants at a research university in the United States. Finally, we obtained 1,844 valid responses, achieving an overall response rate of 73.76%.

2.5 Results

2.5.1 Study 1: Validation of the MSEMP Measure

We validated the measurement properties and second-order structure of MSEMP (Table 2.3 shows descriptive statistics, reliability, and correlations). Following Tanriverdi's (2006) procedure, we assessed the measurement properties of the first-order factors and compared alternative measurement models (i.e., three first-order models and one second-order model) to evaluate the presence of a second-order factor.

Table 2.3. Descriptive Statistics, Reliability, and Correlations among MSEMP Items

Item	Mean	S.D.	alpha	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.
1.Meaning1	4.00	1.033	0.921	1										
2.Meaning2	4.13	1.008		.739	1									
3.Meaning3	4.15	1.087		.894	.752	1								
4.Impact1	3.74	1.103	0.943	.432	.413	.475	1							
5.Impact2	3.55	1.121		.334	.333	.368	.834	1						
6.Impact3	3.54	1.166		.317	.325	.352	.783	.922	1					
7.SelfDetermination1	3.95	1.074	0.921	.371	.433	.434	.749	.743	.748	1				
8.SelfDetermination2	3.72	1.123		.427	.382	.473	.807	.807	.792	.783	1			
9.SelfDetermination3	3.95	1.116		.481	.428	.546	.748	.725	.710	.776	.824	1		
10.Competence1	4.15	0.998	0.743	.395	.464	.419	.608	.573	.571	.716	.616	.662	1	
11.Competence2	4.17	1.040		.426	.436	.460	.576	.534	.539	.647	.584	.687	.906	1
12.Competence3	3.56	1.047		.202	.232	.182	.404	.516	.540	.352	.415	.360	.259	.319

The Cronbach's Alpha and composite reliability values were above 0.77 for all four dimensions of MSEMP, indicating an excellent internal consistency for this measure

(Nunnally 1978). We compared four factor models for MSEMP through a series of confirmative factor analyses (CFAs) using AMOS 18 (results in Table 2.4). Three alternative first-order factor models were tested to evaluate the dimensionality and convergent and discriminant validity of the MSEMP construct. Model 1 assumed that a unidimensional first-order factor accounted for the variance among all 12 measurement items. Model 2 assumed that the 12 items formed four uncorrelated first-order factors: meaning, impact, self-determination, and competence. Model 3 assumed that the 12 items formed four freely correlated first-order factors. Finally, Model 4 assumed a second-order factor that accounted for the relationships among the four first-order factors.

Table 2.4. CFAs for the Alternative Measurement Models for MSEMP

Model	X^2	d.f.	X^2/d.f.	CFI	GFI	NFI	RMSEA	SRMR
1: Unidimensional First-Order Model	1077.8	54	19.959	0.66	0.66	0.65	0.28	0.13
2: Uncorrelated First-Order Model	780.1	54	14.447	0.76	0.67	0.77	0.24	0.44
3: Correlated First-Order Model	241.4	48	5.03	0.94	0.85	0.92	0.09	0.08
4: Second-Order Model	249.4	50	4.99	0.93	0.85	0.92	0.09	0.08
Desired Level			<5	>0.9	>0.9	>0.9	<0.08	<0.08

The CFA results showed that Model 1 and Model 2 did not fit well with the data, suggesting that MSEMP is not a unidimensional first-order construct nor four uncorrelated first-order constructs. Model 3 showed a satisfactory model fit. In Model 3, the standardized factor loadings of measurement items on their respective factors were all highly significant ($p < 0.001$), providing support for convergent validity. The superiority of Model 3 (i.e., the unconstrained model) over Model 2 (i.e., the constrained model) ($\chi^2 = 890.17$, $p < 0.001$) indicated that pairs of correlations among the first-order factors were significantly different from zero. The correlations were also below the cutoff value of 0.90 (Bagozzweet al. 1991), demonstrating the distinctiveness of the theoretical content captured by the individual first-order factors (Law et al. 1998; Wong et al. 2008). We also evaluated discriminant validity by looking at the factor loadings. Each item loaded higher on its appropriate dimension than on any other, thus supporting the discriminant validity (Cook et al. 1981). Following the procedure of Gefen et al. (2003), we further constrained the correlation between each possible pair of dimensions one at a time to be equal to unity and then performed a chi-square test to compare this model to the unconstrained model. In all cases, the chi-square difference was significant, thereby indicating significant distinction between the dimensions (see Table 2.5).

Table 2.5. Pairwise Discriminant Analysis for Study 1

Model	X^2	d.f.	$\Delta\chi^2$	p-value of test
Original	303.75	48	-	-
Combine Meaning and Impact	799.7	49	495.95	0.00
Combine Meaning and Self-Determination	957.4	49	653.65	0.00
Combine Meaning and Competence	871.5	49	567.75	0.00
Combine Impact and Self-Determination	839.5	49	535.75	0.00
Combine Impact and Competence	814.4	49	510.65	0.00
Combine Self-Determination and Competence	626.8	49	323.05	0.00

Finally, we tested whether a second-order factor accounted for the relationships among the first-order factors. Figure 2.2 shows the second-order CFA results. Since the model fit indexes for Model 3 and Model 4 were almost identical ($\Delta\chi^2(2) = 8.0$, $p > 0.05$), the second-order factor model (Model 4) should be accepted because it is a more parsimonious model with fewer parameters to be estimated and more degrees of freedom (Grover et al. 2002; Venkatraman 1990). In addition, all second-order factor loadings were highly significant ($p < 0.001$), supporting the second-order factor model (Tippins and Sohi 2003; Venkatraman 1990). The target coefficient value (i.e., the ratio of the χ^2 of the first-order model to the χ^2 of the higher-order model) T = 0.97 also revealed that the second-order factor accounted for 97% of the relationships among the first-order factors, which indicates the superiority of the second-order factor model (Marsh and Hocevar 1985). Collectively, these results confirm the second-order structure of the

MSEMP construct. To conclude, the results of Study 1 suggest that the measures of MSEMP exhibit adequate psychometric properties.

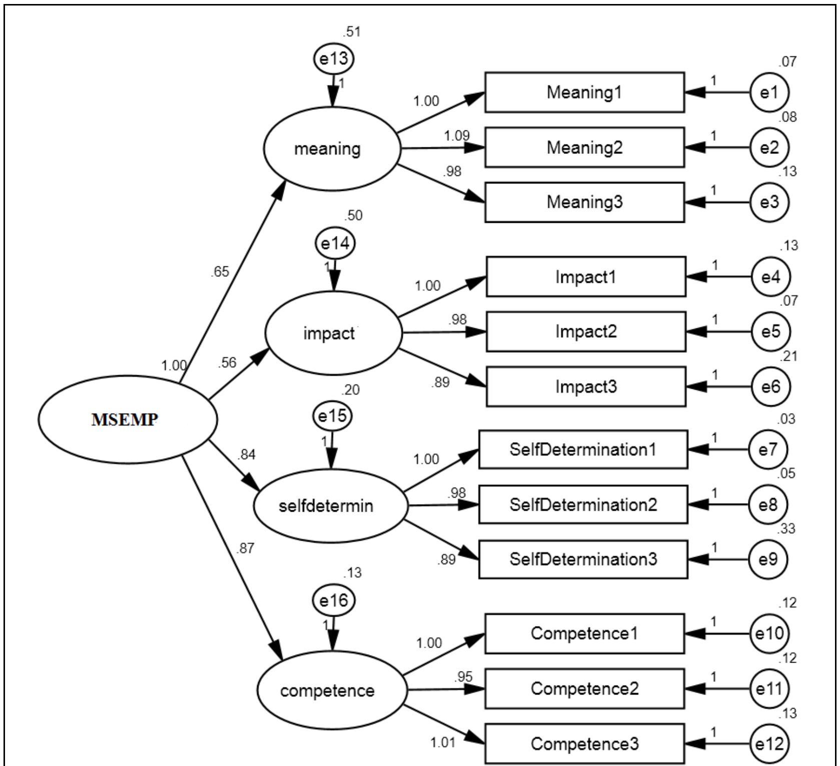


Figure 2.2. Results of the Second-Order CFA for Study 1

2.5.2 Study 2: Model Evaluation and Hypotheses Testing

Sample Characteristics

The demographic profile of participants is shown in Table 2.6. The results of the early versus late stage respondent analyses did not reveal evidence of nonresponse bias. The sample was relatively balanced in terms of gender (882 male and 945 female). Our sample was skewed towards the younger generation. 962 respondents (52.17%) were under 30 years of age. Our sample was disproportionately urban, with 1271 respondents (68.93%) in urban and 573 (31.07%) in rural areas. We also over-sampled subjects with higher education, and 62.15% respondents have a bachelor’s degree or higher. 63.18% of our sample had a monthly income below Indian Rupees (INR) 30000.

Table 2.6. Sample Characteristics							
Variable	**Category**	**Full Sample**		**Urban Sample**		**Rural Sample**	
		N	**%**	**N**	**%**	**N**	**%**
Demographics: Age	18-22	428	23.21	428	33.67	0	0.00
	23-30	534	28.96	389	30.61	145	25.31
	31-40	373	20.23	216	16.99	157	27.4
	41-50	242	13.12	126	9.91	116	20.24
	51-60	136	7.38	62	4.88	74	12.91
	61-70	71	3.85	30	2.36	41	7.16
	71 and above	48	2.60	11	0.87	37	6.46
Demographics: Gender	Male	882	47.83	555	43.67	327	57.07
	Female	945	51.25	701	55.15	244	42.58
Socio-economic Status (SES): Education	Not been to	60	3.25	16	1.26	44	7.68
	1st-5th std	88	4.77	27	2.12	61	10.65
	6th-11th std	263	14.26	91	7.16	172	30.02
	12th std	249	13.50	169	13.3	80	13.96
	College Graduate	565	30.64	452	35.56	113	19.72
	Master's degree	555	30.10	460	36.19	95	16.58
	Doctorate degree	26	1.41	25	1.97	1	0.17
Socio-economic Status (SES): Individual Monthly Income	INR 5,000 or	366	19.85	147	11.57	219	38.22
	INR 5,001-	482	26.14	287	22.58	195	34.03
	INR 15,001-	317	17.19	273	21.48	44	7.68
	INR 30,001-	120	6.51	105	8.26	15	2.62
	INR 50,001-	77	4.18	70	5.51	7	1.22
	INR 75,001 or above	58	3.15	50	3.93	8	1.4
Awareness of mHealth Services	No	628	34.06	342	26.91	286	49.91
	Yes	707	38.34	531	41.78	176	30.72
Use of mHealth Services	No	707	38.34	531	41.78	176	30.72
	Yes	431	23.37	334	26.28	97	16.93

Measurement Evaluation

We performed a series of analyses to assess the quality of the survey measures. Table 2.7 provides a summary of means, standard deviations, and correlations for all variables. Since MSEMP is a multi-item construct, we performed CFA to assess the measurement properties. The model yielded an adequate model fit (CFI = 0.98, GFI = 0.97, and SRMR = 0.02) (Hair et al. 1998). The factor loadings for each indicator on its corresponding construct were greater than 0.70 and significant at $p < 0.05$, thus supporting convergent validity. The average variance extracted (AVE) was 0.70, suggesting that the explained variance was more than the unexplained variance (Segars 1997). Additionally, the square root of the AVE for MSEMP was also more than all the inter-construct correlations, thereby establishing discriminant validity (Fornell and Larcker 1981). In terms of reliability, Cronbach alphas and composite reliabilities were 0.90 and 0.90 respectively, all greater than the recommended 0.70 level (Nunnally 1978). These results suggest that the measurement scales for MSEMP exhibit good psychometric properties.

Table 2.7. Descriptive Statistics and Correlations among Variables

	Constructs	Mean	Std.	1	2	3	4	5	6	7	8	9
1	Age	2.43	1.43	1.00								
2	Gender	1.50	0.53	-0.34	1.00							
3	Education	4.52	1.54	-0.19	0.14	1.00						
4	Income	1.90	1.56	0.41	-0.34	0.26	1.00					
5	PHV	2.27	1.10	0.25	-0.11	-0.05	0.16	1.00				
6	PHT	2.67	1.40	-0.03	0.13	0.13	0.02	0.07	1.00			
7	PIMS	25.90	12.26	-0.25	0.00	0.35	0.13	-	0.08	1.00		
8	MSEMP	3.12	1.03	0.05	-0.16	0.02	0.09	0.08	0.06	0.19	1.00	
9	AWARE	0.53	0.50	-0.09	0.07	0.28	0.12	-	0.11	0.55	0.07	1.00
10	USE	0.38	0.49	-0.04	0.04	0.10	0.04	-	0.13	0.42	0.14	NA

Diagonals represent the square root of average variance extracted. The off-diagonal elements are inter-construct correlations.

Measurement Invariance

To ensure that the comparison between rural and urban consumers was meaningful, we conducted a measurement invariance analyses (Steenkamp and Baumgartner 1998). Following the procedures set forth by Steenkamp and Baumgartner (1998) and the evaluation criteria developed by Cheung and Rensvold (2002), we performed configural invariance and metric invariance analyses for the MSEMP construct. Following Steenkamp and Baumgartner's (1998) procedures and using Cheung and Rensvold's (2002) evaluation criteria, the results revealed strong support for configural and metric invariance between the rural and urban groups, thereby allowing for meaningful comparison of path coefficients between rural and urban consumers (Doll et al. 1998; Steenkamp and Baumgartner 1998).

Common Method Bias

To assess common method bias in our data, we conducted Harman's single-factor test (Podsakoff and Organ 1986) as well as the common method variance factor test (Podsakoff et al. 2003). The results of the single-factor test revealed that no single factor accounted for the majority of the variance in the items. The loading of each item on its principal factor was significant and much higher than its loadings on other factors. In addition, the results of the common method variance factor test (Podsakoff et al. 2003) suggested that the factor loadings, path coefficients, and corresponding significance levels remained stable across the original measurement model and the measurement model with a common method variance factor. The collective evidence suggests that common method bias is not a serious threat to the validity of our findings.

Mediation Effects

Our hypotheses pertain to mediation and moderated mediation. Accordingly, we followed Hayes' (2009) suggestion and used bootstrap confidence intervals (Preacher and Hayes 2008) to test the mediation effects in the urban and rural samples (results are shown in Table 2.8 and 2.9). To test H1a, the indirect effect of MSEMP on AWARE through PIMS in the urban sample was not zero by a 95% bias-corrected bootstrap confidence interval based on 5,000 bootstrap samples (0.325 to 0.586 with a point estimate of 0.444), suggesting the existence of a mediation effect. We then followed similar procedures to test H1b, H1c, and H1d. We found that the indirect effects were not zero (0.082 to 0.377 with a point estimate of 0.217 for H1b, 0.189 to 0.356 with a point estimate of 0.268 for H1c, 0.019 to 0.300 with a point estimate of 0.135 for H1d), suggesting the existence of mediation effects. Through a series of T-tests, we further found that all reported coefficients were significantly different between the urban and rural samples. Accordingly, H1a, H1b, H1c and H1d were all supported.

Table 2.8. Results of Mediation Effects MSEMP→PIMS→AWARE							
	Urban(H1a)			Rural (H1b)			T
	Coeff	S.E.	p	Coeff	S.E.	p	
MSEMP→PIMS (a)	2.211***	0.301	0.000	1.234***	0.439	0.005	55.52***
PIMS→AWARE (b)	0.201***	0.148	0.000	0.176***	0.018	0.000	4.03***
Total effect of MSEMP on AWARE (c)	0.143**	0.069	0.039	0.228*	0.118	0.054	-19.37***
Direct effect of MSEMP on AWARE (c')	-0.160*	0.086	0.063	0.067	0.135	0.620	-43.49***
Indirect effect (ab): bias corrected confidence intervals	lower: 0.325, upper: 0.586			lower: 0.082, upper: 0.377			

*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$
Control variables: age, gender, education, income, regularity of preventive monitoring, perceived usefulness, perceived ease of use, social norms

Table 2.9. Results of Mediation Effects MSEMP→PIMS→USE							
	Urban (H1c)			Rural (H1d)			T
	Coeff	S.E.	p	Coeff	S.E.	p	
MSEMP→PIMS (a)	2.854***	0.380	0.000	1.737**	0.726	0.018	43.27***
PIMS→USE (b)	0.094***	0.009	0.000	0.078***	0.015	0.000	28.36***
Total effect of MSEMP on USE (c)	0.382***	0.081	0.000	0.289*	0.150	0.054	17.23***
Direct effect of MSEMP on USE (c')	0.166*	0.088	0.060	0.182	0.158	0.248	-2.78**
Indirect effect (ab): bias corrected confidence intervals	lower: 0.189, upper: 0.356			lower: 0.019, upper: 0.3			

*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$
Control variables: age, gender, education, income, regularity of preventive monitoring, perceived usefulness, perceived ease of use, social norms

Although mediation effects were significant for both AWARE and USE across urban and rural samples, we observed that the direct effect of MSEMP on AWARE was negative for urban consumers in H1a. This unexpected result indicates that, on the one hand, empowered urban consumers may be more likely to be aware of mHealth because of their innovativeness to explore various mobile services in general; on the other hand, empowered urban consumers may be more conscious about their exposure to mobile services and deliberately choose to ignore services that they are less interested in, including mHealth services. Consequently, these two opposite mechanisms work together to present an overall confounding effect of MSEMP on AWARE. We performed additional analysis to discover the heterogeneity in this effect among sub-segments in the urban sample, the results are further discussed in the robustness analysis section.

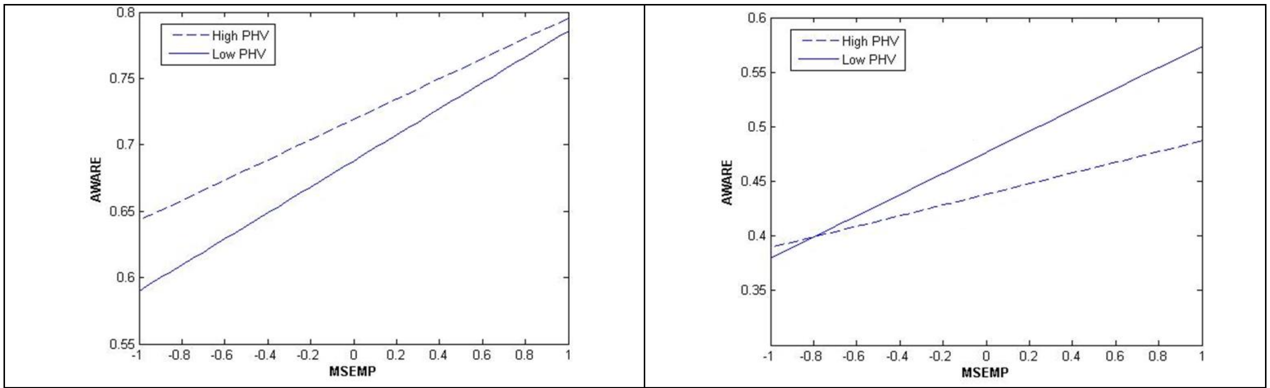
Moderated Mediation Effects (DV: AWARE)

To test the moderated mediation effects, we followed the approach by Edwards and Lambert (2007) and used the Constrained Nonlinear Regression module to estimate coefficients from 1,000 bootstrap samples. In Table 2.10, we reported the mean value of bootstrap coefficients. For the rural sample, our results show that PHV significantly moderated the direct effect (High-Low difference = -0.077; $p < 0.1$), indirect effect (High-Low difference = -0.045; $p < 0.05$), and total effect (High-Low difference = -0.122; $p < 0.001$) of the mediation MSEMP→PIMS→AWARE. Yet, the moderated mediation effect was not found in the urban sample. We depicted the moderated mediation effects in Figure 2.3. These findings collectively suggest that, the effects of MSEMP on AWARE, both directly and indirectly through PIMS, were stronger for people who perceived less vulnerable to chronic diseases than for those who perceived more vulnerable. In addition, this moderated mediation effect was more salient for rural consumers than for urban consumers. Hence, H2 was fully supported.

Table 2.10. Results of the Moderated Mediation Effects : The Role of PHV (H2)

	Urban			**Rural**		
	Direct Effect	Indirect Effect	Total Effect	Direct Effect	Indirect Effect	Total Effect
High PHV	-0.037^{*}	0.077^{***}	0.040	-0.017	0.050^{**}	0.031
Low PHV	-0.043^{**}	0.097^{***}	0.054^{***}	0.060^{*}	0.095^{***}	0.155^{***}
High-Low	0.006	-0.020	-0.014	-0.077	-0.045	-0.122
T	0.000	-1.239	-0.696	-1.988^{*}	-2.199^{**}	-2.878^{***}

*** $p < 0.001$; * $p < 0.1$
Control variables: age, gender, education, income, regularity of preventive monitoring, perceived usefulness, perceived ease of use, social norms



Urban Indirect Effect	Rural Indirect Effect

Figure 2.3. The Moderation Effect of PHV

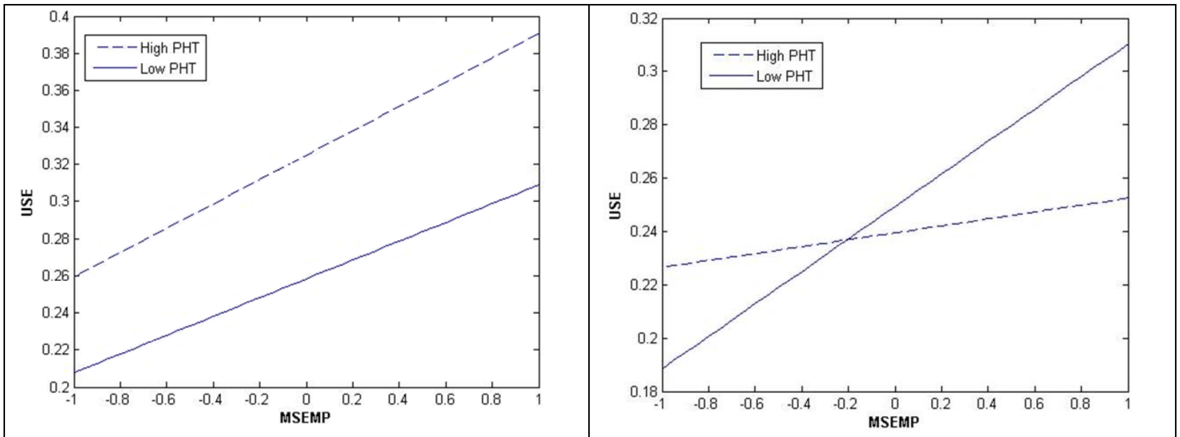
Moderated Mediation Effects (DV: USE)

Following the same procedure to test the moderating effect of PHT on the mediation path of MSEMP→PIMS→USE (results summarized in Table 2.11). We found that, for the rural sample, the indirect effect of MSEMP on USE through PIMS was significantly stronger for people who perceived themselves less healthy (β = 0.058, $p < 0.05$) than those who perceived healthier (β = 0.015, $p > 0.1$). Such moderated mediation effect was not significant for the urban sample (High-Low difference = 0.013, $p > 0.1$). These results suggest that empowered rural consumers tend to use mHealth to a larger extent if they perceive themselves less healthy. Figure 2.4 depicted the moderated mediation effects for the urban and rural samples. Thus, H3 was fully supported.

Table 2.11. Results of the Moderated Mediation Effects : The Role of PHT (H4)

	Urban			Rural		
	Direct Effect	Indirect Effect	Total Effect	Direct Effect	Indirect Effect	Total Effect
High PHT	0.053^{**}	0.064^{***}	0.117^{***}	0.078	0.015	0.094
Low PHT	0.001	0.051^{***}	0.052^{**}	0.027	0.058^{**}	0.085^{*}
High-Low	0.051	0.013	0.065	0.051	-0.043	0.008
T	1.692^{*}	1.211	2.036^{**}	0.528	-2.111^{**}	-0.238

***: $p<0.001$; *: $p<0.1$
Control variables: age, gender, education, income, regularity of preventive monitoring, perceived usefulness, perceived ease of use, social norms



Urban Indirect Effect	Rural Indirect Effect

Figure 2.4. The Moderating Effect of PHT

2.5.3 Robustness Analysis

The Impact of MSEMP on AWARE for Urban Consumers

We observed that the direct effect of MSEMP on AWARE was negative for urban consumers in H1a. To better understand this unexpected yet interesting relationship, we performed additional analysis and discovered heterogeneity in this effect among sub-segments in the urban sample. Specifically, our measure of the awareness of mHealth allowed us to separate respondents who were aware of mHealth into two groups: those who were aware of mHealth and planned to use it in the near future, and those who were aware of mHealth but did not plan to use it. We performed mediation analyses for these two sub-groups (results in Table 2.12). We found that the negative impact of MSEMP on AWARE was only observed for consumers who were aware of and planned to use mHealth in the future. This result indicates that empowered consumers in urban India are less likely to stay in the awareness stage without transmitting to use mHealth.

Table 2.12. Results of Mediation Effects MSEMP→PIMS→AWARE						
	AWARE_PLAN			AWARE_REFUSE (N=497)		
	Coeff	S.E.	p	Coeff	S.E.	p
MSEMP→PIMS (a)	1.609	0.277	0.00	2.266	0.427	0.000
PIMS→AWARE (b)	0.183	0.016	0.00	0.178	0.019	0.000
Total effect of MSEMP on AWARE	0.004	0.078	0.96	0.480	0.123	0.001
Direct effect of MSEMP on	-0.264	0.093	0.00	0.158	0.142	0.266
Indirect effect (ab): bias corrected confidence intervals	Lower:0.185; Upper:0.409			Lower: 0.242; Upper: 0.570 Point estimate: 0.418		

*** $p < 0.001$; ** $p < 0.05$; * $p < 0.1$
Control variables: age, gender, education, income, regularity of preventive monitoring, perceived usefulness, perceived ease of use, social norms

Endogeneity

To rule out the reverse causality between MSEMP and PIMS, we performed a two-step Heckman analysis to control for potential endogeneity bias (Heckman 1979). Following Bharadwaj et al.'s (2007) procedure, we first separated our sample into two groups using the median of MSEMP. We then estimated a probit model using maximum likelihood to assess the effects of independent variables on MSEMP. Endogeneity was accounted for by creating an inverse Mill's ratio (IMR). Finally, OLS was performed to predict PIMS by including the IMR as an additional independent variable. The results in Table 2.13 show that our findings were robust after controlling for IMR, suggesting that endogeneity is not a threat to the validity of the results.

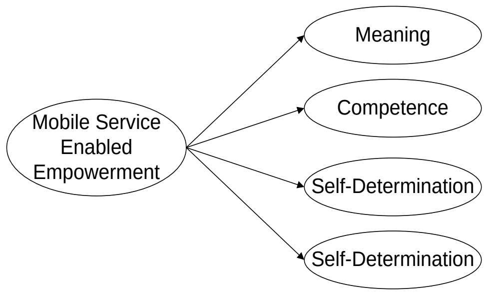
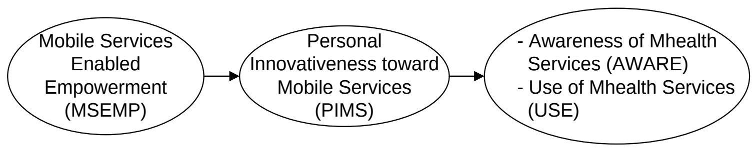
Table 2.13. Results of Endogeneity Test				
DV: PIMS	**Urban**		**Rural**	
PHV	0.19	0.22	-0.64	-0.63
PHT	-0.34	-0.35	0.52*	0.53*
MSEMP	2.56***	2.16***	2.15***	2.41***
PHV*MSEMP	-0.51*	-0.56**	0.30	0.30
PHT*MSEMP	0.23	0.23	-0.58*	-0.56*
IMR		0.68		-0.42
Constant	26.36***	26.35***	19.27***	19.17***

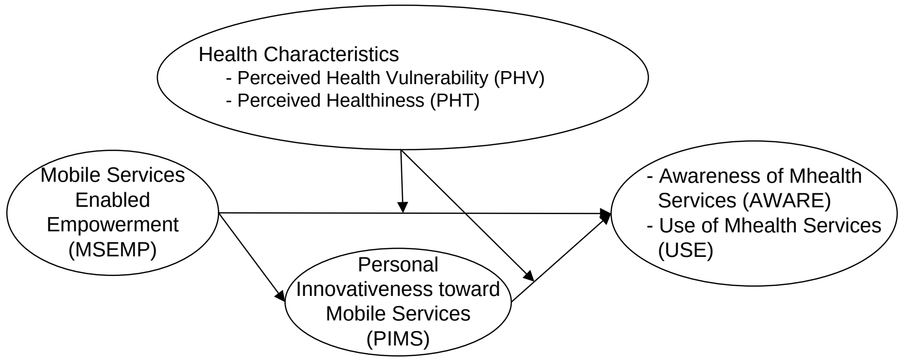
*** $p < 0.001$; ** $p < 0.05$; * $p < 0.1$
Control variables: age, gender, education, income, regularity of preventive monitoring, perceived usefulness, perceived ease of use, social norms

2.6 Discussion

This research contributes to theory development in several aspects (summarized in Table 2.14). First, it constitutes an important contribution to the literature on IT-enabled psychological empowerment. Although psychological empowerment has been studied for decades, this concept generally refers to an overall intrinsic motivation in the work context (Conger and Kanungo 1988; Spreitzer 1995; Thomas and Velthouse 1990). To extend this stream of literature, IS scholars have recently stressed the need to specify the empowering role of IT and contextualize psychological empowerment to aspects of IT use (Doll et al. 2003). We adopted the psychological perspective of empowerment, appropriated the construct of IT-enabled psychological empowerment in a non-work context, and proposed the construct of MSEMP by emphasizing the empowering role of mobile services for energizing consumers to engage in health management. We further adapted and validated the measures for mobile service enabled psychological empowerment across two empirical studies. This newly developed construct, together with validated measures, represent a meaningful extension of the psychological empowerment literature and, more importantly, a critical advancement in the IS literature that opens up a new research stream centering on the empowering role of IT-enabled services.

Table 2.14. Summary of Theoretical Contributions

Research Objectives	Model	Theoretical Contributions
Mobile Service Enabled Empowerment		- Appropriated the psychological empowerment construct from social psychology and developed the mobile service enabled empowerment construct for the mobile service context. - Adapted and validated measures for the mobile service enabled empowerment construct using one empirical study.
Mediation Effect of Personal Innovativeness toward Mobile Services		- Highlighted the empowering nature of mobile services and correspondingly identified mobile service enabled empowerment as an antecedent of personal innovativeness toward mobile services, as well as the awareness and use of mHealth services. -Revealed personal innovativeness toward mobile services as the mediating mechanism that channels the effect of mobile service enabled empowerment on the awareness and use of mHealth services. These mediation effects was detected among mobile service consumers in both urban (H1a and H1c are supported) and urban (H1b and H1d are supported) areas.

Moderating Effect of Health Characteristics		- Discovered that health characteristics (i.e., perceived healthiness, perceived health vulnerability, and regularity of preventive monitoring) moderated the mediation mechanisms for mHealth awareness and use (i.e., MSEMP→ PIMS→ AWARE; MSEMP→ PIMS →USE). - Discovered that (1) the effect of MSEMP on AWARE, directly or indirectly through PIMS is more salient for consumers who perceived less vulnerable to chronic diseases than for those who perceive more vulnerable; (2) the moderating effect of perceived health vulnerability is stronger for rural consumers than for urban consumers (H2 is supported). - Discovered that (1) the effect of MSEMP on USE, directly or indirectly through PIMS, is more salient for consumers who perceived healthier than for those who perceived less healthy in both rural and urban areas; (2) the moderating effect of perceived healthiness is more salient for rural consumers than for urban consumers (H3 is supported).

Second, this study contributes to the IT use literature by identifying the role of MSEMP on promoting the awareness and use of mHealth through encouraging innovativeness toward mobile services. Specifically, we recognize that, in addition to technology use, the awareness of technology is also an important stage in technology acceptance and merits attention. We specifically compared how awareness and use of mHealth were promoted among different segments of consumers. In detail, we found that consumers who generated a sense of power with the assistance of mobile services were more likely to be aware of and consequently use mHealth services through increased innovativeness toward mobile services. Thus, this work provides more in-depth understanding of the spillover effect that empowerment feelings derived from general mobile service experience may help motivate consumers to seek for and explore emerging mobile services in new domains such as mHealth.

Third, this research provides a comprehensive and nuanced understanding on how consumers' sense of power influences their risk propensities (i.e., risk seeking or risk aversive) in a different way across consumers with different health needs. We also observe interesting contrast between consumers in rural and urban areas, thus enriching the discussion on digital divide and health disparity. Specifically, we found that factors reflecting future health needs (i.e., perceived health vulnerability) matter for initiating the awareness of mHealth services; while factors reflecting current health needs (i.e., perceived healthiness) play a role for motivating consumers to go beyond awareness and actually use mHealth services. In addition, consumers in rural areas are more sensitive to their anticipated and current health needs compared to consumers in urban areas. In detail, the suppressing effect of future health needs on the empowering mechanism for mHealth awareness, as well as the augmenting effect of current health needs on the empowering mechanism for mHealth use, is more salient for rural consumers than for urban consumers.

Our findings also reveal implications for practitioners. We suggest that awareness of IT-enabled services is an important stage that precedes ultimate use of these services. Mhealth providers are encouraged to pay more attention to empowering consumers to promote their awareness of services before transmitting them into actual users. Of particular interest is the finding that the effectiveness of the empowering mechanism may vary depending upon consumers' health needs and geographic locations. Consumers who have existing health concerns and consumers who expect themselves to need health services in the near future may react in different patterns. Such influences of health needs are observed more salient among rural consumers than urban consumers. Given these results, individuals who are suffering from or are worrying about diet, weight, blood pressure, exercise, and other health issues might be more likely to develop awareness of mHealth apps and consider using these apps such as MyFitnessPal, Healthonphone, 1mg, and Fooducate. Such proactive management of one's health, especially in rural areas where access to health services is limited, demonstrates meaningful implications since it will significantly reduce the incidence of chronic disease and alleviate the burden of such conditions on our health system.

We acknowledge that our study is limited by the cross-sectional nature of our survey. Our robustness checks included 2-stage estimation models to account for potential endogeneity. All our findings held up to these checks, but future research could consider longitudinal research designs to elaborate our understanding of the mechanisms through which awareness and use of mHealth develop. Although our models have the feature of parsimony, they may exclude other situational, demographic, or individual characteristics. Future research could expand upon our findings by including additional characteristics. Finally, our results are generalizable to the general population because the chosen sampling strategy and the use of statistical controls. Yet, future research could delve into subgroup differences and provide more nuanced findings regarding between and within group heterogeneity.

2.7 Conclusion

This study presents a picture of how empowerment and innovativeness related to mobile services, together with health needs, affect awareness and use of mHealth services in urban and rural areas. Our findings contribute to the literature by demonstrating the mechanisms through which individual traits affect awareness and use of mHealth among urban and rural consumers in India and discovering the interdependence of individual traits and health needs in affecting mHealth awareness and use among urban and rural consumers. Specifically, we find that consumers who are empowered by various mobile services are more likely to become innovative toward mobile services, and consequently be aware of and use the mHealth services. We also find that the mediation mechanisms for mHealth awareness as well as for mHealth use are moderated by current and anticipated health needs and these moderating effects significantly differ between rural and urban consumers. These findings have implications of how mHealth awareness and use can be developed among consumers in rural and urban areas and in developing country contexts.

Chapter 3

Online Patient Base and Price Premium for Online Health Consultations: A Combined Signaling Theory and Online Feedback Mechanisms Explanation

Abstract

This study adopts the structural empowerment perspective to investigate how online health consultation communities (OHCCs) can empower physicians to build trust with patients, increase online patient base, and achieve price premium for online health consultations. OHCCs enable physicians to signal their professional competence and compassionate care for patients, and allow patients to spread word-of-mouth reviews and share online feedback with peer patients. The valence, volume, and variance of online feedback may shape the effectiveness of credibility and benevolence signals transmitted by physicians in OHCCs. We investigate the interactions between the signaling and online feedback mechanisms that explain how physicians increase online patient base and achieve price premium for online health consultations. We used web scraping techniques to collect multi-level data on 3,178 physicians traced on a bi-weekly basis over 12 months from a large OHCC in China. Using mixed effects modeling and panel regression techniques on the data collected, we find interesting interaction effects between trustworthiness signals and properties of feedback on online patient base and price premium for online health consultations. We discuss the theoretical contributions and implications for multiple stakeholders.

Keywords: Online health consultation community, signaling theory, word-of-mouth, online trustworthiness

3.1 Health Consultation in China

With economic and social reforms during the past 35 years, China has experienced dramatic improvement in the delivery of quality services in many industries but not healthcare. The access and affordability of health consultation services in China has been an ongoing challenge and resulted in market inefficiency (Eggleston et al. 2010; Yip and Hsiao 2009). Without a public referral system, patients have to search physicians based on very limited information, and can hardly assess the service quality even after their doctor visits. As more evidence has been revealed on physicians' inappropriate care such as misdiagnosis, overtreatment and overcharging, patients recognize that physicians may be either not qualified or not willing to care about the interests of patients. As a result, trust between patients and physicians begins to collapse. Such trust crisis leads to the erosion of patient base and service efficiency, contributing to more serious social problems. For example, patients may refuse medical treatment or other procedures even when the refusal will threaten their health. Patients also tend to crowd at higher-graded hospitals to seek what they perceive to be higher-quality care, resulting in inefficient consumption of public health resources and decreased service quality. Even worse, the strained patient-physician relationship has deteriorated and caused a surge in medical disputes that has even involved violence or illegal forms of behavior in China in the past decade (Zhang and Sleeboom-Faulkner 2011; Wu et al. 2012; Xu and Lu 2008).

Under this situation, online health consultation communities (OHCCs) have developed rapidly and have become prevalent in China. OHCCs serve as an empowering digital platform that allows open participation and visible involvement by both physicians and patients. In OHCCs, physicians can signal their credentials and professional experience through their online personal profiles. Physicians can also engage in various pro-social behaviors online, by extending work hours to respond to patients and by educating patients to ease their concerns and fears. In addition, OHCCs establish a platform for patients to communicate with each other and share experience and opinions toward physicians. With these unique features, OHCCs exhibit a great potential to build trust between patients and physicians through online interactions, and to alleviate the inefficiency puzzles in the health consultation market. Therefore, how to make OHCCs function successfully to support the delivery of effective online health consultation services becomes an important issue.

We focus on two outcomes that physicians may benefit from OHCCs: online patient base and price premium. The former outcome refers to the number of patients who consulted with a physician online, and the latter refers to the price premium for online health consultation services by a physician. We believe that both outcomes are essential to drive physicians to continue contributing and participating in the emerging digital platform. In a context where the trust crisis between patients and physicians is escalating, we are interested in understanding how OHCCs can be used as a trust-building platform to transmit the wisdom of crowds to assist patients to process the expert knowledge and guide physicians to adjust their signaling efforts, and ultimately achieve online patient base increase and price premium in OHCCs.

From a theoretical perspective, we conceive health consultations as a type of credence service. By definition, the delivery of credence service requires an accumulation of high level of expertise over a long period of time, therefore service consumers can hardly obtain the professional knowledge to accurately assess the quality of credence services (Darby and Karni 1973). Economic theories have recognized such knowledge asymmetry in the market for credence services and differentiated issues raised by knowledge asymmetry from those by information asymmetry. In fact, information asymmetry is assumed to be reducible since information is fundamentally considered as a commodity that has a cost and can be purchased (Eisenhardt 1989). In contrast, knowledge asymmetry arises from a difference in the possession of task-related knowledge, and cannot be reduced by virtue of service providers' professional expertise, functional indispensability, and intrinsic ambiguity associated with the services (Sharma 1997). Thus, credence service consumers do not have the technical knowledge to evaluate the efforts invested or the outcomes accomplished by providers. In the exemplary context of health consultation services, as Nobel Laureate Arrow (1963) pinpointed, medical knowledge is so complicated that physicians are believed to possess much greater knowledge regarding the possibilities and consequences of treatment than patients.

Prior literature has identified two mechanisms that may reduce the asymmetry of information in general: signaling mechanism and online feedback mechanism. First, the signaling mechanism refers to the process that service providers send observable signals to consumers to convey information about the initially unobservable attributes, and consumers in turn rely on providers' signals to infer the service quality (Connelly et al. 2011). Unfortunately, signaling efforts are often found to be less effective than expected for credence services (Kirmani and Rao 2000). In this context, consumers are found to follow a heuristic-based approach, rather than a systematic approach, to process providers' signals, since heuristic processing minimizes their use of cognitive resources (McEvily et al. 2003). In particular, trust commonly acts as a heuristic in such a way that consumers seek for signals to form trust in service providers, and use the formed trust to infer service quality (Hastie 1983; Singh and Sirdeshmukh 2000). In other words, the knowledge asymmetry inherent in credence services makes credence attributes ambiguous and costly to verify, and heightens the value of trustworthiness signals to assess service quality. As credence consumers are also aware of such knowledge inequality, they need to rely on not only uninformed subjective judgment, but also other sources of information, such as experience of other patients, to help process signals (Larson 1977).

Second, the online feedback mechanism refers to the process that consumers share information about their service experience through online reviews to help other consumers make informed selection decision. Theoretically, experience sharing would reduce the information asymmetry between potential consumers and service providers because many attributes of service experience that are unobservable prior to consumption can be evaluated after the consumption (Huang et al. 2009). However, credence services contain credence attributes that can hardly be evaluated even after consumption, the credibility of shared experience is threatened and impedes the effectiveness of online feedback mechanism for credence services. For instance, although consumers may use online reviews as sources for credence quality evaluation (Lim and Chung 2011), the credibility of credence service reviews are questioned because consumer reviewers may not have full insights to evaluate credence attributes (Lantzy et al 2014; Mittal 2004). As a result, the established role of online feedback mechanism in reducing information asymmetry and promoting sales performance may not be fully applied to the context of credence services where there is significant knowledge asymmetry between service providers and consumers (Chevalier and Mayzlin 2006).

The above-stated knowledge puzzles make it important to consider the intertwinement between both information-asymmetry-reducing mechanisms for credence services. In our context, due to the nature of knowledge asymmetry and outcome uncertainty embedded in health consultation services, successful delivery of services requires convergent expectations from physicians and patients, which is greatly achieved with the assistance of clear and prominent signals (Arrow 1963). With limited experience and medical knowledge to process signals, patients are essentially assessing the extent to which physicians use their knowledge to the best advantage to realize patients' welfare (Arrow 1963). In other words, physicians are socially obligated to establish trust with their patients, and meanwhile patients replace direct observations with their generalized belief in the trustworthiness of the physicians. Yet, because of the limited possibility of learning from one's own experience, patients often have difficulties in processing signals transmitted by physicians and evaluating physicians' trustworthiness. Shared experience among patients in turn serves a critical role to help other patients process the trustworthiness signals in a more effective way. Therefore, we are interested in understanding the interaction between the signaling and online feedback mechanisms, specifically, how the online feedback from patients could influence the effectiveness of signaling efforts transmitted by physicians.

From the structural empowerment perspective, OHCCs, served as an online platform to shape the power structure between physicians and patients by facilitating stable exchange of knowledge and experience and simultaneously supporting both the signaling mechanism and online feedback mechanism. First, OHCCs enable the signaling mechanism by allowing physicians to send observable signals to show their trustworthiness to patients. For example, physicians may complete their online profiles to share information on their education background, professional rank, work experience, and certificates and awards they obtained. Physicians may also engage in various pro-social behaviors online by providing after-hour services, responding to patients in a timely manner, and proactively educating patients to show their care about their patients. Second, OHCCs support the online feedback mechanism that patients can quickly share opinions, experiences and reviews on online health consultation services. The collective features of online reviews (e.g., volume, valence and variance of online reviews) can be used to interpret the signaling efforts and adjust the credence quality evaluation. Accordingly, we aim to address the following research question in this study: How does *online feedback from patients* influence the effectiveness of physicians' *trustworthiness signals* in affecting their *online patient base* and *price premium* for online health consultations?

3.2 Theory and Hypotheses

In the context of credence services, we draw upon signaling theory and the literature on online feedback to develop our model and hypotheses. Conceptually, we view that physicians' presentation of information and engagement in OHCCs represent their efforts to signal their trustworthiness in providing quality health consultation services. We conceptualize online feedback as accumulated experience shared among patients. In brief, we argue for interaction effects between the signals for credence services by physicians and experience of credence services by patients to reflect the compensatory relationship between these two groups of factors that affect credence service outcomes. The conceptual framework is shown in Figure 3.1.

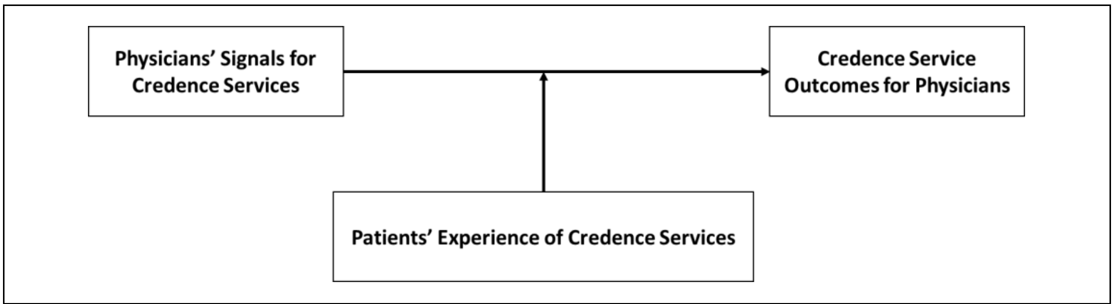


Figure 3.1. Conceptual Framework

From the signaling perspective, physicians' signaling efforts are expected to help patients infer the quality of physicians' services and make informed selection decisions. However, because of the nature of credence services, patients do not possess the professional knowledge and can hardly evaluate the unobservable trustworthiness simply based on signals transmitted by physicians. Thus, the inevitable knowledge asymmetry between patients and physicians urges patients to seek for additional information, such as shared experience among peer patients. The shared experience allows patients to have better knowledge of the signalers (i.e., physicians), influences patients' interpretations of the unobservable qualities of the signaler, and shapes the effectiveness of the signaling efforts invested by physicians. In short, we are examining the moderating effects of collective online feedback features on the effectiveness of physicians' signaling efforts to increase online patient base and price premium for online health consultation services. We focus on the interaction effects between two dimensions of trustworthiness signals sent by physicians (i.e., competence signals and benevolence signals) and three dimensions of collective online feedback features (i.e., the volume, valence and variance of online feedback among patients). The research model is presented in Figure 3.2 and Table 3.1 summarizes the definition of each construct in this model.

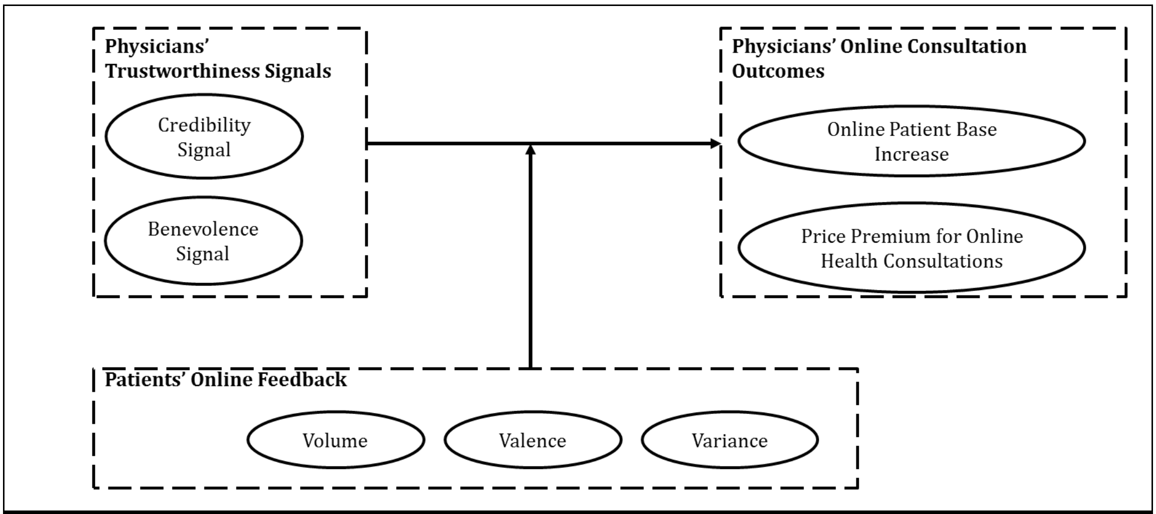


Figure 3.2. Research Model

Table 3.1. Definitions of Constructs		
Constructs	**Definition**	**References**
Online Patient Base Increase $_{it}$	Number of online patients for physician *i* increased from time t-1 to *t*.	Turban and Greening (1997)
Price Premium $_{it}$	The monetary amount above the average price for an online health consultation service that is charged by physician *i* at time *t*.	Ba and Pavlou (2002)
Credibility Signal $_{it}$	The extent to which a physician *i* signals his/her competence and reliability in providing health consultation services at time *t*.	Ganesan (1994)
Benevolence Signal $_{it}$	The extent to which a physician *i* signals an act of kindness in providing health consultation services at time *t*.	
Volume of Feedback $_{it}$	The total amount of feedback provided by patients about physician *i* at time *t*.	Duan et al. (2008)
Valence of Feedback $_{it}$	The rating values (i.e., from negative to positive) assigned by patients to physician *i* at time *t* when they review their online health consultation experience.	Duan et al. (2008)
Variance of Feedback $_{it}$	The extent to which patients hold different opinions about physician *i* at time *t* when they review the physician's online health consultation services (i.e., standard deviation of satisfaction ratings for physician *i* at time *t*).	Godes and Mayzlin (2004)

3.2.1 Signaling Theory

Signaling theory describes the decision making process used by decision makers in situations of information asymmetry (Spence 1973). When one party has more information than the other, the former party (i.e., the signaler) sends observable attributes (i.e., signals) to the latter (i.e., the receiver) to convey information about the unobservable attributes and reduce information asymmetry (Connelly et al. 2011). As signals are qualitative and require interpretation, the receiver has to decide whether to attend to and how to interpret the signals. Factors that influence the attention, perception, and interpretation of signals are expected to influence the effectiveness of signaling efforts (Connelly et al. 2011).

From a signaling perspective, credence services such as health consultations require physicians to signal their trustworthiness. Given the patients' dependency on physicians and the uncertainties associated with diagnoses and treatments, patients have indicated a strong need to trust that their physician are making decisions in their best interest and doing everything possible to obtain desirable treatment outcomes

(Holwerda et al. 2013). Empirical evidence has shown that physicians' trustworthiness in terms of competence and courtesy influences the way in which patients interpret physicians' actions and evaluate the health consultation services, especially the credence attributes of such services, and ultimately affects patients' selection of physicians (Crane and Lynch 1988).

Prior literature identifies two major dimensions of trustworthiness: credibility and benevolence (Ganesan 1994; Doney and Cannon 1997). First, credibility refers to the extent to which a trustor believes that a trustee has the required expertise to provide the service effectively and reliably. In our context, physicians can disclose their professional credentials in the OHCCs. By disclosing these information, physicians are signaling their credibility in terms of their competence and ability to deliver effective and reliable health consultation services. As a result, physicians who send stronger signals of credibility are in a better position to increase their online patient base and gain price premium from patients.

Second, benevolence refers to the extent to which a trustor believes that a trustee is genuinely interested in the other partner's welfare and has intentions and motives beneficial to the trustor. In OHCCs, physicians can answer questions posted by patients, provide medical advice for public audience, and disseminate knowledge concerning specific health conditions. The platform of OHCCs offers a tool for physicians to keep track of these interactions and make part of interactions transparent to other community members. As a result, patients can well observe the way in which physicians care about their patients and help patients deal with their health concerns. Since physicians' benevolence is a key predictor of patient's selection of physicians (Balint and Shelton 1996), physicians who send stronger signals of benevolence are at a better position to increase online patient base and achieve a higher level of price premium from patients.

3.2.2 Effectiveness of Signaling Efforts

Signaling theory suggests that the social environment may influence individual patient's detection of signals as well as his/her interpretation of the received signals (Connelly et al. 2011). In OHCCs, patients as signal receivers are situated in a social community that allows them to exchange information about their interpretations of signals or their perceptions on the signalers. Such information exchange will in turn influence patients' awareness, perceptions, and interpretations of signals, and ultimately determine the effectiveness of the signaling efforts invested by physicians. Specifically, patients may be attracted by a physician not only by the professional information exposed by the physician himself, but also by the collective feedback information shared among peer patients in the community.

Prior research has identified three metrics of online feedback: volume, valence, and variance (Dellarocas and Narayan 2006). We argue that these three metrics correspond with two important factors that affect signaling effectiveness: signal observability and signal consistency. First, signal observability refers to the extent to which outsiders are able to notice the signal. The effectiveness of signaling mechanisms will be enhanced if the signals become more observable among the target population. The volume of online feedback corresponds with the notion of signal observability by reflecting the strength of awareness effects. A large volume of feedback helps spread information among the target receivers and consequently arouses a huge amount of awareness. In our context, we expect that the volume of the online feedback will enhance the effectiveness of signaling efforts. Physicians who receive a large amount of online feedback from patients may benefit from the large amount of online discussion that enables more patients to be aware of the existence of the service. As a result, physicians' signals of trustworthiness, both credibility and benevolence, tend to accelerate more rapid increase in online patient base and generate higher price premium. Accordingly, we hypothesize that:

H1: The Volume of Feedback moderates the impacts of Signals of Trustworthiness in such a way that,

> *H1a: The impact of Credibility Signal on Online Patient Base Increase is augmented by the Volume of Feedback*
>
> *H1b: The impact of Credibility Signal on Price Premium is augmented by the Volume of Feedback*
>
> *H1c: The impact of Benevolence Signal on Online Patient Base Increase is augmented by the Volume of Feedback*
>
> *H1d: The impact of Benevolence Signal on Price Premium is augmented by the Volume of Feedback*

Besides signal observability, another important factor that influences the effectiveness of signaling efforts is signal consistency. Signal consistency refers to the agreement between multiple signals for the same signaler (Connelly et al. 2011). Conflicting signals confuse the receiver, making communication less effective, while consistent signals can help mitigate this problem and reinforce the persuasiveness of signals (Chung and Kalnins 2001; Fischer and Reuber 2007). Valence of online feedback from patients, as a responsive signal, describes the persuasive effect of online feedback. It reflects the extent to which patients' opinions are favorable or unfavorable to a service. We argue that the valence of feedback can be used to assess the consistency of signals. Negative online feedback reveals information that the physician may not have the competence or proactive intention to help patients. Such information conflicts with trustworthiness signals sent by the physicians, and thus impedes signal effectiveness. By contrast, positive online feedback transmits information that is consistent with signals sent by the physician, thereby reinforcing the effectiveness of signaling efforts (Miyazaki et al 2005).

H2: The Valence of Feedback moderates the impact of Signals of Trustworthiness in such a way that,

H2a: The impact of Credibility Signal on Online Patient Base Increase is augmented by the Valence of Feedback

H2b: The impact of Credibility Signal on Price Premium is augmented by the Valence of Feedback

H2c: The impact of Benevolence Signal on Online Patient Base Increase is augmented by the Valence of Feedback

H2d: The impact of Benevolence Signal on Price Premium is augmented by the Valence of Feedback

In addition to the valence of online feedback, signal consistency may also be reflected by the variance of online feedback. Unlike the valence of feedback that reflects the central tendency of patient opinions, the variance of feedback captures the degree of disagreement among patients, knowing as the dispersion effects of online feedback. Online feedback with little variance indicates that patients in OHCCs provide consistent feedback in evaluating certain physicians and transmit consistent messages on their experiences with these physicians. The agreement of opinions hence reinforces the impacts of trustworthiness signals on signaling outcomes. However, online feedback with large variance transmits conflicting information that mitigates the effectiveness of signaling efforts, thus decreasing the impacts of trustworthiness signals on signaling outcomes.

H3: The Variance of Feedback moderates the impacts of Signals of Trustworthiness in such a way that,

H3a: The impact of Credibility Signal on Online Patient Base Increase is augmented by the Variance of Feedback.

H3b: The impact of Credibility Signal on Price Premium is augmented by the Variance of Feedback.

H3c: The impact of Benevolence Signal on Online Patient Base Increase is augmented by the Variance of Feedback.

H3d: The impact of Benevolence Signal on Price Premium is augmented by the Variance of Feedback.

3.3 Methodology

3.3.1 Research Site

The Good Doctor community (www.haodf.com) is the largest online health consultation community in China. Founded in 2006, the Good Doctor has collected and shared information of over 370 thousand physicians from 4,600 regular hospitals across the nation. The website allows physicians to provide text-based consultations as freemium services and audio-based consultations as premium services. By January 2016, 90,000 physicians had registered in the Good Doctor community and provided online text consultations for 18 million patients. Among these physicians, over 18,000 physicians were providing audio-based consultations and had successfully established 627 thousand phone consultations through the Good Doctor community. Physicians may charge their audio-based services with a fee ranging from 6 RMB to 40 RMB per minute, which is about ten times higher than the regular doctor visit rates in hospitals. The relatively high consultation rates are acceptable for patients since consultations in

OHCCs remarkably reduce the waiting time and long distance transportation expenses of in-person doctor visits.

In addition to the intensive interactions between physicians and patients, the Good Doctor provides an open platform for patients to exchange information and share experience with each other. By January 2016, patients had shared 1.5 million consultation experience with specific physicians, posted 157 thousand thanks letters to physicians they consulted, and sent 820 thousand virtual gifts with values of 5-100 RMB for physicians in this community. Moreover, patients can directly network with the physician's other patients, seeking emotional support and communicating their health conditions.

Because of the wide user base in both physicians and patients and the rich interactions between physicians and patients as well as among patients, the Good Doctor community is an ideal setting to investigate the effectiveness of signaling mechanism and online feedback mechanism on accelerating physician's online patient base and on gaining price premium for online health consultation services. Therefore, we use this community as the research site to collect the empirical data.

3.3.2 Sampling

To test the hypotheses, we sampled all physicians who were specialized in obstetrics and gynecology (OBGYN) or cardiology. Both health conditions have standardized tests for diagnosis and are commonly consulted health conditions in the Good Doctor community. Yet, these two health conditions differ in their danger to the patient's life as well as the complexity of diagnosis. In addition, there is low level of comorbidity between these two health conditions. The sampled physicians vary in terms of the location and level of hospitals they work for. In total, our sample covers

6058 physicians (i.e., 4053 in Cardiology and 2005 in OBGYN) across 1556 hospitals in 30 provinces. From the system log, we find that some physicians had not logged into the Good Doctor website during our sampling window. After removing these inactive physicians from the sample, we use data on 64132 observations from 3,178 physicians for the following analyses.

3.3.3 Data Collection

Data were gathered using automated Java scripts to access and parse HTML and XML pages on physician's personal page on the Good Doctor website. We collected data on a bi-weekly basis from 2014 October to 2015 October at three levels. First, at the physician time-invariant level, we collected information on each physician *i*'s demographics, affiliated hospital, specialty, and OHCC use history. Second, at the physician time-varying level, we tracked the activities of physicians on a bi-weekly basis for one year period. For each physician *i* at time *t*, we captured data on the dependent variables (i.e., *Online Patient Base Increase* and *Price Premium*) and independent variables (i.e., *Credibility Signal* and *Benevolence Signal*). Third, at the patient review level, we collected all patient reviews for physician *i* up till each time t. We then aggregated patient satisfaction ratings to generate measures for *Volume, Valence, and Variance of Feedback*, the three moderators in our model.

3.3.4 Measures

Dependent Variables: To measure *Online Patient Base Increase*, we collected the number of online patients for physician i increased from *t-1* to *t*. Because the distribution of this variable was skewed, we used a log transformation before the analysis. Due to the fact that the data contained some zeros, we added 1 to each value for the log transformation. We then calculated the group mean for each of the two specialties (i.e., OBGYN and cardiology) and normalized the variable by dividing the group-centered measure by the group mean. To measure *Price Premium*, we collected the service fee per unit of time (i.e., price per minute) for physician *i* at time point *t*. We then calculated the group mean for each of the two specialties (i.e., OBGYN and cardiology) and normalized the variable by dividing the group-centered measure by the group mean. This transformed measure was used to proxy for *Price Premium* and it reflected the extent to which a physician charged higher than the average price charged by all physicians with the same specialty.

Independent Variables: We used professional rank to proxy for *Credibility Signal*. We coded physicians' professional rank into a four-point scale: 1= resident physician, 2= attending physician, 3=associate chief physician, and 4= chief physician. Physicians with a higher number on this scale demonstrated stronger trustworthiness signals on credibility. As for the *Benevolence Signal*, we used a contribution score generated by the Good Doctor community as the proxy. This contribution score was automatically calculated based on the extent to which a physician was engaged in various pro-social behaviors in OHCCs. Such behaviors included the responsiveness to patients, the number of blogs for patient education, and the frequency of updates on consultation information.

Moderators: We focused on three features of online patient feedback as the moderators. First, we proxy the *Volume of Feedback* with the total number of patient satisfaction ratings for physician *i* until time *t*. Second, *Valence of Feedback* reflected the extent to which the feedback was a favorable persuasion. Thus, we used the following formula $Valence_{it} = \frac{\sum_{j=1}^{m} rating_{ji(t-1,t]}}{m}$, where i indexes the physician, (t-1, t] indicates the time interval from t-1 to t, j indexes the patient rating, and m refers to the number of patient ratings from t-1 to t. In other words, we computed the mean value of patient satisfaction ratings from t-1 to t for a given physician to capture the central tendency of patient feedback at t. Third, *Variance* referred to the dispersion of feedback and was measured by the standard deviation of patient satisfaction ratings.

Control Variables: We collected physicians' demographics, personal page traffic, and OHCC registration date for control purposes. Information on physicians' affiliated hospital and department were also collected, including the location of hospitals, the level of hospitals, percentage of doctors in the same department who used OHCC for text-based consultations, percentage of doctors in the same department who used OHCC for audio-based consultations, percentage of doctors in the same hospital who used OHCC for text-based consultations, and percentage of doctors in the same hospital who used OHCC for audio-based consultations. Table 3.2 provides more detail on the measures of key constructs.

Table 3.2. Measures of Key Constructs

Constructs	Measures
Online Patient Base Increase $_{it}$	The number of online patients for physician i increased from time t-1 to time t
Price Premium $_{it}$	The rate of phone consultation services for a physician
Credibility Signal $_{it}$	Professional rank (ordinal variable)
Benevolence Signal $_{it}$	The benevolence score provided by the website, which is calculated based on number of articles posted by a physician, the frequency of updates on health consultation information, the frequency of replies to patient's questions
Volume of Feedback $_{it}$	The number of health consultation experience shared by patients
Valence of Feedback $_{it}$	The average score on patient satisfaction rated by patients
Variance of Feedback $_{it}$	The standard deviation on patient satisfaction rated by patients
Physician Time-Invariant Level Control Variables: Location of affiliated hospital, level of affiliated hospital, OHCC registration date. Physician Time-Varying Level Control Variables: Personal page traffic, percentage of doctors in the same department who used OHCC for text-based consultations, percentage of doctors in the same department who used OHCC for audio-based consultations, percentage of doctors in the same hospital who used OHCC for text-based consultations, and percentage of doctors in the same hospital who used OHCC for audio-based consultations.	

3.4 Analyses and Results

3.4.1 Descriptive Statistics

Table 3.3 reports the descriptive statistics for all constructs as well as the correlations among constructs. Table 3.4 reports the distribution of physicians along categorical variables. Because of the positively skewed distributions, we used natural log transformation for *Online Patient Base Increase*, *Benevolence Signal*, *Volume* and *Variance* before using them in the analyses. We also conducted Hartigans' dip test (Hartigan and Hartigan 1985) and found the distribution of *Valence* was negatively skewed and resembled a bimodal J-shaped distribution observed in prior studies on customer reviews (Hu et al. 2009). Thus, we used reflected log transformation (Cohen et al. 2003) on this variable using the formula, ln [max ($Valence_{it}$) - $Valence_{it}$ + 1], before we included it in the analyses.

Table 3.3. Descriptive Statistics of Variables and Correlations among Variables

Variable	N	Mean	S.D.	Min	Max	1	2	3	4	5	6
1. Online Patient Base Increase	64132	6.48	34.88	-11	1706	1.00					
2. Price Per Min	15765	10.13	4.95	2	40	-0.05^{***}	1.00				
3. Credibility Signal	63767	3.04	0.90	1	4	-0.02^{***}	0.36^{***}	1.00			
4. Benevolence Signal	64132	5957.5	19763.9	0	483608	0.23^{***}	-0.01^{*}	0.15^{***}	1.00		
5. Volume	64132	8.46	22.12	0	478	0.14^{***}	0.27^{***}	0.26^{***}	0.49^{***}	1.00	
6. Valence	42523	4.83	0.34	2	5	-0.01	-0.03^{***}	-0.03^{***}	-0.02^{***}	0.01^{*}	1.00
7. Variance	42523	0.21	0.33	0	2.12	0.03^{***}	0.19^{***}	0.21^{***}	0.09^{***}	0.18^{***}	-0.54^{***}

*** $p < 0.01$, ** $p<0.05$, * $p<0.1$

Table 3.4. Distribution of Physicians

Variable	Category	Number of Physicians	Percentage
Gender	Male	1019	32.06%
	Female	735	23.14%
	Missing	1424	44.80%
Credibility Signal	Resident Physician	300	5.78%
	Attending Physician	855	26.90%
	Associate Chief Physician	1120	35.24%
	Chief Physician	1058	33.29%
	Missing	39	1.23%
Hospital Level	Upper First-Class Hospital (i.e., highest level)	2364	74.39%
	First-Class Hospital	316	9.94%
	Upper Second-Class Hospital	264	8.31%
	Second-Class Hospital	47	1.48%
	Missing	187	5.88%
Service Type	Text-Based Consultation Only	2529	79.58%
	Both Text and Audio Based Consultation (Sample for the *Price Premium* model)	649	20.42%
	Total (Sample for the *Online Patient Base Increase* model)	3178	100%

All correlations were observed to be in the expected directions. Interestingly, we found that *Credibility Signal* was positively associated with *Cumulative Online Patient Base* (*r* = 0.18, *p* < 0.01), but negatively associated with *Online Patient Base Increase* (*r* = -0.02, *p* < 0.01). In other words, although physicians with a higher level of professional rank tended to accumulate a larger online patient base in total, it was physicians with a lower level of professional rank who obtained a more rapid increase in online patient base in the investigated OHCC. Following a similar pattern, *Credibility Signal* was positively correlated with *Cumulative Benevolence Signal* (*r* = 0.15, *p* < 0.01), but was negatively correlated with *Change in Benevolence Signal* (*r* = -0.02, *p* < 0.01). While physicians with a higher level of professional rank engaged in more pro-social behaviors in OHCCs in general, those with a lower level of professional rank increased in their pro-social engagement to a larger extent. To validate the above interpretations, we checked the descriptive statistics for physicians with different levels of professional rank. Table 3.5 showed that although chief physicians established greater online patient base and demonstrated stronger cumulative benevolence signals, it is attending physicians who achieved the most rapid increase in online patient base and the strongest change in demonstrating benevolence signals. In short, OHCCs empowered junior physicians to compensate for their relatively weaker credibility signals with increased demonstration of benevolence, and to obtain a sharper increase in online patient base.

Table 3.5. Online Patient Base and Benevolence Signals by Groups

Credibility Signal	**Online Patient Base**		**Online Patient Base Increase**		**Cumulative Benevolence Signal**		**Change in Benevolence Signal**	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Resident Physician	93.30	250.47	7.64	45.05	899.05	2453.47	81.52	509.23
Attending Physician	221.76	672.62	8.48	44.16	3017.43	13595.38	91.54	499.00
Associate Chief	329.34	905.01	4.84	27.38	4361.18	14401.82	49.97	333.18
Chief Physician	712.95	1605.57	6.71	33.45	9850.85	26600.00	69.43	422.66
Missing	1020.13	2165.32	5.10	16.39	14477.91	32315.63	48.34	159.50

3.4.2 Mixed Effects Models

We applied mixed-effects models to test our hypotheses. Mixed effects modeling provides an appropriate mechanism for handling the repeated measure nature of our data. Model specifications are expressed as follows:

Online Patient Base Increase $_{it}$

= Physicians-Level Control Variables $_{i}$ +Physician Time-Varying Control Variables $_{it}$

+ Credibility Signal $_{it}$ + Benevolence Signal $_{it}$

+Volume of Feedback $_{it}$ +Valence of Feedback $_{it}$ +Variance of Feedback $_{it}$

+ Credibility Signal*Volume of Feedback $_{it}$

+ Benevolence Signal*Volume of Feedback $_{it}$

+ Credibility Signal*Valence of Feedback $_{it}$

+ Benevolence Signal*Valence of Feedback $_{it}$

+ Credibility Signal*Variance of Feedback $_{it}$

+ Benevolence Signal*Variance of Feedback $_{\mathrm{it}}$

Price Premium $_{it}$

= Physicians-Level Control Variables $_{i}$ +Physician Time-Varying Control Variables $_{it}$

+ Credibility Signal $_{it}$ + Benevolence Signal $_{it}$

+Volume of Feedback $_{it}$ +Valence of Feedback $_{it}$ +Variance of Feedback $_{it}$

+ Credibility Signal*Volume of Feedback $_{it}$

+ Benevolence Signal*Volume of Feedback $_{it}$

+ Credibility Signal*Valence of Feedback $_{it}$

+ Benevolence Signal*Valence of Feedback $_{\mathrm{it}}$

+ Credibility Signal*Variance of Feedback $_{it}$

+ Benevolence Signal*Variance of Feedback $_{\mathrm{it}}$

The step-wise analysis results were summarized in Table 3.6. For the *Online Patient Base Increase* model, after entering control variables at both the physician time-invariant level and the physician time-varying level, we first entered main effects of independent variables (i.e., *Credibility Signal* and *Benevolence Signal*) and moderators (i.e., *Volume*, *Valence*, and *Variance of Feedback*). We found that physicians who had a lower level of professional credentials ($\beta_{Credibility}$ = -0.0728, $p < 0.05$), who engaged in more pro-social behaviors in OHCCs ($\beta_{Benevolence}$ = 0.968, $p < 0.01$), and who obtained a larger amount of patient reviews (β_{Volume} = 0.205, $p < 0.01$) tended to increase their online patient base to larger extent.

Second, we added six interaction effects to the model. The negative impact of *Credibility Signal* on *Online Patient Base Increase* was moderated by (1) *Volume of Feedback* ($\beta_{Credibility*Volume}$ = 0.114, $p < 0.01$), supporting H1a; and (2) *Variance of Feedback* ($\beta_{Credibility*Variance}$ = -0.075, $p < 0.05$), supporting H3a. In addition, the positive impact of *Benevolence Signal* on *Online Patient Base Increase* was moderated by *Variance of Feedback* ($\beta_{Benevolence*Variance}$ = -0.078, $p < 0.05$), supporting H3c.

A similar procedure was applied to predict the *Price Premium* model. Among the main effects of independent variables and moderators, physicians who had a higher level of professional credentials ($\beta_{Credibility}$ = 0.014, $p < 0.01$), who engaged in more pro-social behaviors in OHCCs ($\beta_{Benevolence}$ = 0.023, $p < 0.01$), and who received less favorable ($\beta_{Valence}$ = 0.015 (reflected transformation), $p < 0.01$) and more varied ratings ($\beta_{Variance}$ = 0.016, $p < 0.01$) from patients are charging higher-than-average prices for their services.

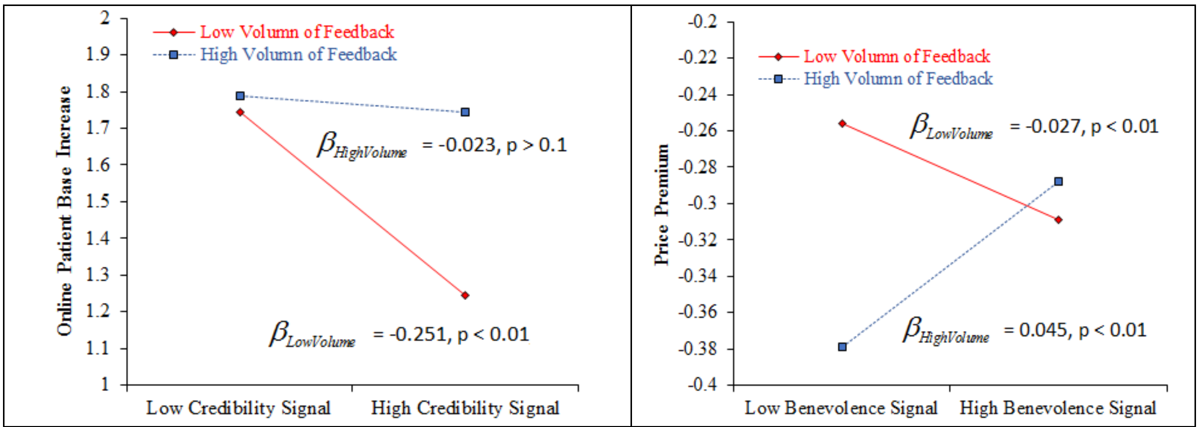
Table 3.6. Results of Mixed-Effects Models				
	Online Patient Base Increase		Price Premium	
	Direct Effects	Interaction Effects	Direct Effects	Interaction Effects
State	…	…	…	…
HospitalLevel $_i$	-0.096*	-0.092*	0.051	0.048
HospitalOnlineDoctorRate$_{it}$	-0.369	-0.359	0.236	0.219
HospitalPhoneDoctorRate$_{it}$	0.715	0.592	0.844*	0.867**
DeptOnlineDoctorRate$_{it}$	0.305*	0.282	-0.146	-0.149
DeptPhoneDoctorRate$_{it}$	-0.002	0.071	-0.435***	-0.463***
Specialty$_i$	-0.833***	-0.839***	0.031	0.029
Gender$_i$	0.219***	0.227***	0.075*	0.081*
Week	0.020***	0.021***	0.001***	0.001***
Tenure in OHCC	-0.000***	-0.000***	-0.000	-0.000**
DaysSinceLastLogin	-0.000**	-0.000**	-0.000**	-0.000***
PersonalPageTraffic	-0.178***	-0.178***	-0.021***	-0.019***
Premium ServicesProvided	0.291***	0.278***		
Credibility Signal $_{it}$	-0.073**	-0.137***	0.014***	0.015**
Benevolence Signal $_{it}$	0.968***	0.971***	0.023***	0.009*
Volume of Feedback $_{it}$	0.205***	0.136***	-0.006	-0.025***
Valence of Feedback $_{it}$	-0.033	-0.069*	0.015***	0.002
Variance of Feedback $_{it}$	0.010	0.076*	0.016***	0.026***
Credibility*Volume $_{it}$		0.114***[H1a]		-0.001 [H1b]
Benevolence*Volume $_{it}$		0.012 [H1c]		0.036*** [H1d]
Credibility *Valence $_{it}$		0.054 [H2a]		-0.012** [H2b]
Benevolence*Valence $_{it}$		0.048 [H2c]		0.016*** [H2d]
Credibility*Variance $_{it}$		-0.075** [H3a]		-0.005 [H3b]
Benevolence*Variance $_{it}$		-0.078** [H3c]		-0.008** [H3d]
_cons	1.643***	1.631***	-0.328	-0.308
Random-effects Parameters				
sd(Week)	0.034***	0.034***	0.004***	0.004***
sd(_cons)	0.842***	0.834***	0.340***	0.342***
corr(Week,_cons)	-0.536***	-0.535***	-0.082	-0.090
sd(Residual)	0.917***	0.917***	0.039***	0.039***
Number of consultations	30,586	30,586	9,678	9,678
Number of physicians (Level 2)	1,328	1,328	392	392
Chi-square test		11.75*		76.20***

*** $p < 0.01$, ** $p < 0.05$
sd(Week) : standard deviation of the coefficient of *Week* at the physician level (level 2)
sd (Constant): standard deviation of the intercept at the physician level (level 2)
sd (Residual): standard deviation of the intercept at the observation level (level 1)
corr (Week, Constant): correlation between sd(Week) and sd(Constant)

In terms of the moderating effects, the positive impact of *Benevolence Signal* on *Price Premium* was moderated by (1) *Volume* ($\beta_{Benevolence*Volume} = 0.036$, $p < 0.01$), supporting H1d; (2) *Valence* ($\beta_{Benevolence*Valence} = 0.016$, $p < 0.01$), supporting H2d, and (3) *Variance* ($\beta_{Benevolence*Variance} = -0.008$, $p < 0.05$), supporting H3d. In addition, the positive impact of *Credibility Signal* on *Price Premium* was moderated by *Valence* ($\beta_{Credibility*Valence} = -0.012$, $p < 0.05$), supporting H2b.

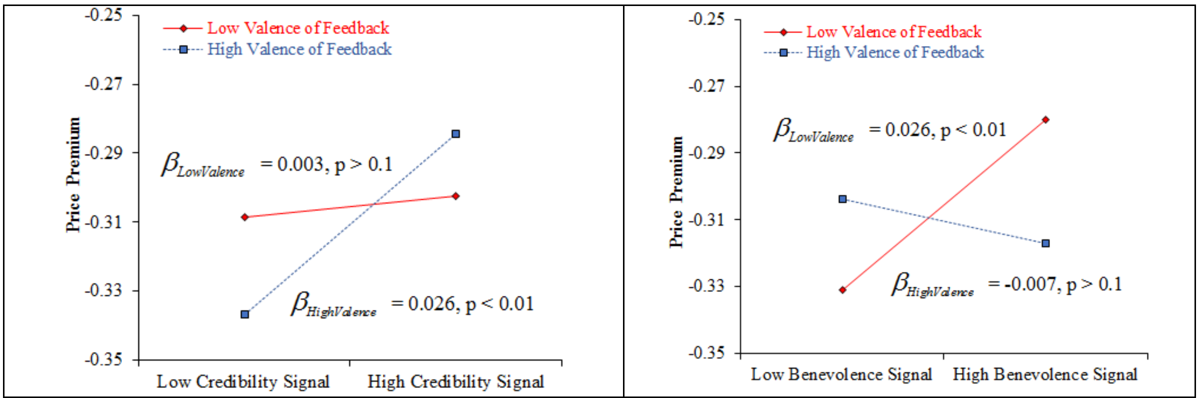
Figure 3.3-3.5 depicted the significant moderating effects of *Volume, Valence, and Variance of Feedback*, respectively. When a physician received a larger amount of feedback from patients, the negative impact of *Credibility Signal* on *Online Patient Base Increase* was mitigated (Figure 3.3a), and the impact of *Benevolence Signal* on *Price Premium* was changed from negative (simple slope = -0.027, $p < 0.01$) to positive (simple slope = 0.045, $p < 0.01$) (Figure 3.3b).

As shown in Figure 3.4, if physicians received favorable feedback from patients, their credibility signal would generate larger marginal returns on price premium for their online health consultation services (Figure 3.4a). However, if physicians received favorable feedback from patients, their engagement in pro-social behaviors to signal their benevolence would compensate for the unfavorable feedback to generate higher marginal returns on price premium (Figure 3.4b).



a.Credibility * Volume → Online Patient Base Increase | b.Benevolence* Volume → Price Premium

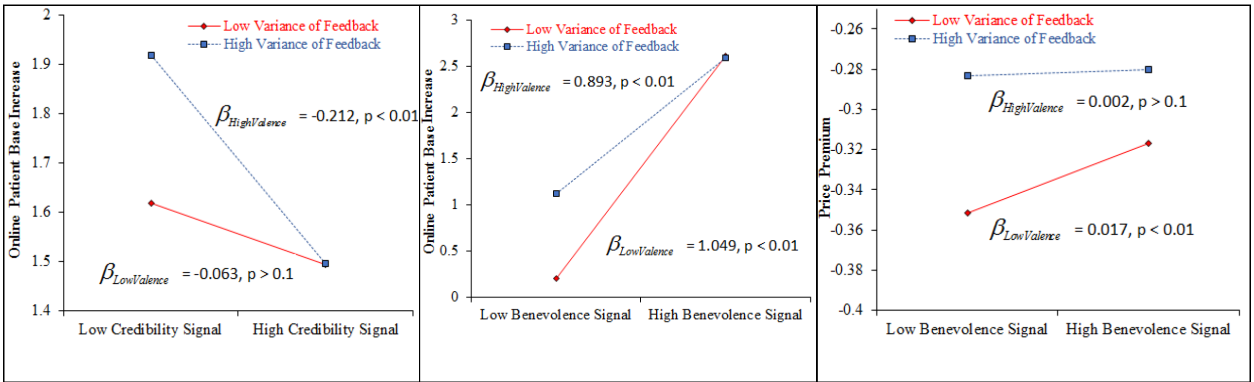
Figure 3.3. Moderating Effects of Volume of Feedback



Credibility * Valence → Price Premium | Benevolence * Valence → Price Premium

Figure 3.4. Moderating Effects of Valence of Feedback

In terms of the moderating effects of *Variance of Feedback*, inconsistent feedback with larger variance from patients would amplify the negative impact of *Credibility Signal* on *Online Patient Base Increase* (see Figure 3.5a). In contrast, consistent feedback from patients would amplify the effectiveness of *Benevolence Signals* on generating greater online patient base (see Figure 3.5b) and achieving higher price premium (see Figure 3.5c).



a. Credibility * Variance → Online Patient Base Increase	b. Benevolence* Variance → Online Patient Base Increase	c. Benevolence * Variance→ Price Premium

Figure 3.5. Moderating Effects of Variance of Feedback

3.4.3 Robustness Tests

Endogeneity Assessment. We evaluated the endogeneity of *Benevolence Signal* by following the recommended Garen whole residual (Garen 1984; Garen 1988; Mooi and Ghosh 2010) procedure. Specifically, *Benevolence Signal* may be endogenous in our models in two ways: 1) we may not have accounted for all unobserved heterogeneity associated with Benevolence Signal when predicting *Online Patient Base Increase* and *Price Premium*; and 2) reverse causation may be present as *Online Patient Base Increase*, *Price Premium*, as well as the features of online feedback from patients (i.e., *Volume, Valence, and Variance of Feedback*) may impact *Benevolence Signal*.

To assess robustness for continuous endogenous variables, which aligns with the nature of our endogenous variables, we followed the whole residual approach (Garen 1984; Garen 1988) to allow for the use of continuous endogenous variables and to control for unobserved heterogeneity associated with endogeneity of *Benevolence Signal* (results in Table 3.7). Following Mooi and Ghosh (2010) that applied the Garen procedure, we regressed *Benevolence Signal* on *Volume, Valence, and Variance of Feedback, Online Patient Base Increase* and *Price Premium*. We then computed the residual for *Benevolence Signal* ($\eta_{BenevolenceSignal}$).

Table 3.7. Results of Endogeneity Test

	Online Patient Base Increase		Price Premium	
	Stage 1	**Stage 2**	**Stage 1**	**Stage 2**
HospitalLevel $_i$	-0.179***		-0.144**	
HospitalOnlineDoctorRate$_{it}$	0.486***		0.377	
HospitalPhoneDoctorRate$_{it}$	-1.607***		-1.948***	
DeptOnlineDoctorRate$_{it}$	0.176		0.024	
DeptPhoneDoctorRate$_{it}$	0.026		0.310	
Specialty$_i$		-0.814***		0.057
Gender$_i$		0.234***		0.085*
Week		0.022***		0.001**
Tenure in OHCC		-0.000***		-0.000
DaysSinceLastLogin		-0.001***		-0.000
PersonalPageTraffic		0.187***		-0.024***
Premium Services Provided		0.384***		
Credibility Signal $_{it}$		-0.188***		0.019**
Residual $_{it}$		0.028***		0.002**
Volume of Feedback $_{it}$	0.183***	0.128***	0.134***	0.002
Valence of Feedback $_{it}$	0.013*	-0.049	0.019**	0.017***
Variance of Feedback $_{it}$	-0.021***	0.032	-0.010	0.021***
Credibility*Volume $_{it}$		0.120***		-0.001
Residual *Volume $_{it}$		-0.150***		0.005***
Credibility *Valence $_{it}$		0.061*		-0.014**
Residual *Valence $_{it}$		-0.079***		0.004**
Credibility*Variance $_{it}$		-0.079**		-0.003
Residual *Variance $_{it}$		0.101***		-0.003**
Online Patient Base Increase	0.014***		0.010***	
Price Premium	0.539***		-0.012	
Constant	1.096***	-2.171***	1.585***	0.029
Random-effects Parameters				
sd(Week)		0.021***		0.006***
sd(Constant)		0.921***		0.360***
corr(Week,_Constant)		-0.766***		-0.205***
sd(Residual)		0.066***		0.040***
Number of observations	39,878	30,586	12,527	9,678
Number of physicians	1,848	1,328	528	392

*** $p < 0.01$, ** $p < 0.05$

Predictors for the first stage equation: Level, HsptOnlineDocRate, DeptOnlineDocRate HsptPhoneDocRate, DeptPhoneDocRate, zVolume, zPerfValence, zPerfVariance lnRelPatientChange, Price Premium

sd(Week) : standard deviation of the coefficient of *Week* at the physician level (level 2)

sd (Constant): standard deviation of the intercept at the physician level (level 2)

sd (Residual): standard deviation of the intercept at the observation level (level 1)

corr (Week, Constant): correlation between sd(Week) and sd(Constant)

In the second stage regression, we used the residual term to substitute *Benevolence Signal* in the model to predict *Online Patient Base Increase* and *Price Premium*. The parameters estimated for the main effect of the residual term as well as the interaction effects involving the residual term were all significant, indicating that *Benevolence Signal* are indeed endogenous to the identified variables. After accounting for such endogeneity with the Garen whole residual analysis procedure, our original reported results were robust in such a way that *Volume, Valence, Variance of Feedback* significantly moderated the impacts of *Credibility* and *Benevolence Signals* on *Online Patient Base Increase* and *Price Premium.* Overall, the above results collectively suggest that our previously reported results were robust to endogeneity associated with unobserved heterogeneity of *Benevolence Signal* as well as reverse causality.

Self-Selection Bias. To test whether the provision of freemium services (i.e., text-based consultations) versus premium services (i.e., audio-based consultations) contributed to results different from the main analyses, we conducted a two-step Heckman analysis (Heckman 1979; Bharadwaj et al. 2007) to evaluate the existence of self-selection bias (results in Table 3.8). In the first step, we differentiated our sample into two groups: physicians who only provided freemium services (i.e., text-based consultations, coded as *FreeServices* = 1), and physicians who provided both freemium and premium services (i.e., both text-based and audio-based consultations, coded as *FreeServices* = 0). We then estimated a probit model using maximum likelihood to assess the effects of predictors (i.e., the location of affiliated hospitals, the level of affiliated hospitals, the rate of doctors who provide freemium and premium services within the same department, and the rate of doctors who provide freemium and premium services within the same hospital) on *FreeServices*.

Table 3.8. Results of Two-Step Heckman Analysis for the Online Patient Base Increase Model		
	Stage 1 Equation	**Stage 2 Equation**
State	…	
HospitalLevel $_i$	0.383***	
HospitalOnlineDoctorRate$_{it}$	0.847***	
HospitalPhoneDoctorRate$_{it}$	-1.792***	
DeptOnlineDoctorRate$_{it}$	-1.209***	
DeptPhoneDoctorRate$_{it}$	3.581***	
Specialty$_i$		-0.881***
Gender$_i$		0.248***
Week		0.021***
Tenure in OHCC		-0.000***
DaysSinceLastLogin		-0.000**
PersonalPageTraffic		-0.187***
Credibility Signal $_{it}$		-0.167***
Benevolence Signal $_{it}$		1.002***
Volume of Feedback $_{it}$		0.150***
Valence of Feedback $_{it}$		-0.078*
Variance of Feedback $_{it}$		0.088**
Credibility*Volume $_{it}$		0.111***
Benevolence*Volume $_{it}$		0.020
Credibility *Valence $_{it}$		0.075**
Benevolence *Valence $_{it}$		0.064*
Credibility*Variance $_{it}$		-0.086**
Benevolence *Variance $_{it}$		-0.094**
λ		0.164***
Constant	-3.180***	1.259***
Random-effects Parameters		
sd(Week)		0.034***
sd(Constant)		0.835***
corr(Week, Constant)		-0.511***
sd(Residual)		0.917***
Number of observations	59,701	30,586
Number of physicians	3,003	1,328

sd(Week) : standard deviation of the coefficient of *Week* at the physician level (level 2)
sd (Constant): standard deviation of the intercept at the physician level (level 2)
sd (Residual): standard deviation of the intercept at the observation level (level 1)
corr (Week, Constant): correlation between sd(Week) and sd(Constant)
*** $p < 0.01$, ** $p < 0.05$

The potential self-selection bias were accounted for by including the inverse mills ratio (IMR) from the first stage regressions (*λFreeServices*) in the second stage regression and then comparing the results to our previous mixed effects model results. Specifically, *λFreeServices* were calculated as $\hat{\lambda}_i = \phi(\hat{\gamma}_i\omega_i) / \Phi(\hat{\gamma}_i\omega_i)$, where ϕ is the standard normal density function; ω_i and γ_i are the vectors of independent variables and coefficients from the first stage probit model; and Φ is the standard normal distribution function. In the second stage regression, we estimated a mixed effects model with *Online Patient Base Increase* as the dependent variable and *λFreeServices* as additional independent variables, above and beyond variables used earlier to explain *Online Patient Base Increase*. As shown in Table 3.8, the two-step Heckman analysis results supported the existence of self-selection bias ($\lambda = 0.164$, $p < 0.01$) and indicated that our results in the main analysis were robust and largely consistent after controlling for the potential endogeneity bias. The significance and direction of interaction terms (i.e., *Credibility *Volume, Credibility*Valence, Benevolence* Valence, Credibility*Variance, Benevolence * Variance*) were the same as those in the main analyses results.

As an alternative approach, we tested the *Online Patient Base Increase* model using a subsample that only included physicians who provided premium services (i.e., *FreeServices* = 0). As expected, we observed similar interaction effects for the subsample that have ruled out the self-selection bias. These results collectively supported the relationships among variables proposed in this study.

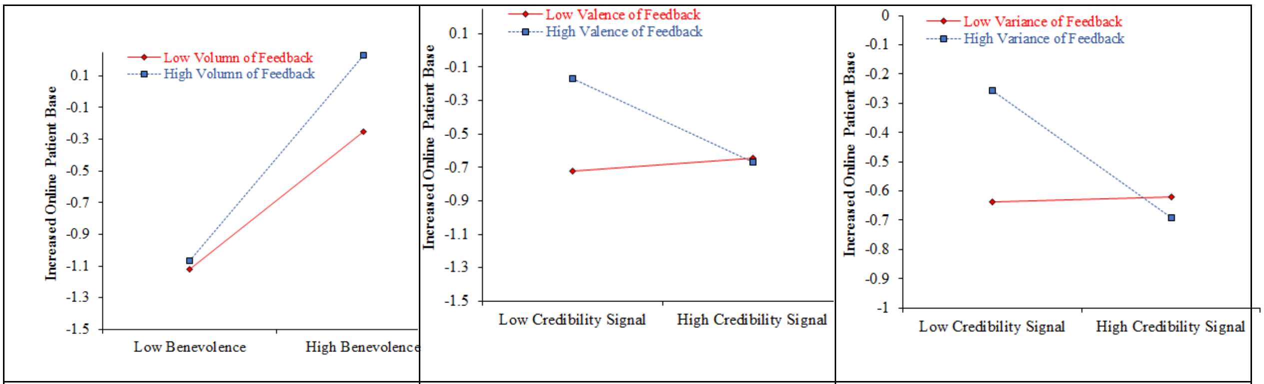
Heterogeneity between Health Conditions**.** As we sampled physicians from two specialties (i.e., cardiology and OBGYN), we are interested in the robustness of our results for physicians in each of the two specialties. We tested the same mixed-effects models for the two subsamples and summarized the results in Table 3.9.

Consistent with results using the full sample, *Credibility Signal* displayed a negative impact, while *Benevolence Signal* exhibited a positive impact, on *Online Patient Base Increase* for both cardiologists and OBGYNs. Although physicians' efforts on signaling trustworthiness (i.e., credibility and benevolence) revealed significant impacts on *Price Premium* for cardiologists, such efforts were not found to significantly affect *Price Premium* for OBGYNs. Similarly, while features of online feedback significantly affected *Online Patient Base Increase* and *Price Premium* for cardiologists, they only showed significant impacts on *Price Premium* for OBGYNs.

Table 3.9. Results of Mixed-Effects Models for Subsamples				
	Online Patient Base Increase		**Price Premium**	
	Cardiologists	**OBGYNs**	**Cardiologists**	**OBGYNs**
State	…	…	…	…
HospitalLevel $_{i}$	0.019	-0.141*	-0.026	0.249***
HospitalOnlineDoctorRate$_{it}$	-0.194	-0.100	0.032	0.276
HospitalPhoneDoctorRate$_{it}$	0.643	0.0641	0.740	0.706
DepartmentOnlineDoctorRate$_{it}$	-0.208	0.571*	-0.063	-0.299
DepartmentPhoneDoctorRate$_{it}$	0.151	0.802	-0.632***	-0.130
Gender$_{i}$	0.110	0.244**	0.096	0.075
Week	0.025***	0.013***	0.001**	0.002**
Tenure in OHCC	-0.000***	-0.000	0.000	-0.000***
DaysSinceLastLogin	-0.000**	-0.000***	-0.000***	0.000***
PersonalPageTraffic	-0.024	-0.338***	-0.036***	-0.012**
Premium Service Provided	0.158**	0.383***		
Credibility Signal $_{it}$	-0.105**	-0.204***	0.010*	0.011
Benevolence Signal $_{it}$	0.542***	1.444***	0.035***	-0.012
Volume of Feedback $_{it}$	0.133**	0.069	-0.028***	-0.057***
Valence of Feedback $_{it}$	-0.131**	-0.019	-0.001	-0.081***
Variance of Feedback $_{it}$	0.078	0.105	0.011*	0.114***
Credibility*Volume $_{it}$	0.082	0.183**	0.006	-0.010
Benevolence*Volume $_{it}$	0.108**	-0.057	0.045***	0.069***
Credibility *Valence $_{it}$	0.144**	0.043	-0.010	-0.009
Benevolence*Valence $_{it}$	-0.049	0.046	0.053***	0.084***
Credibility*Variance $_{it}$	-0.112*	-0.111**	0.006	-0.037***
Benevolence*Variance $_{it}$	-0.026	-0.094*	-0.042***	-0.056***
cons	-0.551	2.513***	-0.026	-1.359**
Random-effects Parameters				
sd(Week)	0.030***	0.039***	0.004***	0.005***
sd(_cons)	0.740***	0.853***	0.347***	0.334***
corr(Week,_cons)	-0.591***	-0.505***	-0.145**	-0.197**
sd(Residual)	0.896***	0.942***	0.031***	0.048***
Number of observations	18,722	11,864	6,095	3,583
Number of physicians	783	545	240	152

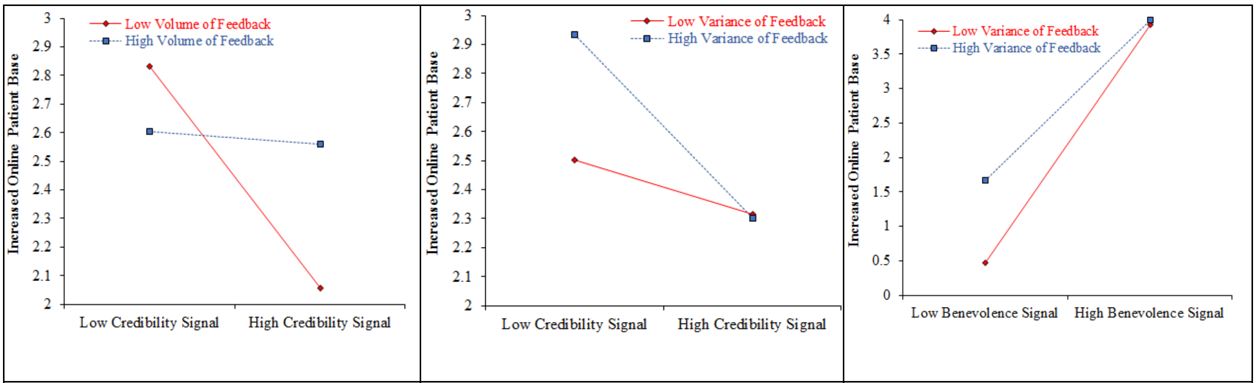
sd(Week) : standard deviation of the coefficient of *Week* at the physician level (level 2)
sd (Constant): standard deviation of the intercept at the physician level (level 2)
sd (Residual): standard deviation of the intercept at the observation level (level 1)
corr (Week, Constant): correlation between sd(Week) and sd(Constant)
*** $p < 0.01$, ** $p < 0.05$

In terms of interaction effects, four significant interactions (i.e., *Credibility* Variance* → *Online Patient Base Increase, Benevolence* Volume* → *Price Premium, Benevolence*Valence* → *Price Premium, Benevolence* Variance* → *Price Premium*) were observed in both subsamples and were consistent with the full sample results. In addition, *Volume* exhibited significant moderating effects on *Credibility Signal* → *Online Patient Base Increase* for only OBGYNs and on *Benevolence Signal* → *Online Patient Base Increase* for only Cardiologists. *Valence* significantly moderated *Credibility Signal* → *Online Patient Base Increase* for only cardiologists. The moderating effects of *Valence on Benevolence Signal* → *Online Patient Base Increase* and *Credibility Signal* → *Price Premium* were significant for only OBGYNs. Figures 3.6-3.9 depicted the above significant interaction effects for the subsamples.



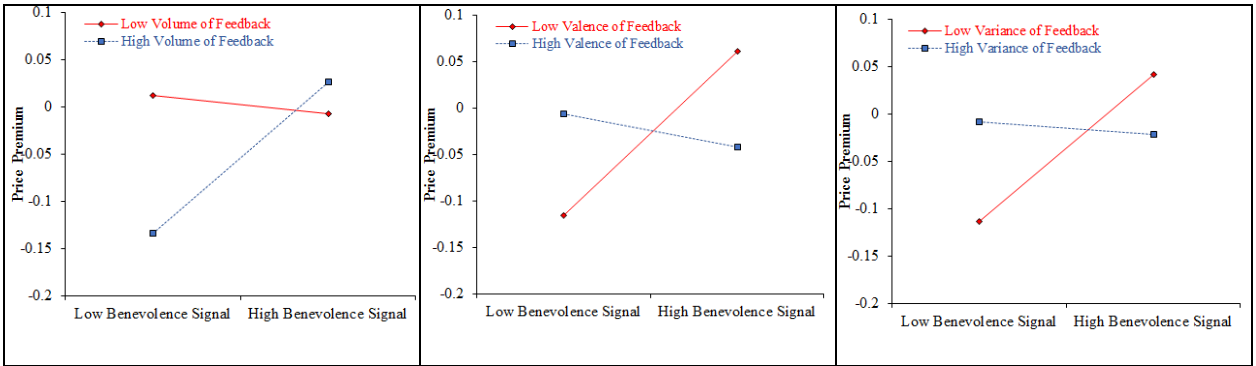
a.Benevolence*Volume | b. Credibility * Valence | c.Credibility * Variance

Figure 3.6. Moderating Effects to Affect Online Patient Base Increase among Cardiologists



a.Credibility *Volume | b. Credibility * Variance | c.Benevolence * Variance

Figure 3.7. Moderating Effects to Affect Online Patient Base Increase among OBGYNs



a.Benevolence*Volume | b. Benevolence*Valence | c.Benevolence*Variance

Figure 3.8. Moderating Effects to Affect Price Premium among Cardiologists

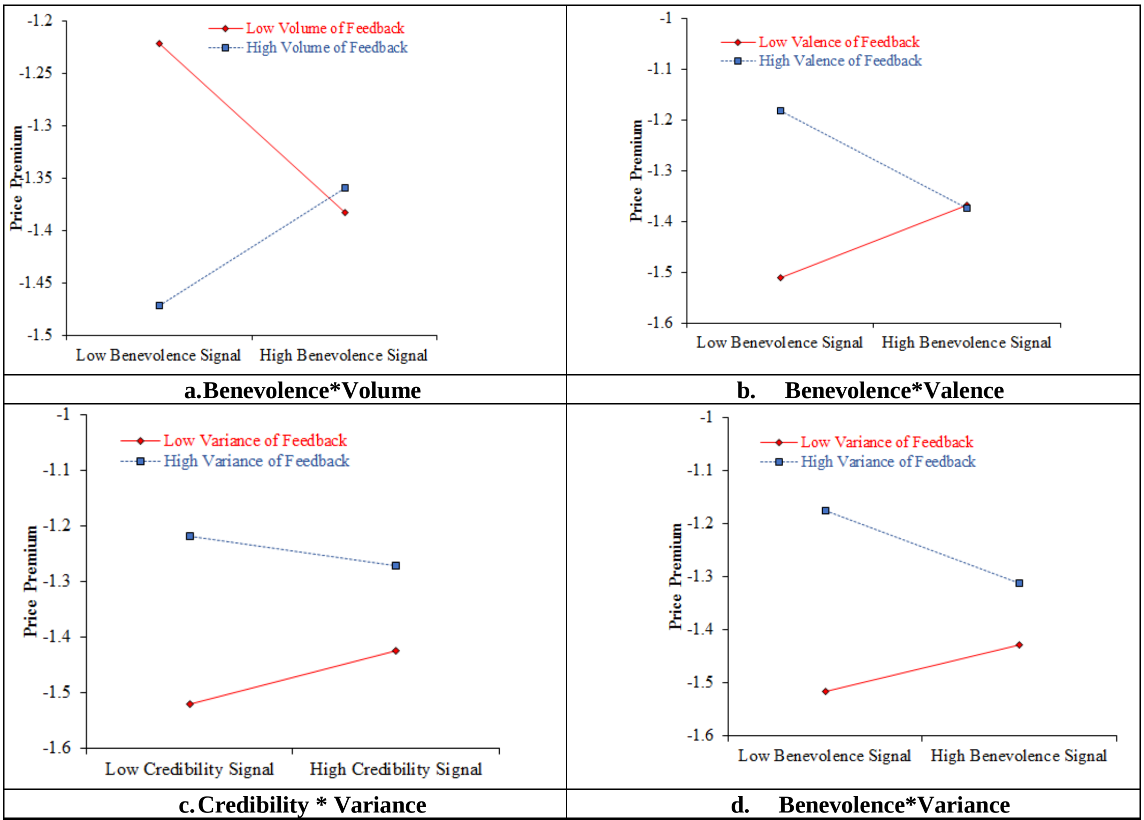


Figure 3.9. Moderating Effects to Affect Price Premium among OBGYNs

3.5 Discussion

In general, this study demonstrates the empowerment role of online communities in facilitating the transmission and exchange of information to strengthen the service provider-consumer relationship given knowledge asymmetry between the provider and consumer characterizes credence services. Focusing on health consultation services in China where the trust between patients and physicians has atrophied, this study develops our understanding on how collective online feedback (i.e., *Volume*, *Valence* and *Variance of Feedback*) influences the effectiveness of trustworthiness signals (i.e., *Competence* and *Benevolence Signals*) to affect online patient base and price premium of online health consultation services. Table 3.10 summarizes key findings and implications.

3.5.1 Theoretical Contributions

This study focuses on the empowerment role of online communities for credence services. Credence service is a unique context where knowledge asymmetry between service providers and consumers cannot be eliminated (Darby and Karni 1973). Health consultation is a typical example of credence service where consumers (e.g., patients) can hardly evaluate the quality of services even after their consumption. The nature of knowledge asymmetry in the health consultation market results in the imbalance in power between physicians and patients. Physicians may engage in misconduct, overcharging, overtreatment, and misdiagnosis, leading to inefficiency in the health consultation market. It is interesting to find that OHCCs may facilitate the flow of signals from physicians to patients and feedback from patients to physicians, thus altering the traditional role of physicians and patients in health consultation services that are of a credence nature. In other words, OHCCs provide an extended opportunity for assessing mechanisms to effectively deliver credence services that feature knowledge asymmetry between service providers and consumers.

In general, the marketing and information systems literature has examined how service providers can overcome consumers' lack of information about service quality. One commonly adopted approach is through signaling efforts. Service providers send signals, such as investments in advertising, branding, and using warranties or price strategies, to inform consumers about the initially unobservable quality (e.g., Bloom and Pailin 1995; Galetzka et al. 2006; Lim and Chung 2011; Srinivasan and Till 2002). Effective signals provide consumers insights into the unobservable quality and reduce the information asymmetry (Erdem and Swait 1998).

Table 3.10. Summary of Findings					
	Findings	**FULL**	**CARD**	**OBGYN**	**Implications**
Signaling Mechanism	Credibility Signal → Online Patient Base Increase	-	-	-	• Trustworthiness signals affect the outcomes of credence services where there is significant knowledge asymmetry between service providers and consumers. • Different dimensions of trustworthiness signals contribute to different outcomes of interests. • The effectiveness of different dimensions of trustworthiness signals varies depending on service domains.
	Benevolence Signal → Online Patient Base Increase	+	+	+	
	Credibility Signal → Price Premium	+	+	NS	
	Benevolence Signal → Price Premium	+	+	NS	
Online Feedback Mechanism	Volume → Online Patient Base Increase	+	+	NS	• Collective features of online feedback (i.e., Volume, Valence, and Variance of Feedback) affect the outcomes of credence services where there is significant knowledge asymmetry between service providers and consumers. • Volume and Valence is more salient to increase online patient base for cardiologists than for OBGYNs • Valence is more salient to obtain price premium for OBGYNs than for cardiologists.
	Valence→ Online Patient Base Increase	+	+	NS	
	Variance → Online Patient Base Increase	-	NS	NS	
	Volume → Price Premium	-	-	-	
	Valence→ Price Premium	NS	NS	+	
	Variance → Price Premium	+	+	+	
Signaling Mechanism* Online Feedback Mechanism	Credibility * Volume → Online Patient Base Increase (H1a)	+	NS	+	• Volume mitigates the negative effect of Credibility Signal on Online Patient Base Increase (for the full sample and the OBGYN subsample), amplifies the positive effects of Benevolence Signal on Online Patient Base Increase (for the cardiologists sample) and Price Premium (for the full sample and the two subsamples). • Valence amplifies the positive effect of Credibility Signal on Price Premium (for the full sample), and compensates with the effect of Benevolence Signal on Price Premium (for the full sample and the two subsamples). • Variance amplifies the effect of Credibility Signal on Online Patient Base Increase, and the effects of Benevolence Signal on Online Patient Base Increase and Price Premium (for the full sample and the two subsamples).
	Credibility * Volume → Price Premium (H1b)	NS	NS	NS	
	Benevolence * Volume → Online Patient Base Increase (H1c)	NS	+	NS	
	Benevolence * Volume → Price Premium (H1d)	+	+	+	
	Credibility * Valence → Online Patient Base Increase (H2a)	NS	-	NS	
	Credibility * Valence → Price Premium (H2b)	+	NS	NS	
	Benevolence * Valence → Online Patient Base Increase (H2c)	NS	NS	NS	
	Benevolence * Valence → Price Premium (H2d)	-	-	-	
	Credibility * Variance → Online Patient Base Increase (H3a)	-	-	-	
	Credibility * Variance → Price Premium (H3b)	NS	NS	-	
	Benevolence * Variance → Online Patient Base Increase (H3c)	-	NS	-	
	Benevolence * Variance → Price Premium (H3d)	-	-	-	

However, the signaling mechanism has been found less effective in the context of credence services (e.g., Kirmani and Rao 2000; Lantzy et al. 2014). Such ineffectiveness may be attributed to the nature of knowledge asymmetry embedded in credence services. Unlike information asymmetry, which is assumed to be reducible, knowledge asymmetry exists due to the unbalanced possession of professional knowledge that is accumulated over a long period of time. In such circumstances, credence service consumers have to not only rely on uninformed subjective judgment to interpret and evaluate the transmitted signals, but also seek additional information from other consumers to learn from their service experiences (Larson 1977). Along this line, this study explicitly differentiates knowledge asymmetry from information asymmetry and extends signaling theory and the word-of-mouth literature to credence service evaluations. We find that signaling mechanism and online feedback mechanism may independently and interactively enable effective delivery of credence services where significant knowledge asymmetry is embedded. We now elaborate on the following three points: the roles of 1) physicians' trustworthiness signals, 2) experience shared among patients, and 3) the interaction between signaling and experience-sharing mechanisms in delivering the credence services given knowledge asymmetry between service providers and consumers.

First, the knowledge asymmetry inherent in many credence services renders the consumer vulnerable to exploitation and heightens the value of well-founded trust. Suffering from limited cognitive resources and professional knowledge to systematically evaluate service quality, consumers of credence services may use available information to form trust in the service providers and providers' trustworthiness is used by consumers to infer service quality (Hastie 1983). Accordingly, we find that trustworthiness signals delivered by credence service providers are particularly salient for the evaluation of credence attributes, a process that is complex and ambiguous and requires significant amount of cognitive resources of consumers. Our results have further implications on how different dimensions of trustworthiness signals contribute to different impacts and exhibit different magnitudes across service domains. For example, *Credence Signals* transmit messages on physicians' professional credentials. Interestingly, we find that physicians with lower level of professional credentials benefit more by gaining greater increase in online patient base, while physicians with higher level of professional credentials obtain higher price premium. In contrast, *Benevolence Signals* indicate the extent to which physicians care about patients' interests and engage in pro-social behaviors to help patients in OHCCs. Physicians who signaled higher level of benevolence are found to achieve greater increase in online patient base and higher price premium for their online health consultation services. In addition, the marginal returns of physicians' signals on price premium are stronger in cardiology where the risk of health conditions is higher and the interpretation of diagnosis is more complex.

Second, our findings complement the existing word-of-mouth literature by revealing the roles of collective features of online feedback in affecting outcomes of credence services that feature knowledge asymmetry between service providers and consumers. We confirm that consumers are relying on other consumers' evaluation of services, although that other consumers also have limited insight into the missing credence attributes (Mittal 2004). In general, we find physicians with larger volume of patient reviews, more favorable patient reviews, and more consistent patient reviews are more likely to obtain greater increase in online patient base and higher price premium.

Particularly, we observe that *Volume* and *Valence of Feedback* are more salient to increase online patient base for cardiologists than for OBGYNs. In contrast, services by OBGYNs are more price sensitive to the *Volume, Valence, and Variance of Feedback* than those by cardiologists. We view that cardiologists and OBGYNs deal with health conditions that differ in the level of danger to the patient's life as well as in the complexity of diagnosis. Therefore, there is more risk involved in the process of selecting cardiologists than in the process of selecting OBGYNs. From this perspective, for a freemium credence service, the power of the wisdom of crowd might be stronger to accelerate consumer base for services with higher risk than for those with lower risk. Yet, consumers may be more reluctant to go beyond freemium to premium for higher-risk credence services than for lower-risk credence services.

Third, this study demonstrates that signaling mechanism and online feedback mechanism work independently and interactively affect the outcomes of credence services that, in contrast to other types of services, feature knowledge asymmetry between service providers and consumers. In general, we find that *Volume of Feedback* mitigates the negative effect of *Credibility Signal* on *Online Patient Base Increase* and amplifies the positive effect of *Benevolence Signal* on *Price Premium*. *Valence of Feedback* amplifies the positive effect of *Credibility Signal* on *Price Premium*, and compensates with the effect of *Benevolence Signal* on *Price Premium*. *Variance of Feedback* amplifies the effect of *Credibility Signal* on *Online Patient Base Increase*, and the effects of *Benevolence Signal* on *Online Patient Base Increase* and *Price Premium*. The strength of the above interaction effects is found to differ between cardiology and OBGYN where the risk of health conditions and the complexity of interpreting diagnosis reports are different. In brief, the collective online feedback features moderate the impacts of trustworthiness signals on *Price Premium* in a very similar pattern between cardiologists and OBGYNs. In contrast, interaction effects that affect *Online Patient Base Increase* may only be significant for cardiologists but not OBGYNS, or vice versa. For example, among OBGYNs, the negative impact of *Credibility Signal on Online Patient Base* is mitigated for those who receive a large amount of feedback from online patients. However, among cardiologists, the same negative impact is not found to be significantly alleviated by the *Volume of Feedback*, but by the *Valence of Feedback* instead. These interesting findings open up opportunities to understand the heterogeneity in effective delivery of credence services with different levels of decision-making risk.

3.5.2 Practical Implications

Our findings also provide pragmatic guidelines for service providers and platform designers to deal with the co-existence of expert knowledge and wisdom of crowd and deliver effective credence services with the support of online communities. To start with, this study enriches our understanding on how online credence service communities can be used by service providers to communicate trustworthiness signals, given the presence of collective online feedback from consumers. Specifically, the features of collective online feedback (e.g., the volume, valence, and variance of online reviews) are found to significantly shape the effectiveness of the signaling mechanism. First, when the volume of online feedback is limited, credibility signals may harm physicians by slowing down the increase in online patient base, while benevolence signals may be ineffective by reducing the price premium of services. However, as the volume of feedback becomes extensive, physicians' benevolence behaviors will amplify the marginal returns on price premium. Second, physicians' credibility amplify the marginal returns on price premium when online feedback is favorable. Interestingly, physicians should engage in more benevolent behaviors when online feedback is unfavorable, since such pro-social behaviors would help compensate for the decrease in price premium in this situation. Third, senior physicians who are sending stronger credibility signals should pay more attention to the variance of online feedback. These physicians may suffer more from the slowdown of the accumulation of online patient base when they receive inconsistent online feedback from patients.

Moreover, our findings shed light on the design of online communities for health consultation services. For example, platform designers should extend the functions of OHCCs and provide more opportunities for physicians to demonstrate their professional credentials and engage in online pro-social behaviors in order to signal their competence and benevolence so that patients may trust them. In addition, OHCCs may also leverage the multiple mechanisms to effectively transmit, represent, and evaluate trustworthiness signals. With various mechanisms to support the transmission and process of signals, OHCCs will retain continuous participation by both service providers and consumers, and thus establish a healthy public referral system to support online health consultation services. Such a system is expected to be meaningful to facilitate the communication among multiple stakeholders, and solve many social problems rooted in the trust crisis between patients and physicians.

3.5.3 Limitations and Future Research

There are several limitations of this study for future research. First, OHCCs are rapidly evolving because of the technological development in social networking and Web

2.0. New features of such communities may present signaling information as well as collective word-of-mouth in different formats. Future work may leverage the development of online communities and design field experiments to investigate how technological features in online community change the way in which information are transmitted, presented and processed.

Second, we conceptualized physicians' trustworthiness signals as their shared information and engagement activities in OHCCs. Future research may consider to examine the effects of other types of signals. For instance, in addition to the signals transmitted by physicians who directly provide online health consultation services, there may be signals transmitted by teams or institutions that physicians are affiliated with. It would be interesting to investigate the effectiveness of multiple signals transmitted by stakeholders at different levels in the general context of online communities and in the specific context of online credence service communities.

Third, we conducted a series of robustness tests such as the whole residual procedure by Garen (1984) to address the potential of reverse causality, and Heckman two-step analysis to account and correct for self-selection bias in our model. Yet, we believe that exogenous variables collected from external sources other than the investigated online community might generate better instrument variables or indicators of self-selection groups to help address endogeneity and establish causal relationships. Future research in this area is recommended to collect empirical materials from multiple sources to cross-validate the robustness and generalizability of our findings.

Fourth, we cannot track online feedback across time from each patient because patients were not identifiable on the OHCC where we collected data. Following prior literature (Li and Hitt 2010), we used average ratings for each physician across every two weeks as the proxy for *Valence of Feedback* instead of using each single patient review. Indeed, average ratings are suggested to be superior to discrete raw ratings because their distribution is closer to a normal distribution according to the central limit theorem (Wasserman 2004). Using average ratings may also provide more conservative estimations. Yet, a fruitful direction for future research is to track online feedback over time at the consumer level (e.g., for each patient), construct a series of interactions between consumers and physicians, and understand the dynamic impacts of online feedback at a granular level.

Lastly, in-person doctor visits and OHCCs are two complementary channels that physicians provide health consultation services. It is possible that physicians' signaling efforts in OHCCs may influence their patient base and price premium in the physical channel instead of the online channel. However, the practical constraints associated with the access to matched data on in-person doctor visits precluded us from pursuing this line of inquiry. Accordingly, future work can focus on the impacts of engagement in OHCCs on health consultation success in both channels.

3.6 Conclusion

This study integrates the theoretical framework of signaling theory with the word-of-mouth literature to provide a foundation for understanding how online communities help deliver effective credence services that, by definition, feature knowledge asymmetry between service providers and consumers. Our findings reveal that expert knowledge and wisdom of crowds are not an either-or choice, but rather interactively work together to achieve an effective delivery of credence services that feature knowledge asymmetry between credence service providers and consumers. Interestingly, online credence service communities play an empowerment role in facilitating the engagement of professional experts with signaling and in assisting the spread of crowd wisdom about the assessment of credence service quality. More importantly, we find collective features of online feedback to amplify the positive impacts, mitigate or compensate for the negative impacts of trustworthiness signals to affect the online patient base increase and price premium for online health consultation services. We als observe heterogeneity in the interaction effects between signaling and online feedback mechanisms in subsegments of physicians with different specialties. Overall, we develop a more complete picture to understand how to deliver effective credence services with the support of online credence service communities through a combination of signaling and online feedback mechanisms.

Chapter 4

The Role of Digital Capabilities in Converting Inventor Team Expertise to Knowledge Capital for Medical Device Innovation

Abstract

Medical device innovation increasingly needs inventor teams that not only have specialized expertise but also are diverse in multiple knowledge domains. Using a multi-level lens, this study focuses on the structural perspective of empowerment and examines how digital capabilities can empower inventor teams to solve the dilemma between broadening knowledge capital via diverse expertise and deepening knowledge capital via specialized expertise. We conceptualize multi-dimensional digital capabilities for innovation development and synthesize literatures on IT-enabled innovation and IT strategy to inform the development of our hypotheses. We constructed a multisource panel dataset by linking data from multiple sources, including the University of California (UC) Berkeley Patent Database and Computer Intelligence Technology (CI) Database. Our study enriches the literature on digital capabilities by developing and empirically validating a theoretical conceptualization of digital capabilities for innovation development in general and medical device innovation in specific. The results shed light on how Innovation Development Digital Capabilities empower inventor teams to convert their diverse or specialized expertise into broad and deep knowledge capital and facilitate knowledge production in terms of patent innovation.

Keywords: Innovation development digital capabilities, knowledge capital generation, inventor team design, medical device innovation

4.1 Introduction

The success of contemporary firms depends largely on their ability to generate innovation, particularly technological innovation (Stuart 2000). Innovation activities such as patent inventions help firms to position their products, gain market share, and achieve profitability (Miller and Cheng 1994; Ferrier et al. 1999; Smith et al 2001; Aboulnasr et al 2008). During the past two decades, the volume of patents applied and granted has surged all over the world. For example, the number of patents in the United States during the period between 2008 and 2011 is more than twice the number during the period between 1980 and 1983 (Kwon et al. 2014).

Although it seems that technological innovation is progressing successfully, serious concerns have been raised regarding the quality of innovation. In terms of patent inventions, Jaffe and Lerner (2004) argued that, due to the reduced cost of patent application and a shortage of qualified examiners, USPTO granted an exponential volume of patents with lower average quality. Studies have found that the value of patents shows a highly skewed distribution characterized by very small number of high-value patents and a large number of low-value patents (Harhoff et al. 2003; Scherer 2001). Given that technological innovation becomes increasingly more competitive, the ability to identify high quality innovation will help innovators manage their resources in a more effective and efficient way. In addition, since innovation quality is positively associated with firm level outcomes such as the stock market value of firms (Lanjouw and Schankerman 2004; Bloom and Van Reenen 2002; Hall et al. 2005; Belenzon 2012), it is important for firms to understand how to generate innovation with high quality.

Viewing innovation as a process of searching for existing knowledge over technology landscapes (Fleming and Sorenson 2004), we consider that the quality of innovation is associated with the knowledge capital accumulated during the innovation process (Adams and Lamon 2003; Cardinal et al. 2001; Darroch and McNaughton 2002; Pyka 2002; Shani et al. 2003). In particular, achieving both knowledge deepening and knowledge broadening is critical to generate impactful innovation (March 1991). In accordance with the organizational learning literature, an appropriate knowledge capital generation structure would help achieve the ambidexterity between exploration and exploitation (Katila and Ahuja 2002).

The design of inventor teams always plays a constructive role in developing patent innovation because inventors contribute important knowledge to the firm (Grant 1996; Rothaermel and Hess 2007; Subramaniam and Youndt 2005). Empirical work has shown that the design of inventor teams lays the foundation for a firm to accumulate knowledge capital and generate patent innovation (Rothaermel and Hess 2007). Specifically, inventors may have expertise in diverse knowledge domains or specialization in the same knowledge domain. Such diversity and specialization properties of inventor team expertise have been found to influence the breadth and depth of knowledge capital in a different way. For instance, the specialty of inventor team expertise invested in an innovation is likely to promote the deepening of knowledge capital, while limiting the broadening of knowledge capital. By contrast, the diversity of inventor team expertise encourages the broadening of knowledge capital, while hampering the deepening of knowledge capital (Hayton 2005). As a result, firms often face a dilemma to achieve the ambidexterity between broadening and deepening knowledge. In many cases, firms have to sacrifice the premium of specialization in order to obtain broader knowledge, or to sacrifice the premium of diverse teams in order to obtain deeper knowledge (Anjos and Fracassi 2015).

From the structural empowerment perspective, IT can serve a key role in fostering an empowerment climate, and mitigating the above-mentioned tension between the diversity and specialization of inventor team expertise to optimize the generation of knowledge capital and develop high quality innovation. Although prior literature has indicated the role of IT in building and augmenting organizational knowledge (e.g., Alavi and Leidner 2001; Joshi et al. 2010), there is the need for a theoretical conceptualization of digital capabilities in the context of innovation development. In addition, the properties of inventor team expertise has been identified as the micro-foundation to knowledge production that can be converted into organizational knowledge capital (Ployhart and Moliterno 2011). Yet, acknowledging the great potential of digital capabilities to bring in structural changes within the innovation environment and create an empowerment climate, we do not know how digital capabilities can be used to effectively convert expertise of inventor teams into knowledge capital in medical device companies confronted with the need to pursue deep within-domain discovery and broad across-domain discovery. Accordingly, we focus on two research objectives:

RO1: To conceptualize a new construct of Innovation Development Digital Capabilities in the context of medical device innovation.

RO2: To examine how Innovation Development Digital Capabilities change the effectiveness of the conversion from human capital into knowledge capital for medical device innovation.

4.2 Research Model and Hypotheses

Informed by the strategic management and R&D literatures on innovation as well as recent literature on IT-enabled innovation, we propose the conceptual framework as shown in Figure 4.1. The overall logic of our framework indicates that human capital will be converted into knowledge capital, which is critical to generate high quality innovation; digital capabilities play a role in fostering empowerment climate and shaping the effectiveness of the conversion from human capital into knowledge capital.

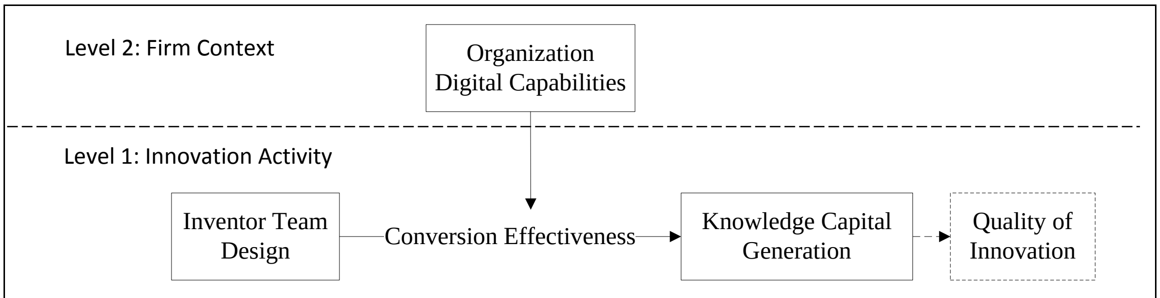


Figure 4.1. Conceptual Framework

Specifically, we focus on two dimensions of knowledge capital generation: Across Class Knowledge Broadening (KB) and Within Primary Class Knowledge Deepening (KD); two dimensions of human capital allocation: Inventor Teams' Expertise Diversity across Classes (ED) and Inventor Teams' Expertise Specialization within the Primary Class (ES); and three dimensions of Innovation Development Digital Capabilities: Reach, Richness, and Protection. Figure 4.2 presents the research model and core constructs in this model are defined in Table 4.1. In the remainder of this section, we elaborate the conceptualization for each of the core constructs and theorize the moderating effects of Innovation Development Digital Capabilities on the impact of inventor team design on knowledge capital generation.

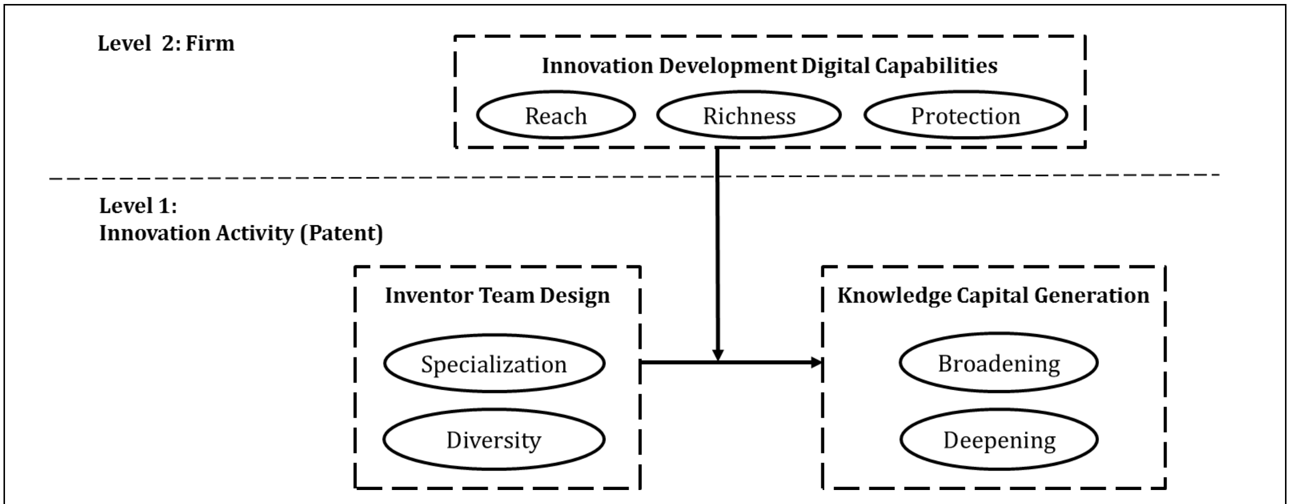


Figure 4.2. Research Model

Table 4.1. Definitions of Constructs

Concepts	Definitions of Concepts	Constructs	Definitions of Constructs	References
Level 1: Knowledge Capital Generation	The combination of knowledge, expertise, and information embedded in a patent innovation	Across-Class Knowledge Broadening (KB)	The breadth of knowledge domains that an innovation is drawing upon the prior state-of-art.	Henderson et al. (1998)
		Within-Primary-Class Knowledge Deepening (KD)	The extent to which an innovation builds upon prior state-of-art within the same knowledge domains.	Rosenkopf and Nerkar (2001)
Level 1: Human Capital Allocation	The stock of knowledge, skills and experiences held by I inventors in a patent innovation.	Inventors' Expertise Diversity across Classes (ED)	The extent to which inventors are different in their expertise as a result of their innovation experience.	Adapted from Carnabuci and Operti (2013)
		Inventors' Expertise Specialization within the Primary Class (ES)	The extent to which inventors are expertized in the primary knowledge domains of an innovation.	Adapted from Toh (2014)
Level 2: Innovation Development Digital Capabilities	A firm's ability to leverage its IT resources in support of innovation development	Reach	The extent to which implemented technologies provide connectivity and access to external knowledge.	Adapted from Sambamurthy et al. (2003)
		Richness	The extent to which implemented technologies provide high-quality knowledge that supports integrating, presenting, sharing, and extracting insights from internal knowledge.	Adapted from Sambamurthy et al. (2003)
		Protection	The extent to which implemented technologies provide security and protect knowledge from inappropriate disclosure or leakage.	Self-developed
Level 1: Innovation activity (patent) level; Level 2: Firm context (firm-year) level				

4.2.1 Knowledge Capital Generation

Consistent with prior research on knowledge recombination and innovation (e.g., Rosenkopf and Nerkar 2001; Gruber et al. 2013; Toh 2010; Miller et al. 2007), we conceptualize knowledge capital generation and inventor team design at the innovation activity level (i.e., patent-firm-year level). To start with, knowledge capital generation refers to the combination of knowledge, expertise, and information embedded in a patent innovation. We focus on two aspects of knowledge capital generation: Across-Class Knowledge Broadening (KB) and Within-Primary- Class Knowledge Deepening (KD). KB refers to the breadth of knowledge domains that an innovation is drawing upon the prior state-of-art; while KD refers to the extent to which an innovation builds upon prior state-of-art within the same knowledge domains.

In view of previous research, the structure of knowledge capital generation affects the quality of innovation as exhibited through the impact of a particular patent innovation (e.g., Argyres and Silverman 2004; Fleming and Sorenson 2004; Gittelman and Kogut 2003; Rosenkopf and Nerkar 2001). In specific, both the breadth and depth of knowledge capital have been found to affect the impact of a patent, that is, the focal patent's relevance to subsequent patents (Lettl et al. 2009).

4.2.2 Impacts of Inventor Team Design on Knowledge Capital Generation

Inventor team design reflects how teams structure their stock of knowledge, skills and experiences held by individual inventors in a patent innovation. We focus on two properties of inventor team design: Inventors' Expertise Specialization within the Primary Class (ES) and Inventors' Expertise Diversity across Classes (ED). ES refers to the extent to which inventors are homogenously expertized in the primary knowledge domains of an innovation; and ED means the extent to which inventors are different in their expertise as a result of their innovation experience.

Prior literature has found that the specialization and diversity of human capital influence the breadth and depth of knowledge capital in a different way. First, ES increases the depth but decreases the breadth of knowledge capital. Specifically, inventors with similar expertise tend to be more familiar with each other's perspectives and backgrounds, and are easier to understand each other when collaborating and sharing knowledge (Tortoriello et al. 2012). Thus, expertise specialization would increase the depth of innovation by repeatedly reusing their existing knowledge in novel ways (Carnabuci and Operti 2013). However, inventors in such teams may gain limited number of additional insights. Inventors' attention may be directed to focus only on the domains of their expertise, resulting in a consensus bias that inhibits divergent views to broaden the knowledge capital of innovation (Stasser and Titus 2003).

By contrast, ED enhances the breadth while impeding the depth of knowledge capital. On the one hand, prior scholars have recognized that teams whose members are diverse in their expertise will expose individual members to new paradigms and perspectives from dissimilar others. Such exposure would expand each inventor's knowledge scope, allow inventors to link and make use of ideas and viewpoints from multiple technological domains, and thus enable cross-fertilization of ideas to broaden the knowledge capital of innovation (Van der Vegt and Bunderson 2005). On the other hand, the limited shared frame of reference may constrain an in-depth understanding of diverse knowledge across domains (van Knippenberg and Schippers 2007). Under this circumstance, inventor teams with diverse expertise may not be able to comprehend complex knowledge, share in-depth knowledge, and engage in deep collaboration (Majchrzak et al. 2012; Williams and O'Reilly 1998) to deepen the knowledge capital.

Since the relationship between inventor team design and knowledge capital generation has been theorized in the prior literature as discussed above, we do not hypothesize direct relationships between inventor team design and knowledge capital generation. Instead, we focus on how these direct relationships are moderated by IT. We now elaborate the conceptualization of Innovation Development Digital Capabilities and theorize its role in shaping the effectiveness of conversion from inventor team design to knowledge capital generation.

4.2.3 Moderating Role of IT

Conceptualizing Innovation Development Digital Capabilities

We define Innovation Development Digital Capabilities as a firm's ability to leverage its IT resources in support of innovation development. Reviewing literature on organizational capabilities and IT-enabled innovation (e.g., Tippins and Sohi 2003; Sambamurthy et al. 2003; Joshi et al. 2010), we identify three dimensions of this construct: Reach, Richness, and Protection. These multi-dimensional digital capabilities lead to structural changes in the work environment, and create an empowering climate in which teams can easily access information, openly communicate with one another, and securely share and exchange information.

Reach refers to the extent to which implemented technologies provide connectivity and access to external knowledge (Evans and Wurster 2000; Sambamurthy et al. 2003). The Reach dimension of Innovation Development Digital Capabilities corresponds to the knowledge acquisition process identified in the knowledge management literature (Inkpen and Dinur 1998). In most cases, *Reach* can be increased by enabling connections with sources outside the firm for emerging ideas and developments. Accordingly, a high degree of effort and expertise of inventor teams is desired to make full use of the IT-enabled *Reach* functionalities in sensing and capturing external knowledge (Gold et al. 2001). A typical means through which inventors obtain external knowledge is Internet access. Internet access is the most basic type of Internet service, and is a necessary condition for the adoption of most other Internet applications. Internet access may range from the most basic level, where users obtain dial-up services to the local Internet service provider (ISP), to superior level, where users obtain high-speed connections through T-1 or T-3 lines (Forman 2005).

Richness is the extent to which implemented technologies provide high-quality knowledge that supports integrating, presenting, sharing, and extracting insights from internal knowledge (Sambamurthy et al. 2003). While *Reach* provides firms with the opportunities to tap into external knowledge resources, *Richness* represents the extent to which these resources are exploited and is manifested in four aspects.

First, the richness capability of restructuring and integrating knowledge help understand relationships among cross-functional knowledge, and retrieve customized information in a timely manner (Grant 1996; Davenport and Klahr 1998). For example, database management systems can integrate knowledge with predefined keywords and meta-data so that the content becomes accessible for inventors and enable them to interpret it in a consistent manner (Gold et al. 2006; Massey and Montoya-Weiss 2006).

Second, the richness capability of presenting knowledge in a variety of formats allows inventors to visualize and communicate the construction of innovation in a more efficient and effective way. For instance, the use of computer-aided tools for design and manufacturing has made product development and manufacturing more modular and flexible (Sanchez 1995). Specifically, CAD/CAM enables both design and manufacturing engineers to access, manipulate and exchange their respective data, to create and modify potential designs, and to accelerate innovation development through cross-functional collaboration (Tanriverdi 2006).

Third, the richness capability of extracting insights from existing knowledge enables firms to quickly and systematically analyze the large amount of complex information, and facilitate automated knowledge discovery (Banker et al. 2006). For instance, visualization and analytical tools in business intelligence allow firms to transform and interpret existing knowledge to gain rich insights and understanding, and identify opportunities for innovation (Sabherwal and Becerra-Fernandez 2010).

Fourth, the richness capability to support perspective sharing and communication helps intensify the interactions among inventors and augment firms' social capital to cultivate knowledge synergies and shared frame of references (Chi et al. 2010). Technologies such as groupware systems provide rich media to increase communication frequency and enhance the effectiveness of socialization efforts among inventors (Chi et al. 2010). The enhanced social interactions and connections among inventors cultivate the exchange of information and ideas, which is crucial for the development of innovation.

Protection refers to the extent to which implemented technologies provide digital security and protect knowledge from inappropriate disclosure or leakage. Different from the *Reach* and *Richness* capabilities, the *Protection* dimension of Innovation

Development Digital Capabilities has received little attention in the literature (Gold et al. 2006). Yet, for firms that rely on innovation as the source of their survival and success, it is vital that their knowledge be protected (Liebeskind 1996). Accordingly, firms may use various forms of IT, such as firewalls, intrusion detection systems or fault detection tools, to restrict or track access to vital knowledge or knowledge generation processes. As a result, *Protection* is an arguably important dimension of Innovation Development Digital Capabilities and should be examined together with *Reach* and *Richness*.

The above discussion indicates that Innovation Development Digital Capabilities may complement specialized-versus-diverse inventor teams through different mechanisms to influence the breadth and depth of knowledge capital for innovation. We next elaborate on how Innovation Development Digital Capabilities interact with the expertise of inventor teams to jointly affect knowledge capital generation.

Innovation Development Digital Capabilities, ES and KB

Inventors who are specialized in the same knowledge domains may not be aware of knowledge beyond their expertise. *Reach* broadens the access to external knowledge resources and exposes inventors to diverse information. This exposure, coupled with specialized inventor teams having the capacity to initiate coordination effectively, could allow inventors to have a broad reach to new ideas, and thus compensate for the limited availability of related knowledge beyond the specialized domains of inventors in the team. Therefore, *Reach* is expected to mitigate the adverse effects of expertise specialization on the broadening of knowledge capital.

Richness is also expected to mitigate the adverse impact of ES on KB. IT that support systematic analysis, integration, representation, and sharing of organizational knowledge allow inventors to process and interpret broader information such as market demand, technological trends, shifts of design, and changes in organizational or government policy. As a result, inventors are able to develop a better understanding of the overall innovation environment and gain richer insights about innovation opportunities in the environment. In other words, the capabilities of enriching organizational knowledge with the help of IT may generate activation triggers that induce or intensify inventors' efforts to move beyond their knowledge repertoire and broaden the knowledge capital when developing innovation. In sum, *Richness* help mitigate the limitation of expertise homogenization on broadening knowledge capital of innovation.

H1: The negative impact of ES on KB is mitigated by a) Reach and b) Richness

Innovation Development Digital Capabilities, ED and KB

Inventors whose expertise is diverse across multiple knowledge domains are likely to face more challenges in coordination and collaboration. Unless the inventor teams have the capacity to deal with the increased complexity in managing the interdependencies among inventors, they are unlikely to attain the full benefits of diverse expertise in inventor teams. *Richness* provides a digital environment that supports the restructuring, processing, transmission, and sharing of complex information in various formats and thus facilitates the communication of diverse knowledge among inventors. Hence, *Richness* allows inventors to process the increased volume and complexity of information, compensates for the coordination difficulties inherent in diverse teams, and amplifies the benefits of heterogeneous expertise to broaden knowledge capital.

Protection provides a digital environment that protects the knowledge within an organization from illegal or inappropriate use. As intensive communication and collaboration among inventors may occur using digital applications and tools, there is a risk of unintended knowledge spillovers or knowledge leakage especially when collaborating and sharing knowledge in an unsecured digital environment. Such leakage exposes inventor teams to the risk of losing strategically important knowledge, and might hamper efforts to share knowledge in collaborations (Baughn et al. 1997; Hamel 1991; Martinez-Noya et al. 2013). Under this situation, an IT-enabled protective environment provides a secure platform that allows inventors to share knowledge and collaborate without worrying about knowledge leakage or inappropriate use of shared knowledge, thus enhancing the benefits of expertise diversity on the broadening of knowledge capital.

H2: The positive impact of ED on KB is amplified by a) Richness and b) Protection

Innovation Development Digital Capabilities, ES and KD

Inventor teams with homogenous knowledge domains are likely to deepen the knowledge capital in innovation development. Digital capabilities supporting a secured environment reduce inventors' concerns on the leakage or inappropriate use of knowledge (Martinez-Noya et al. 2013). As a result, inventors may intensify communication and information exchange among each other (Ford and Staples 2008), and thus amplify the benefits of specialized expertise on deepening knowledge capital. Hence, we expect that the positive impact of ES on KD will be augmented by *Protection*.

H3: The positive impact of ES on KD is amplified by Protection.

Innovation Development Digital Capabilities, ED and KD

Inventor teams with diverse expertise may obstruct the knowledge deepening in specific technological domains. *Richness* allows inventor teams with diverse expertise to share different perspectives and synthesize knowledge, and thus deepens understanding in the interested knowledge domains. In detail, IT facilitating socialization and collaboration allows inventors to exchange tacit knowledge through supporting formal and informal social mechanisms among inventors (Joshi et al. 2010). Similarly, IT that restructures and visualizes the presentation of knowledge would reduce communication barriers and strengthen the mutual understanding among inventors (Sanchez 1995). In addition, IT such as business intelligence tools may help transform existing knowledge to gain new insights (Sabherwal and Becerra-Fernandez 2010). These functionalities for *Richness* collectively help and request inventors to better understand knowledge in each other's specialized domains, thus facilitating the integration and synthesis of innovation ideas to a deeper level and generating innovation with deeper knowledge capital. Accordingly, *Richness* may mitigate the negative relationship between ED and KD.

In addition, *Protection* creates a secure environment with the support of IT. Such digital protective environment may offer protection against unauthorized use of knowledge, and assist the integration of diverse knowledge embedded in individual inventors. As a result, *Protection* may help inventor teams to alleviate the adverse effect of heterogeneous expertise in deepening knowledge capital.

H4: The negative impact of ED on KD is mitigated by a) Richness and b) Protection.

4.3 Methodology

4.3.1 The Medical Device Industry

The empirical context is situated in the medical device industry in the United States for several reasons. First, the medical device industry is growing with a market size of $75 billion in 2002 and $1.5 billion venture capital invested in 2003 (AdvaMed 2004; Pricewaterhouse Coopers 2011). Second, technological innovation is especially valued in the medical device industry because of their enormous potential for improving individual and population health and for igniting national economy (Herzlinger 2006). Significant resources have been invested in medical device innovation to continuously provide groundbreaking and transformational produces and services (U.S. International Trade Commission 2013). Leading medical device manufacturers (e.g. including Johnson and Johnson, GE Healthcare, and Siemens Electronics) commonly spent 9% of their sales revenues on R&D, in contrast to 3-4% for domestic manufactures in other industries. Third, patenting of medical devices is usually considered a crucial part of firm strategy in this sector. By the end of 2013, 120,000 U.S. origin patents have been issued as medical device patents (USPTO Medical Device Report 2015). Therefore, patent data is considered as an appropriate proxy for innovation and is commonly used by prior research (e.g., Argyres and Silverman 2004; Fleming and Sorenson 2004; Gittelman and Kogut 2003; Henderson and Cockburn 1994; Rosenkopf and Nerkar 2001)

4.3.2 Construction of Multisource Panel Dataset

We constructed the panel dataset by linking data from multiple sources. First, we used the UC Berkeley Patent Database to construct measures for *knowledge capital generation* (i.e., KB and KD) and *inventor team design* (i.e., ED and ES). This database provides information regarding the characteristics of each patented innovation (e.g., technological subclasses, application date, grant date, backward citations, and forward citations), the inventor teams involved in the innovation, and the firm wherein the innovation was developed. Second, we used the Computer Intelligence Technology (CI) Database from Harte-Hanks to construct measures for *Innovation Development Digital Capabilities*. The CI database tracks information over 300,000 establishments in North

America, and contains establishment-level data on IT implementation across 10 key areas, including hardware, software, and IT services. This database has been used by a number of researchers to study the adoption of IT (e.g., Bresnahan and Greenstein 1996) and the productivity implications of IT investment (e.g., Bresnahan et al. 2002, Brynjolfsson and Hitt 2003, Bloom et al. 2009), and has been considered as one of the best sources of information on IT investments of private firms (Forman et al. 2005). Third, other firm information is obtained from the COMPUSTAT and Center for Research in Security Prices (CRSP) databases.

4.3.3 Sample

The sampling frame was companies in the *Healthcare Equipment and Services* sector in the S&P 500 list. We first used the three-digit technological classes in the USPTO Medical Device Report (2015) to generate a sample of U.S. medical device patents that are granted between 2010 and 2013. Next, we identified patents whose assignees are one of the companies in the *Healthcare Equipment and Services* sector in the S&P 500 list. We then used GVKEY of patent assignees to match the CI data with COMPUSTAT data. After combining the UC Berkeley patent data with the CI and COMPUSTAT databases and computing the variables of interest, our final dataset included 8757 medical device patents issued by 15 medical device companies during a 4-year period from 2010 to 2013, together with information on IT implementation in these 15 companies during a 4-year period from 2005 to 2008.

4.3.4 Measures

We now discuss the measures of our constructs (summarized in Table 4.2).

Table 4.2. Measures of Constructs				
Role (Level)	**Construct**	**Measure**	**Reference**	**Source**
DV(L1)	Across-Class Knowledge Broadening (KB)	$KB_i = [1 - \sum_{j=1}^{J} (\frac{N_{ij}}{N_i})^2][(\frac{N_i}{N_i - 1})$ patent *i* class *j*; *N*=Number of backward citations	Adapted from Henderson et al. (1998)	UC Berkeley Patent
	Within-Primary-Class Knowledge Deepening (KD)	Number of backward-cited patents that are in the same primary class as the focal patent/ total number of backward citations.	Adapted from Rosenkopf and Nerkar (2001)	UC Berkeley Patent
IV (L1)	Inventors' Expertise Specialization within the Primary Class (ES)	1) Identify the primary technology classes of the focal patent I, inventors of the focal patent, and all patents involved by the identified inventors before the focal patent is granted; 2) Calculate a ratio by dividing the number of patents that involve inventor *j* and are assigned with classes C by the total number of patents involving inventor j; 3) Take the average of the above ratio across all inventors for patent *i* in year *t*.	Adapted from Toh (2014)	UC Berkeley Patent
	Inventors' Expertise Diversity Across Classes (ED)	$\sum_{j=1}^{N} P_j \times \ln(\frac{1}{P_j})$, where P_j is the share of the patent's inventors who filed at least one patent in technology class *j*, summed over the total number of technology classes (N).	Adapted from Carnabuci and Operti (2013)	UC Berkeley Patent
Moderator (L2)	Richness	For firm *i* in year *t*, the implementation rates of the following technologies across all sampled establishments: 1) Database management systems; 2) Business intelligence; 3) Groupware software; 4) CAD/CAM	Self-developed	CI
	Reach	For firm *i* in year *t*, the implementation rates of the following technologies across all sampled establishments: Hardwired Internet access including XDSL line, optical carrier line, T1 line, T3 line, ISDN line, switched 56 line, dial-up line	Self-developed	CI
	Protection	For firm *i* in year *t*, the implementation rates of the following technologies across all sampled establishments: 1) Firewall; 2) Intrusion detection system	Self-developed	CI
CV (L1)	Number of Inventors	Number of inventors for patent i	Carnabuci and Operti (2013)	UC Berkeley Patent
	Number of Classes	Number of technological classes assigned to patent i	Carnabuci and Operti (2013)	UC Berkeley Patent
	Review Time	Number of days from the application date to the issue date of a patent.	Self-developed	UC Berkeley Patent
CV (L2)	Site	Number of sites sampled for firm j in year t	Self-developed	CI
	Technology Experience	Number of medical device patent applied for firm j between year t-3 and year t-1	Carnabuci and Operti (2013)	UC Berkeley Patent
	Firm Size	Number of total employees for firm *i* in year *t*	Hitt and Brynjolfsson (1996)	COMPUSTAT
	Firm Age	Number of years that the firm has been listed on the CRSP daily returns tape	Denis et al. (1997)	CRSP
	R & D Intensity	R & D spending scaled by total assets for firm *i* in year *t*.	Bharadwaj et al. (1999)	COMPUSTAT
	Regular Capital (PPE)	Property, plant, and equipment (*PPE*) scaled by total assets for firm *i* in year *t*	Dewan et al. (2007) Kothari et al. (2002)	COMPUSTAT
	Return on Assets (ROA)	Income before extraordinary items scaled by total assets for firm *i* in year *t*	Dewan et al. (2007) Kothari et al. (2002)	COMPUSTAT
	ERP Implementation	For firm *i* in year *t*, the implementation rates of the following modules of ERP across all sampled establishments: 1) Customer relationship management; 2) Supply chain management; 3) Human resource management; and 4) Accounting	Self-developed	CI
L1: Level 1 (innovation activity level) L2: Level 2 (firm context level)		IV: independent variables M: Moderators	CV: control variables	

Dependent Variables: Knowledge Capital Generation

We follow an established approach of using patent backward citation data (e.g., Trajtenberg et al. 1997; Rosenkopf and Nerkar 2001; Katila and Ahuja 2002) to construct measures for knowledge capital generation. Each patent contains citations to previous patents as relevance to prior art, and we view that backward citations represent the knowledge origins of a focal patent innovation.

Across-Class Knowledge Broadening (KB) refers to the breadth of knowledge domains that a focal patent is drawing upon the cited patent (s). We proxy this construct with a commonly used measure of *patent originality* developed by Trajtenberg et al. (1997). This measure is calculated based on the Herfindahl index at the referenced patent level. Explicitly, it is defined as $KB_i = [1-\sum_{j=1}^{J}(\frac{N_{ij}}{N_i})^2](\frac{N_i}{N_i-1})$, where i indexes the patent, j indexes patent classes, and N represents the number of backward citations (Henderson et al. 1998). The expression outside the square brackets adjusts for bias associated with small numbers of backward patent counts (Hall and Trajtenberg 2004). A value of zero for this measure corresponds to patents with backward citations to patents within one technological class, whereas a higher value from this measure corresponds to patents with backward citations to patents in multiple technological classes. Accordingly, higher values on this measure reflect greater extent of knowledge broadening across technological domains for the referenced patent.

Within-Primary-Class Knowledge Deepening refers to the depth of knowledge domains that a focal patent is drawing upon the cited patent (s). We adapt the approach by Rosenkopf and Nerkar (2001) to proxy this construct at the patent level, and measure this construct as the percentage of backward citations that are in the same primary class as the focal patent. Higher values on this measure correspond to patents with greater extent of knowledge deepening within the focal technological domains.

Independent Variables: Inventor Team Design

Inventor team design refers to the way a team structures the knowledge and expertise domains of inventors to facilitate patenting activities. We view patenting activities that inventors are engaged in represent the knowledge expertized by the inventors. Accordingly, we use the technology classes of prior patents that inventors of a focal patent have been involved in to construct measures for two properties of inventor team expertise of the focal patent.

Inventors' Expertise Diversity across Classes (ED) refers to the extent to which the knowledge held by inventors of a patent is diverse across different technological areas. We adapt the approach by Carnabuci and Operti (2013) and measure this construct at the patent level. We use the Teachman's entropy index (1980): $\sum_{j=1}^{N} P_j \times \ln\left(\frac{1}{P_j}\right)$, where P_j is the share of inventors who have been granted at least one patent in technology class *j* before the focal patent is granted, and N is the total number of technology classes. This index is a direct measure of diversity and ranges from 0 to ln (*N*). The index equals zero when inventors of a particular patent are all specialized in the same technological area; the index equals ln (*N*) when inventors are all specialized in distinct technological areas.

Inventors' Expertise Specialization within the Primary Class (ES) refers to the extent to which inventors of a focal patent are specialized in the primary technological domains of the patent. We adapt the procedures by Toh (2014) and measure the construct of *ES* at the patent level based on the following three steps. First, we identify the primary technology classes of the focal patent (*C*), inventors of the focal patent, and all patents involved by the identified inventors before the focal patent is granted. Second, for each inventor *j* involved in patent *i* in year *t*, we calculate a ratio by dividing the number of patents that involve inventor *j* and are assigned with technology classes *C* by the total number of patents involving inventor *j*. This ratio reflects how focused the inventor *j* is on particular technological areas. In the third step, we compute the average of the above ratio across all inventors for patent *i* in year *t* and use it as the measure of ES.

Moderators: Innovation Development Digital Capabilities

We use composite measures to operationalize the three dimensions of Innovation Development Digital Capabilities. These measures reflect the extent of implementation of IT that support functionalities of *Reach*, *Richness*, and *Protection*.

First, we use Internet access to measure the dimension of *Reach*. Consistent with Forman (2005), we view Internet access as the means through which inventors retrieve external knowledge. In our dataset, technologies for Internet access include XDSL line, optical carrier line, T1 line, T3 line, ISDN line, switched 56 line, and Dial-up line. Since the raw data is at the establishment-year level, we aggregate the raw data to the firm-year level to align with the conceptualization of the *Reach* dimension of Innovation Development Digital Capabilities using the formula: $Reach_{jt} = \frac{\sum_{i=1}^{N} D_{ijt}}{N}$, where *i* represents the establishment, *j* represents the firm, *t* denotes the year and *N* refers to the number of establishment for firm j in year t. $D_{ijt} = 1$ if the establishment j have implemented any of the identified IT supporting *Reach*; $D_{ijt} = 0$, otherwise. Table 4.3 further illustrates the aggregation procedure of constructing *Reach*.

Table 4.3. Example of Constructing the Measure for *Reach* (Firm *j* Year *t*)											
Dimension	Functionality		Ref.	IT Components	Raw Data			D_{Reach}			%
					Site 1	Site 2	Site3	Site 1	Site 2	Site 3	Firm
Reach	Internet Access	Means through which inventors retrieve external knowledge from Internet	Forman (2005)	XDSL Line	0	1	0	0	1	1	0.67
				Optical Carrier Line	0	0	1				
				T1 Line	0	1	0				
				T3 Line	0	0	0				
				Dial-up Line	0	0	0				
				ISDN Line	0	1	0				
				Switched 56 Line	0	0	1				

Second, we identify four IT components that constitute *the Richness* dimension of Innovation Development Digital Capabilities: (1) database management systems as a knowledge architect restructure and organize knowledge in such a way that firms are able to establish relationship among cross-functional knowledge and inquire knowledge across various business functions (Massey and Montoya-Weiss 2006); (2) business intelligence combines a broad set of data analysis and visualization applications, automating the process of knowledge discovery for innovation development (Sabherwal and Becerra-Fernandez 2010); (3) CAD/ CAM represents computer-aided tools that support interactive, collaborative, and customized engineering design. These tools enable inventor teams to create, modify, analyze, and optimize a design, and achieve efficient corporation and integration between manufacturing and engineering design (Chi et al. 2010); and (4) groupware systems are instrumental in nurturing social interactions and connections among individuals and groups (Banker et al. 2006). Such tools could greatly facilitate the communication, coordination and sharing to cultivate knowledge synergies.

Third, we identify firewall and intrusion detection systems (IDS) as components that constitute *Protection*. Firewall functions in a networked environment to block unauthorized access yet permitting authorized communication. IDS is used to monitor and alert intrusion attempts to the network. These applications complement with each other to ensure the security of a digital environment and protect knowledge from inappropriate disclosure or leakage.

Again, since the raw data for the IT implementation is at the establishment-year level whereas our *Richness* and *Protection* constructs are at the firm-year level, we aggregate the data across establishments to a firm using the formula: $\mathit{Richness}\ (\text{or } \mathit{Protection})_{jt} = \frac{\sum_{i=1}^{M} R_{ijt}}{M}$, where i represents the IT component constituting *Richness* (or *Protection*), j is to the firm, t is the time, and M is the total number of IT components constituting *Richness* (or *Protection*). R_{ijt} is the percentage of establishments of firm j in year t that has implemented the i^{th} IT component of *Richness* (or *Protection*). Table 4.4 shows the aggregation procedure of constructing *Richness* and *Protection*.

Table 4.4. Example of Constructing Measures for Richness and Protection (Firm *j* Year *t*)

Dimension	Functionality		Reference	IT	$D_{Richness}$ ($D_{Protection}$)			%	Avg
					Site1	Site2	Site3	Firm	of %
Richness	Integration	- Restructure and integrate knowledge; - Establish relationship among cross-functional knowledge; - Inquire knowledge across functions	Massey & Montoya-Weiss 2006	Database Management	1	1	0	0.67	0.33
	Presentation	- Computer-aided tools supporting interactive, collaborative, and customized engineering design; - Facilitate cross-functional corporation between manufacturing and engineering design	Sabherwal & Becerra-Fernandez 2010	CAD/CAM	0	0	0	0	
	Sharing	- Tools supporting social interactions and communication among individuals and groups; - Synergize knowledge	Chi et al. 2010	Groupware Software	1	1	0	0.67	
	Extraction of insights	- Data visualization and analysis tools; - Discover knowledge	Banker et al. 2006	Business Intelligence	0	0	0	0	
Protection	Security	- Block unauthorized access and monitor intrusion attempts to the network	Gold et al. 2001	IDS	0	0	0	0	0.17
				Firewall	0	1	0	0.33	

$D_{Richness}$ ($D_{Protection}$): whether establishment i of firm j in year t has implemented IT (1=Yes, 0=No)

Control Variables

We include additional variables to control for alternative explanations. At the patent-firm-year level, we control for the review time for each patent *i* using the number of days from the application date to the issue date of each patent. In addition, we control for the number of inventors and the number of technology classes in a patent portfolio to account for the amount of human resources engaged in R&D and the technological components for generating knowledge capital (Carnabuci and Operti 2013).

At the firm-year level, we first control the effect of IT in support of business process, which is measured by the extent of implementations of major ERP modules (i.e., supply chain management, customer relationship management, human resource management, and accounting), for firm *j* in year *t*. We take a similar approach as we did for *Richness* and *Protection* to aggregate the ERP implementation data from the establishment-year level to the firm-year level. In the first step, we calculate the percentage of sampled sites that have implemented each of the four ERP modules. In the second step, we average percentage values over the four modules to reflect the extent to which firm *j* in year *t* has the functionality to support digital process management.

In addition, the generation of knowledge capital for innovation may depend on the R&D intensity of firms. Thus, we control for the ratio of a firm's R&D spending to its net sales (Bharadwaj et al. 1999). Prior studies also suggest that firm-level characteristics such as regular capital (PPE) and return on assets (ROA) affect firm innovative performance (Hitt and Brynjolfsson 1996). Therefore, we include these variables as controls in the model. Finally, we also control for firm age measured by the number of years that the firm has been listed on the CRSP daily returns tape (Denis et al. 1997), firm size measured by the total number of employees (Hitt and Brynjolfsson 1996), the firms' technological experience in the domain of medical device innovation using the number of medical device patents applied by firm *j* between *t-3* and *t -1*.

4.4 Analysis and Results

4.4.1 Model Specification

In essence, we are investigating the moderating role of Innovation Development Digital Capabilities at the firm context level (i.e., firm-year level) on the relationships between inventor team design and knowledge capital generation at the innovation activity level (i.e., patent-firm-year level). Because of the hierarchical structure of our data, we construct a three-level hierarchical linear model (HLM) (Raudenbush and Bryk 2002) to test the hypotheses. Model specifications are described in Figure 4.3. At level-1 (i.e., patent-firm-year level), the dependent variables (i.e., KB or KD) are predicted with the level-1 control variable, level-1 predictors (i.e., ES and ED), the quadratic terms of level-1 predictors (i.e., ES^2 and ED^2), and level-1 random effect (ε) with the assumption that $\varepsilon \sim N(0,\sigma^2)$. At level-2 (i.e., firm-year level), the coefficients at level 1 are treated as outcomes to be predicted. First, the average intercept (π_0) is predicted with level-2 control variables, the main effects of level-2 moderators (i.e., *Richness*, *Reach*, *Protection*) and level-2 random effect (γ_0) with the assumption that $\gamma_0 \sim N(0,\sigma^2)$. Second, the coefficient of ES (π_4) is predicted with level-2 control variables and moderators. This equation examines the moderating effects of *Richness*, *Reach*, and *Protection* on the impact of ES on the dependent variable. Similarly, the coefficient of ED (π_5) is predicted with level-2 control variables and moderators. This equation examines the moderating effects of *Richness*, *Reach,* and *Protection* on the impact of ED on the dependent variable. At level-3 (i.e., firm level), we include level-3 random effect (μ_{00}) to predict the average intercept.

Level 1 Model: Patent-Firm-Year Level

$$KB \text{ (or KD)} = \pi_0 + \pi_1 * Inventor + \pi_2 * Class + \pi_3 * ReviewTime + \pi_4 * \text{ES} + \pi_5 * \text{ED} + \pi_6 * \text{ES}^2 + \pi_7 * \text{ED}^2 + \varepsilon$$

Level 2 Model: Firm-Year Level

$$\pi_0 = \beta_{00} + \beta_{01} * Dummy_{year1} + \beta_{02} * Dummy_{year2} + \beta_{03} * Dummy_{year3} + \beta_{04} * Site + \beta_{05} * MDExp$$
$$+ \beta_{06} * R\&D + \beta_{07} * PPE + \beta_8 * ROA + \beta_9 * FirmSize + \beta_{10} * FirmAge + \beta_{10} * ERP$$
$$+ \beta_{12} * Richness + \beta_{13} * Reach + \beta_{14} * Protection + \gamma_0$$

$$\pi_i = \beta_{i0}, \quad i = 1, 2, 3, 6, 7$$

$$\pi_4 = \beta_{40} + \beta_{41} * Dummy_{year1} + \beta_{42} * Dummy_{year2} + \beta_{43} * Dummy_{year3} + \beta_{44} * Richness + \beta_{45} * Reach + \beta_{46} * Protection$$

$$\pi_5 = \beta_{50} + \beta_{51} * Dummy_{year1} + \beta_{52} * Dummy_{year2} + \beta_{53} * Dummy_{year3} + \beta_{54} * Richness + \beta_{55} * Reach + \beta_{56} * Protection$$

Level 3 Model: Firm Level

$$\beta_{00} = \gamma_{000} + \mu_{00}$$

$$\beta_{0i} = \gamma_{0i0}, \quad i = 1 \sim 14$$

$$\beta_{i0} = \gamma_{i00}, \quad i = 1, 2, 3, 6, 7$$

$$\beta_{4i} = \gamma_{4i0}, \quad i = 0 \sim 6$$

$$\beta_{5i} = \gamma_{5i0}, \quad i = 0 \sim 6$$

Figure 4.3. Model Specifications

4.4.2 Descriptive Statistics

Our sample consists of 8757 patents issued by 15 firms across 4 years. Table 4.5 reports the number of patents issued by each firm in each year. In general, we see sufficient variation in patenting activities across the firms we sampled. As expected, the number of patents granted to each firm remains stable or increases steadily from 2010 to 2013. Table 4.6 shows the IT profile of each firm averaged over 4 years along the three dimensions of *Innovation Development Digital Capabilities*. We also see diverse IT profiles and reasonable variation on the extent of implementation of each identified IT components composing *Innovation Development Digital Capabilities*. Table 4.7 summarizes the descriptive statistics for level-1 and level-2 variables, as well as the within-level and cross-level correlations among these variables.

Table 4.5. Number of Medical Device Patent for Sampled Firms from 2010 to 2013

	2010	2011	2012	2013	Total
Abbott Laboratories	45	109	101	124	379
C.R. Bard	32	66	93	84	275
Baxter International	22	47	55	52	176
Becton Dickinson & Company	46	51	46	78	221
Boston Scientific	431	468	428	463	1790
Covidien	65	48	93	651	857
Edwards Lifesciences	31	34	30	46	141
Hospira	4	10	8	7	29
Johnson & Johnson	373	342	439	552	1706
Medtronic	472	467	506	614	2059
St Jude Medical	57	68	101	129	355
Stryker	71	87	98	115	371
Thermo Fisher Scientific	0	3	4	3	10
Varian Medical System	5	2	7	12	26
Zimmer Biomet Holdings	94	88	94	86	362
Total	1748	1890	2103	3016	8757

Table 4.6. Technology Profile for the Sampled Companies

	Reach	Richness					Protection		
		CAD/CAM	BI	DB	GW	Overall	IDS	FW	Overall
Abbott Laboratories	58.41%	4.36%	21.40%	82.95%	82.95%	47.92%	6.86%	0.00%	3.43%
C.R. Bard	45.83%	17.36%	11.46%	71.88%	66.32%	41.75%	11.11%	0.00%	5.56%
Baxter International	53.52%	8.12%	28.16%	83.73%	86.51%	51.63%	23.59%	4.06%	13.83%
Becton Dickinson & Company	66.67%	20.83%	12.50%	70.83%	77.08%	45.31%	50.00%	0.00%	25.00%
Boston Scientific	28.81%	20.48%	16.90%	71.67%	71.67%	45.18%	8.33%	0.00%	4.17%
Covidien	39.61%	0.00%	11.69%	65.58%	65.58%	35.71%	23.38%	0.00%	11.69%
Edwards Lifesciences	0.00%	100.00%	0.00%	100.00%	100.00%	75.00%	0.00%	0.00%	0.00%
Hospira	43.33%	0.00%	8.33%	46.67%	55.00%	27.50%	0.00%	0.00%	0.00%
Johnson & Johnson	42.92%	5.00%	10.00%	77.08%	77.08%	42.29%	14.58%	5.00%	9.79%
Medtronic	67.56%	12.67%	17.14%	67.80%	69.27%	41.72%	3.71%	9.53%	6.62%
St Jude Medical	0.00%	0.00%	0.00%	60.42%	60.42%	30.21%	0.00%	14.58%	7.29%
Stryker	51.43%	15.71%	7.14%	80.00%	80.00%	45.71%	18.57%	0.00%	9.29%
Thermo Fisher Scientific	46.97%	0.00%	15.15%	65.15%	65.15%	36.36%	12.12%	0.00%	6.06%
Varian Medical System	100.00%	0.00%	0.00%	25.00%	62.50%	21.88%	0.00%	0.00%	0.00%
Zimmer Biomet Holdings	0.00%	25.83%	9.17%	64.17%	64.17%	40.83%	5.00%	0.00%	2.50%

Numbers represent the average percentage of establishments of firm i that implemented IT j from 2005 to 2008.

Table 4.7. Descriptive Statistics and Correlations

	N	Min	Max	Mean	S.D.	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
1. KB (L1)	8757	0.00	0.98	0.78	0.18	1																	
2. KD (L1)	8757	0.00	1.00	0.71	0.25	-.445**	1																
3. ES (L1)	8757	0.01	1.00	0.70	0.23	-.223**	.282**	1															
4. ED (L1)	8757	0.00	23.61	1.81	2.13	.162**	-.159**	-.207**	1														
5. Inventor (L1)	8757	1.00	26.00	3.07	2.14	.077**	-.056**	.033**	.499**	1													
6. Class (L1)	8757	1.00	5.00	1.21	0.47	.128**	.162**	-.262**	-.043**	-.008	1												
7.Review Time(L1)	8757	154	6633	1581.76	745.72	.049**	.018	-.057**	.014	.005	.043**	1											
8. FW Citation (L1)	3968	0	163	5.93	11.48	-.002	-.049**	-.046**	.096**	.048**	-.024	.011	1										
9. Richness (L2)	53	.00	.75	0.41	0.16	.040**	.006	-.018	.011	-.014	.022*	.147**	.144**	1	-.137	-.024	.312*	.176	.134	.119	.028	.168	.030
10. Reach (L2)	53	.00	1.00	0.45	0.28	.031**	-.070**	.034**	.062**	.077**	-.031**	-.055**	.044**	-.017	1	.155	.182	-.005	-.009	.043	.296*	.134	.491**
11. Protection (L2)	53	.00	.50	0.07	0.09	-.055**	-.007	.035**	.033**	.021*	-.055**	-.054**	.005	-.190**	.352**	1	-.026	.013	-.120	.348*	.064	.164	.207
12. Site (L2)	53	1	17	6.77	4.06	.058**	-.043	.053**	.005	.032**	.000	-.077**	-.046**	.131**	.556**	-.155**	1	399**	-.215	-.157	-.018	.307*	.179
13. MD Exp (L2)	53	5	935	250.17	283.70	.070**	-.056**	-.049**	.026*	.026*	.026*	.016	.072**	.181**	.363**	-.129**	.546**	1	.006	-.306*	-.196	417**	-.051
14. R&D (L2)	53	0.01	0.12	0.05	0.02	.041**	-.030**	-.068**	.086**	.061**	.043**	.121**	.109**	.102**	-.052**	.033**	-.365**	.067**	1	.079	.190	.179	.296*
15. PPE (L2)	53	0.10	0.68	0.30	0.16	-.075**	.005	.051**	.062**	.061**	-.065**	-.030**	.053**	-.004	-.055**	.413**	-.358**	.498**	152**	1	.061	.040	-.039
16. ROA (L2)	53	-.24	.16	0.08	0.06	-.052**	-.023*	.084**	-.006	.064**	-.018	-.028**	.116**	-.136**	.324**	.174**	.196**	.059**	-.013	.211**	1	.027	.359**
17. Firm Size (L2)	53	5	128	37.01	32.70	.035**	-.099**	-.071**	.096**	.094**	-.018	.031**	.150**	-.046**	.259**	.245**	-.180	205**	556**	.212**	.329**	1	.486**
18. Firm Age (L2)	53	5	76	38.85	20.12	-.002	-.040**	-.003	.110**	.111**	.013	.092**	.098**	.079**	.428**	.187**	-.046**	.022*	668**	.177**	.319**	631**	1

L1:Level-1 (i.e., innovation activity level) construct
L2: Level-2 (i.e., firm context level) construct
KB: Across-class knowledge broadening
KD: Within-primary- class knowledge deepening
ES: Inventors' expertise specialization within the primary class
ED: Inventors' expertise diversity across classes
FWCitation: Number of forward citation
RevewTime: Number of days since the application Date to the issue date
MD Exp: Firm j's technological experience in the domain of medical device innovation
Elements below the diagonals are correlations at the innovation activity level, elements above the diagonals are correlations at the firm context level

4.4.3 Hierarchical Linear Modeling

The HLM results are summarized in Table 4.8 for the KB model and Table 4.9 for the KD model. In the KB model, we entered the two properties of *inventor team design* after including control variables at both level 1 and level 2. We find that ES shows a negative impact (γ_{ES} = -0.130, p < 0.01), yet ED shows a positive impact (γ_{ED} = 0.008, p < 0.01), on KB. In other words, expertise specialization impedes, but expertise diversity enhances, knowledge broadening across domains.

In the next step, we included the quadratic terms of ES and ED. Interestingly, we observed a significant curvilinear relationship between ED and KB (γ_{ED^2} = -0.003, p < 0.01). Moreover, we followed the approach by Lind and Mehlum (2007) to conduct a formal test for the existence of an inverted U-shaped relationship between ED and KB. The results (t= 3.37, p < 0.05) rejected the null hypotheses, indicating that the significant curvilinear relationship we found was an inverted U-shaped relationship. As depicted in Figure 4.4, expertise diversity of inventor teams initially increases the broadening of knowledge capital, whereas the relationship turns negative as the level of diversity further increases and reaches a threshold.

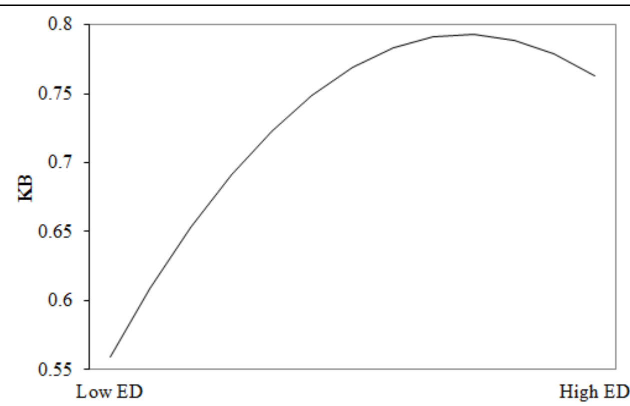


Figure 4.4. Curvilinear Relationship between ED and KB

Table 4.8. HLM Results for the KB Model													
		+ Direct Effects of IV			+ Quadratic Effects of IV			+Direct Effects of M			+Two-way interactions		
		Coeff.	S.E.	P	Coeff.	S.E.	P	Coeff.	S.E.	P	Coeff.	S.E.	P
Constant		0.762	0.047	0.000	0.771	0.047	0.000	0.754	0.047	0.000	0.769	0.048	0.000
L1 CVs	Inventor	0.003	0.001	0.006	0.002	0.001	0.142	0.002	0.001	0.141	0.001	0.001	0.158
	Class	0.033	0.004	0.000	0.033	0.004	0.000	0.033	0.004	0.000	0.033	0.004	0.000
	ReviewTime	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
L2 CVs	Site	-0.001	0.002	0.496	-0.001	0.002	0.502	-0.001	0.002	0.782	-0.001	0.002	0.562
	MD Exp	0.000	0.000	0.635	0.000	0.000	0.601	0.000	0.000	0.495	0.000	0.000	0.560
	DYear1	-0.005	0.006	0.425	-0.005	0.006	0.402	-0.002	0.007	0.747	-0.003	0.007	0.623
	DYear2	-0.007	0.008	0.332	-0.007	0.008	0.342	0.001	0.011	0.949	-0.005	0.011	0.644
	DYear3	-0.022	0.009	0.025	-0.022	0.009	0.026	-0.007	0.019	0.718	-0.020	0.019	0.308
	R&D	-0.487	0.373	0.199	-0.484	0.373	0.202	-0.386	0.377	0.313	-0.483	0.381	0.213
	PPE	-0.002	0.089	0.982	0.005	0.089	0.957	0.005	0.090	0.953	0.002	0.092	0.986
	ROA	0.000	0.046	0.995	0.004	0.046	0.935	0.029	0.057	0.613	-0.004	0.058	0.941
	Firm Size	0.000	0.000	0.475	0.000	0.000	0.461	0.000	0.000	0.428	0.000	0.000	0.475
	Firm Age	0.000	0.001	0.789	0.000	0.001	0.766	0.000	0.001	0.680	0.000	0.001	0.760
	ERP	0.003	0.033	0.931	0.001	0.033	0.965	-0.012	0.034	0.720	-0.001	0.035	0.967
IV	ES	-0.130	0.009	0.000	-0.134	0.010	0.000	-0.133	0.010	0.000	-0.187	0.027	0.000
	ED	0.008	0.001	0.000	0.012	0.001	0.000	0.012	0.001	0.000	0.017	0.003	0.000
IV^2	ES^2				-0.002	0.002	0.235	-0.002	0.002	0.233	-0.002	0.002	0.211
	ED^2				-0.003	0.001	0.000	-0.003	0.001	0.000	-0.003	0.001	0.000
M	Protection							-0.013	0.043	0.758	-0.024	0.045	0.600
	Richness							0.041	0.054	0.454	0.007	0.055	0.903
	Reach							0.031	0.021	0.151	0.030	0.022	0.176
IV*M	ES*DYear1										0.007	0.027	0.808
	ES*DYear2										0.043	0.032	0.173
	ES*DYear3										0.148	0.053	0.006
	ES*Protection										-0.145	0.194	0.454
	ES*Richness										0.461	0.152	0.003
	ES*Reach										0.158	0.093	0.089
	ED*DYear1										0.000	0.003	0.899
	ED*DYear2										-0.004	0.003	0.268
	ED*DYear3										-0.013	0.006	0.026
	ED*Protectio										-0.033	0.019	0.082
	ED*Richness										-0.038	0.017	0.023
	ED*Reach										0.013	0.010	0.177

L1 CVs: control variables at the innovation activity level (i.e., patent-firm-year level)
L2 CVs: control variables at the firm context level (i.e., firm-year level)
IV: independent variables
M: Moderators
ES: Inventors' expertise specialization within the primary class
ED: Inventors' expertise diversity across classes
Inventor: Number of inventors for patent i
Class: Number of technological classes for patent i
ReviewTime: Number of days since the application Date to the issue date
Site: Number of sites sample for firm j in year t
MD Exp: Firm j's technological experience in the domain of medical device innovation

We then introduced direct effects of the three-dimensional *Innovation Development Digital Capabilities* into the model, and found none of the three dimensions exhibited significant direct impacts on KB. Lastly, we included cross-level interaction effects between *Innovation Development Digital Capabilities* and *Human Capital Allocation* into the model. *Richness* ($\gamma_{Richness}$ = 0.461, $p < 0.01$) and *Reach* (γ_{Reach} = 0.158, p < 0.1) significantly moderate the impacts of ES on KB. As depicted in Figure 4.5, we clearly see that *Richness* (Figure 4.5a) and *Reach* (Figure 4.5b) mitigate the adverse effects of expertise specialization on the broadening of knowledge capital. In addition, *Richness* ($\gamma_{ED*Richness}$ = -0.038, p < 0.05) and *Protection* ($\gamma_{ED*Protection}$ = -0.033, p < 0.1) significantly moderate the impacts of ED on KB. Figure 4 further shows that, instead of amplifying the benefits of ED on KB, *Richness* (Figure 4.5c) and *Protection* (Figure 4.5d) serve as substitutes for expertise diversity to broaden the knowledge capital.

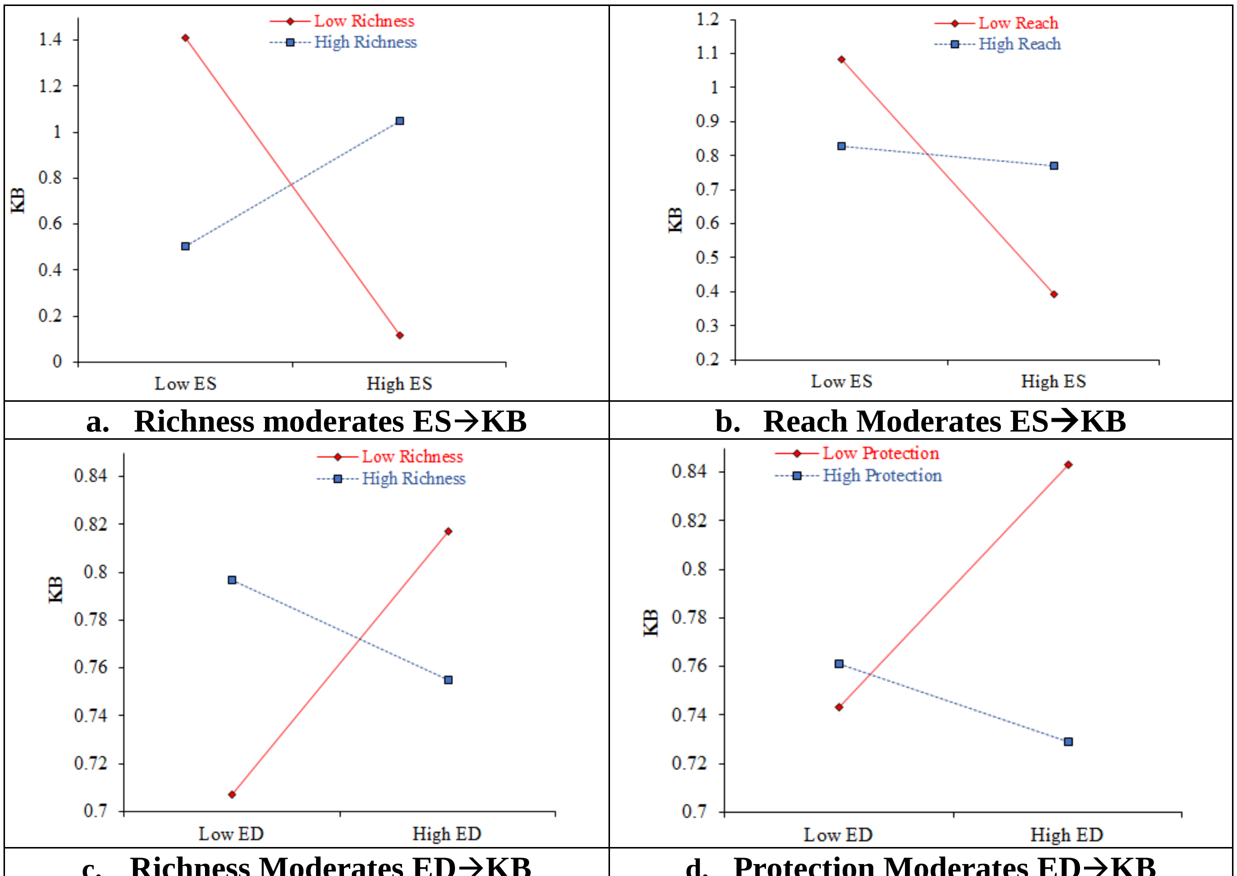


Figure 4.5. Moderating Effects of Innovation Development Digital Capabilities on ES→KB and ED→KB

We followed a similar procedure to analyze the KD model. As shown in Table 4.9, we entered the direct effects of ES and ED into the model after adding the control variables at both level 1 and level 2. As expected, we find a positive impact of ES on KD

(γ_{ES} = 0.363, p < 0.01), while a negative impact of ED on KD (γ_{ED} = -0.006, p < 0.01). In other words, expertise specialization enhances, while expertise diversity impedes, knowledge deepening within the primary domains.

Table 4.9. HLM Results for the KD Model

		+ Direct Effects of IV			+ Quadratic Effects of IV			+Direct Effects of M			+Two-way interactions		
		Coeff.	S.E.	P	Coeff.	S.E.	P	Coeff.	S.E.	P	Coeff.	S.E.	P
Constant		0.485	0.055	0.000	0.508	0.055	0.000	0.483	0.056	0.000	0.485	0.057	0.000
L1 CVs	Inventor	-0.003	0.001	0.019	-0.003	0.001	0.032	-0.003	0.001	0.032	-0.003	0.001	0.041
	Class	0.128	0.005	0.000	0.120	0.006	0.000	0.120	0.006	0.000	0.119	0.006	0.000
	ReviewTime	0.000	0.000	0.064	0.000	0.000	0.069	0.000	0.000	0.068	0.000	0.000	0.064
L2 CVs	Site	0.001	0.003	0.799	0.001	0.003	0.782	0.001	0.003	0.664	0.001	0.003	0.700
	MD Exp	0.000	0.000	0.058	0.000	0.000	0.066	0.000	0.000	0.160	0.000	0.000	0.164
	DYear1	0.003	0.008	0.688	0.002	0.008	0.846	0.002	0.009	0.778	0.001	0.009	0.919
	DYear2	-0.001	0.010	0.914	-0.001	0.010	0.885	0.007	0.014	0.611	0.008	0.015	0.565
	DYear3	0.020	0.012	0.098	0.019	0.012	0.120	0.037	0.025	0.142	0.041	0.025	0.110
	R&D	0.574	0.461	0.220	0.512	0.456	0.268	0.543	0.465	0.251	0.610	0.469	0.201
	PPE	0.034	0.104	0.744	0.054	0.102	0.597	0.059	0.104	0.571	0.056	0.105	0.594
	ROA	-0.087	0.061	0.160	-0.077	0.061	0.210	-0.043	0.075	0.571	-0.028	0.076	0.709
	Firm Size	-0.001	0.001	0.336	-0.001	0.001	0.330	0.000	0.001	0.401	0.000	0.001	0.515
	Firm Age	0.000	0.001	0.912	0.000	0.001	0.857	0.000	0.001	0.953	0.000	0.001	0.943
	ERP	0.017	0.043	0.694	0.012	0.042	0.773	0.005	0.045	0.914	-0.017	0.045	0.705
IV	ES	0.363	0.012	0.000	0.304	0.013	0.000	0.304	0.013	0.000	0.258	0.036	0.000
	ED	-0.006	0.001	0.000	-0.012	0.002	0.000	-0.012	0.002	0.000	-0.018	0.004	0.000
IV^2	ES^2				-0.020	0.002	0.000	-0.020	0.002	0.000	-0.020	0.002	0.000
	ED^2				0.003	0.001	0.004	0.003	0.001	0.004	0.004	0.001	0.002
M	Protection							-0.008	0.057	0.896	-0.015	0.058	0.800
	Richness							0.058	0.070	0.410	0.075	0.071	0.297
	Reach							0.003	0.028	0.924	0.004	0.028	0.883
IV*M	ES*DYear1										0.072	0.036	0.047
	ES*DYear2										0.054	0.042	0.202
	ES*DYear3										0.062	0.070	0.380
	ES*Protection										0.467	0.258	0.070
	ES*Richness										0.248	0.202	0.219
	ES*Reach										-0.110	0.123	0.375
	ED*DYear1										-0.001	0.004	0.877
	ED*DYear2										0.004	0.005	0.360
	ED*DYear3										0.021	0.008	0.007
	ED*Protection										0.043	0.026	0.089
	ED*Richness										0.081	0.022	0.000
	ED*Reach										-0.014	0.013	0.279

L1 CVs: control variables at the innovation activity level (i.e., patent-firm-year level)
L2 CVs: control variables at the firm context level (i.e., firm-year level)
IV: independent variables
M: Moderators
ES: Inventors' expertise specialization within the primary class
ED: Inventors' expertise diversity across classes
Inventor: Number of inventors for patent i
Class: Number of technological classes for patent i
ReviewTime: Number of days since the application Date to the issue date
Site: Number of sites sample for firm j in year t
MD Exp: Firm j's technological experience in the domain of medical device innovation

As we are interested in the curvilinear relationship between *inventor team design* and *knowledge capital generation*, we include the quadratic terms of ES and ED into the model. We observed interesting curvilinear relationships between ES and KD (γ_{ES^2} = -0.02, p < 0.01), and between ED and KD (γ_{ED^2} = 0.003, p < 0.01). We further followed the approach by Lind and Mehlum (2007) to conduct formal tests for the existence of an inverted U-shaped relationship between ES and KD or a U-shaped relationship between ED and KD. The results ($ES^2 \rightarrow$KD: t= 1.19, p > 0.05; $ED^2 \rightarrow$KD: t = 1.27, p > 0.05) do not reject the null hypotheses, indicating that the significant curvilinear relationships we found are not inverted U-shaped or U-shaped relationships. As shown Figure 4.6, we interpret that the marginal effects on the deepening of knowledge capital decrease, but do not turn negative, as the level of expertise specialization or expertise diversity increases.

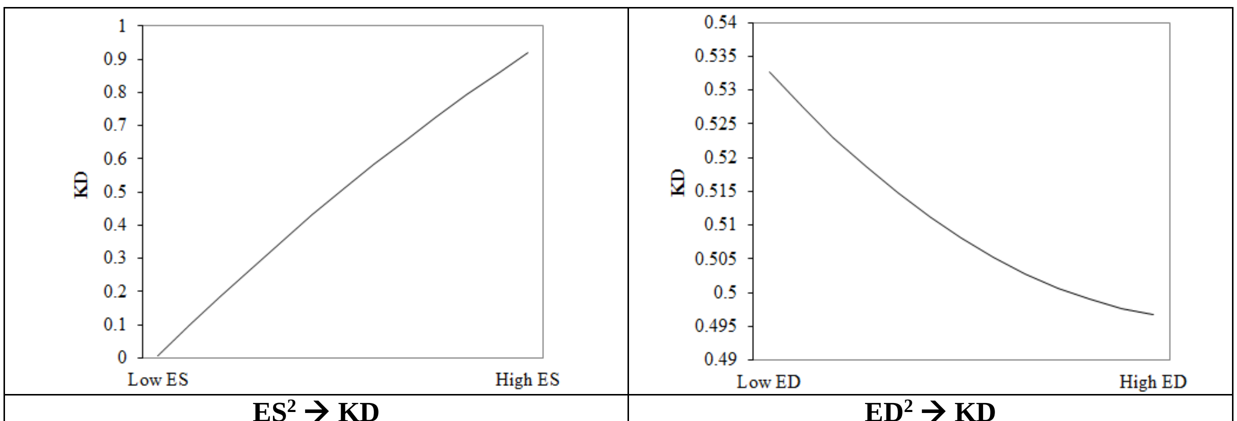
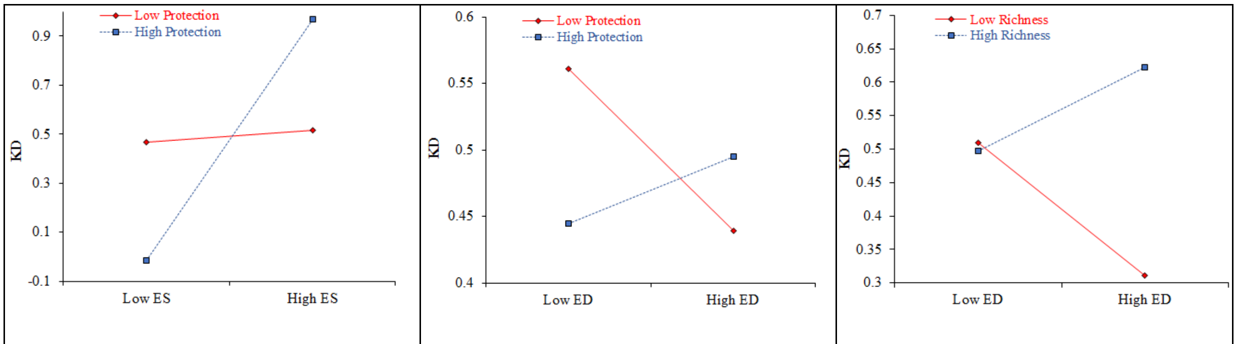


Figure 4.6.Curvilinear Relationships $ES^2 \rightarrow$ KD and $ED^2 \rightarrow$ KD

As for the moderating effects of *Innovation Development Digital Capabilities*, the results are consistent with our expectation. *Protection* significantly amplifies the positive impact of ES on KD ($\gamma_{ES*Protection}$ = 0.467, p < 0.01; Figure 4.7a). In addition, both *Protection* ($\gamma_{ED*Protection}$ = 0.043, p < 0.1; Figure 4.7b) and *Richness* ($\gamma_{ED*Richness}$ = 0.081, p < 0.01; Figure 4.7c) significantly mitigate the adverse effect of ED on KD.



a. Protection Moderates ES→KD	b. Protection Moderates ED→KD	c. Richness Moderates ED→KD

Figure 4.7. Moderating Effects of Innovation Development Digital Capabilities on ES→KD and ED→KD

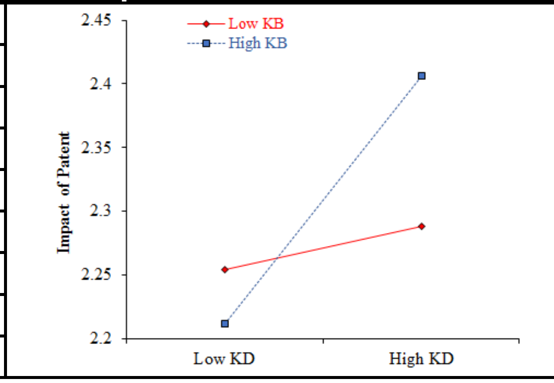
4.4.4 Post-hoc Analysis

Effects of KB and KD on Innovation Impact

As part of the conceptual framework, we conduct post-hoc analysis to examine the impacts of *Knowledge Capital Generation* on *Innovation Impact.* As shown in Table 4.10, we observe that both KB (γ_{KB} = 0.043, p < 0.01) and KD (γ_{KD} = 0.068, p < 0.01) increase the impact of innovation. After including the interaction between KB and KD into the model, we found that KB and KD interactively influence *Innovation Impact* (γ_{KB*KD} = 0.040, p < 0.01). The interaction plot shown in Table 4.10 shows that KB reinforces the effects of KD to increase the impact of innovation. These results collectively support that firms need to both broaden and deepen knowledge capital in order to maximize the impact of their patent innovation.

Table 4.10. OLS Results to Predict Impactful Innovation

	Direct Effects			Interaction Effects		
	B	S.E.	p	B	S.E.	p
Constant	2.294	.045	.000	2.311	.045	.000
ReviewTime	.000	.000	.000	.000	.000	.000
DaysCited	.000	.000	.000	.000	.000	.000
Claims	.010	.001	.000	.010	.001	.000
KB	.043	.015	.005	.019	.018	.275
KD	.068	.015	.000	.057	.015	.000
KB*KD				.040	.014	.004



Dependent Variable: Natural log of the number of forward citations
KB: Across-class knowledge broadening; KD: Within-primary- class knowledge deepening

Robustness Tests

We conducted several post-hoc analyses to assess the robustness of our results. First, we examined the moderating effects of *Reach*, *Richness*, and *Protection* on the quadratic impacts of inventor team design on knowledge capital generation. Figure 4.8 shows the model specification and Table 4.11 presents the HLM results.

Level 1 Model: Patent-Firm-Year Level

$$KB \text{ (or KD)} = \pi_0 + \pi_1 * Inventor + \pi_2 * Class + \pi_3 * ReviewTime + \pi_4 * \text{ES} + \pi_5 * \text{ED} + \pi_6 * \text{ES}^2 + \pi_7 * \text{ED}^2 + \varepsilon$$

Level 2 Model: Firm-Year Level

$$\pi_0 = \beta_{00} + \beta_{01} * Dummy_{year1} + \beta_{02} * Dummy_{year2} + \beta_{03} * Dummy_{year3} + \beta_{04} * Site + \beta_{05} * MDExp$$
$$+\beta_{06} * R\&D + \beta_{07} * PPE + \beta_8 * ROA + \beta_9 * FirmSize + \beta_{10} * FirmAge + \beta_{10} * ERP$$
$$+\beta_{12} * Richness + \beta_{13} * Reach + \beta_{14} * Protection + \gamma_0$$
$$\pi_1 = \beta_{10}$$
$$\pi_2 = \beta_{20}$$
$$\pi_3 = \beta_{30}$$
$$\pi_4 = \beta_{40} + \beta_{41} * Dummy_{year1} + \beta_{42} * Dummy_{year2} + \beta_{43} * Dummy_{year3} + \beta_{44} * Richness + \beta_{45} * Reach + \beta_{46} * Protection$$
$$\pi_5 = \beta_{50} + \beta_{51} * Dummy_{year1} + \beta_{52} * Dummy_{year2} + \beta_{53} * Dummy_{year3} + \beta_{54} * Richness + \beta_{55} * Reach + \beta_{56} * Protection$$
$$\pi_6 = \beta_{60} + \beta_{61} * Dummy_{year1} + \beta_{62} * Dummy_{year2} + \beta_{63} * Dummy_{year3} + \beta_{64} * Richness + \beta_{65} * Reach + \beta_{66} * Protection$$
$$\pi_7 = \beta_{70} + \beta_{71} * Dummy_{year1} + \beta_{72} * Dummy_{year2} + \beta_{73} * Dummy_{year3} + \beta_{74} * Richness + \beta_{75} * Reach + \beta_{76} * Protection$$

Level 3 Model: Firm Level

$$\beta_{00} = \gamma_{000} + \mu_{00}$$
$$\beta_{0i} = \gamma_{0i0}, \quad i = 1 \sim 14$$
$$\beta_{i0} = \gamma_{i00}, \quad i = 1, 2, 3$$
$$\beta_{ij} = \gamma_{ij0}, \quad i = 4 \sim 7; j = 0 \sim 6$$

Figure 4.8. Model Specifications with Curvilinear Moderation Effects

Table 4.11. HLM Results with Curvilinear Moderation Effects

		KB			KD		
		Coeff.	S.E.	P	Coeff.	S.E.	P
Constant		0.769	0.048	0.000	0.490	0.057	0.000
L1 CVs	Inventor	0.001	0.001	0.206	-0.003	0.001	0.051
	Class	0.033	0.004	0.000	0.119	0.006	0.000
	ReviewTime	0.000	0.000	0.000	0.000	0.000	0.057
L2 CVs	Site	-0.001	0.002	0.581	0.001	0.003	0.718
	MD Exp	0.000	0.000	0.564	0.000	0.000	0.173
	DYear1	-0.004	0.007	0.595	0.002	0.009	0.860
	DYear2	-0.007	0.011	0.566	0.008	0.015	0.567
	DYear3	-0.021	0.019	0.275	0.038	0.025	0.138
	R&D	-0.484	0.381	0.211	0.573	0.468	0.229
	PPE	0.002	0.092	0.983	0.051	0.105	0.628
	ROA	-0.009	0.058	0.883	-0.036	0.076	0.639
	Firm Size	0.000	0.000	0.473	0.000	0.001	0.516
	Firm Age	0.000	0.001	0.759	0.000	0.001	0.957
	ERP	-0.001	0.035	0.969	-0.015	0.045	0.739
IV	ES	-0.201	0.030	0.000	0.246	0.040	0.000
	ED	0.019	0.004	0.000	-0.020	0.005	0.000
IV^2	ES^2	-0.009	0.006	0.091	-0.024	0.007	0.002
	ED^2	-0.006	0.003	0.036	0.004	0.004	0.249
M	Protection	-0.027	0.045	0.551	-0.016	0.058	0.785
	Richness	0.002	0.055	0.977	0.068	0.071	0.349
	Reach	0.027	0.022	0.215	0.006	0.028	0.821
IV*M	ES*DYear1	0.011	0.031	0.730	0.114	0.041	0.006
	ES*DYear2	0.056	0.036	0.122	0.062	0.048	0.197
	ES*DYear3	0.188	0.059	0.002	0.053	0.078	0.498
	ES*Protection	-0.093	0.207	0.653	0.252	0.274	0.358
	ES*Richness	0.625	0.171	0.000	0.083	0.226	0.712
	ES*Reach	0.189	0.107	0.076	-0.060	0.141	0.673
	ED*DYear1	0.001	0.004	0.896	0.001	0.005	0.810
	ED*DYear2	-0.003	0.005	0.512	0.004	0.006	0.503
	ED*DYear3	-0.020	0.008	0.015	0.025	0.011	0.021
	ED*Protection	-0.015	0.027	0.585	0.002	0.036	0.946
	ED*Richness	-0.052	0.023	0.024	0.093	0.031	0.003
	ED*Reach	0.021	0.015	0.142	-0.014	0.019	0.458
M*IV^2	ES^2*DYear1	0.002	0.006	0.745	0.018	0.008	0.019
	ES^2*DYear2	0.005	0.007	0.420	0.005	0.009	0.544
	ES^2*DYear3	0.021	0.011	0.051	-0.010	0.015	0.477
	ES^2*Protection	0.039	0.041	0.346	-0.144	0.054	0.009
	ES^2*Richness	0.078	0.031	0.013	-0.083	0.041	0.046
	ES^2*Reach	0.005	0.019	0.782	0.035	0.025	0.157
	ED^2*DYear1	-0.001	0.003	0.702	0.000	0.004	0.928
	ED^2*DYear2	-0.001	0.003	0.796	0.001	0.005	0.745
	ED^2*DYear3	0.008	0.005	0.106	-0.004	0.007	0.593
	ED^2*Protection	-0.013	0.021	0.534	0.035	0.027	0.199
	ED^2*Richness	0.022	0.015	0.130	-0.021	0.019	0.286
	ED^2*Reach	-0.011	0.012	0.339	0.008	0.016	0.610

ES: Inventors' expertise specialization within the primary class
ReviewTime: Number of days from the application date to the issue date
Class: Number of technological classes for patent i
MD Exp: Firm j's technological experience in medical device innovation
Site: Number of sites sample for firm j in year t
ED: Inventors' expertise diversity across classes
Inventor: Number of inventors for patent i

We find that the results with curvilinear moderation terms included are generally consistent with our main analysis results. As compared in Table 4.12, most of the significant moderating effects remain significant. Among the three exceptions we observed, ED*Protection became non-significant for both KB and KD, yet the direction of the moderation effect is consistent with that in the main analysis results. In addition, we found that the moderating effect of *Protection* was not significant on the impact of ES on KD, but was significant on the impact of ES^2 on KD. We plot the curvilinear moderation effect in Figure 4.9 and observe a similar pattern as the main analysis results that *Protection* amplifies the benefits of expertise specialization on the deepening of knowledge capital.

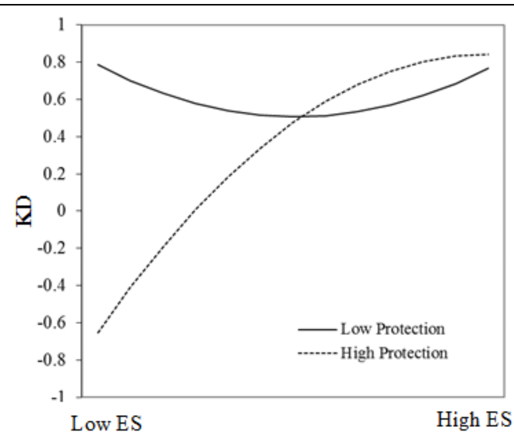


Figure 4.9. Moderation of Curvilinear Effect (ES^2*Protection→KD)

In the second robustness analysis, we view that low-speed Internet access and high-speed Internet access make different impacts in the process of innovation development. More specifically, we argue that it is the digital capabilities of high-speed Internet access that support the functionality of knowledge reach.

Table 4.12. Comparing Linear HLM Results with Curvilinear HLM Results

	KB			KD		
	Main	**Curvilinear Moderation**	**Comparison**	**Main**	**Curvilinear Moderation**	**Comparison**
ES	-	-	Results remain consistent	+	+	Results remain consistent
ED	+	+		-	-	
ES^2	n.s.	-	$ES^2 \rightarrow$KB becomes significant; $ED^2 \rightarrow$KB remains significant	-	-	$ES^2 \rightarrow$KD remains significant; $ED^2 \rightarrow$KD is nonsignificant
ED^2	-	-		+	n.s.	
ES*Richness	+	+	ES*Richness and ES*Reach remain significant	n.s.	n.s.	ES*Protection becomes nonsignificant, but ES^2* Protection is significant.
ES*Reach	+	+		n.s.	n.s.	
ES*Protection	n.s.	n.s.		+	n.s.	
ES^2*Richness	NA	+		NA	-	
ES^2*Reach	NA	n.s.		NA	n.s.	
ES^2*Protection	NA	n.s.		NA	-	
ED*Richness	-	-	ED*Richness remains significant but ED*Protection becomes nonsignificant	+	+	ED*Richness remains significant but ED* Protection becomes nonsignificant
ED*Reach	n.s.	n.s.		n.s.	n.s.	
ED*Protection	-	n.s.		+	n.s.	
ED^2*Richness	NA	n.s.		NA	n.s.	
ED^2*Reach	NA	n.s.		NA	n.s.	
ED^2*Protection	NA	n.s.		NA	n.s.	

Therefore, we generate two constructs: 1) *Reach_High*, which refers to high-speed Internet access and is measured by the extent of implementation on any of the following technologies: XDSL line, optical carrier line, T1 line, and T3 line; and 2) *Reach_Low*, which refers to low-speed Internet access and is measured by the extent of implementation on any of the following technologies: ISDN line, switched 56 line, and dial-up line. In the HLM models, we controlled for the direct effect of *Reach_Low*, and evaluated the moderating effects of *Reach_High*. We observed consistent interaction effects as what we found in the main analyses (Table 4.13).

Table 4.13. HLM Results with Reach_High							
		KB			KD		
		Coeff.	S.E.	P	Coeff.	S.E.	P
Constant		0.764	0.048	0.000	0.485	0.057	0.000
L1 CVs	Inventor	0.001	0.001	0.155	-0.003	0.001	0.042
	Class	0.033	0.004	0.000	0.119	0.006	0.000
	ReviewTime	0.000	0.000	0.000	0.000	0.000	0.064
L2 CVs	Site	0.000	0.003	0.888	0.001	0.003	0.654
	MD Exp	0.000	0.000	0.585	0.000	0.000	0.162
	DYear1	-0.004	0.007	0.539	0.000	0.009	0.974
	DYear2	-0.005	0.011	0.651	0.008	0.015	0.580
	DYear3	-0.019	0.019	0.313	0.040	0.025	0.113
	R&D	-0.456	0.383	0.242	0.614	0.470	0.199
	PPE	0.019	0.094	0.842	0.063	0.106	0.559
	ROA	0.006	0.060	0.916	-0.024	0.078	0.757
	Firm Size	0.000	0.000	0.475	0.000	0.001	0.489
	Firm Age	0.000	0.001	0.919	0.000	0.001	0.965
	ERP	-0.007	0.036	0.847	-0.021	0.047	0.664
	REACH_Low	-0.037	0.062	0.551	-0.019	0.074	0.793
IV	ES	-0.185	0.027	0.000	0.257	0.036	0.000
	ED	0.017	0.003	0.000	-0.019	0.004	0.000
IV2	ES^2	-0.002	0.002	0.210	-0.020	0.002	0.000
	ED^2	-0.003	0.001	0.000	0.004	0.001	0.003
M	Protection	-0.018	0.044	0.679	-0.011	0.057	0.844
	Richness	0.012	0.055	0.834	0.076	0.071	0.294
	Reach	0.068	0.067	0.316	0.021	0.080	0.791
IV*M	ES*DYear1	0.004	0.027	0.884	0.073	0.036	0.039
	ES*DYear2	0.041	0.031	0.188	0.055	0.041	0.186
	ES*DYear3	0.145	0.053	0.006	0.063	0.070	0.366
	ES*Protection	-0.133	0.190	0.484	0.465	0.252	0.064
	ES*Richness	0.470	0.153	0.003	0.243	0.202	0.231
	ES*Reach	0.162	0.092	0.077	-0.123	0.121	0.310
	ED*DYear1	-0.001	0.003	0.826	0.000	0.004	0.908
	ED*DYear2	-0.004	0.003	0.228	0.004	0.004	0.342
	ED*DYear3	-0.013	0.006	0.021	0.021	0.008	0.006
	ED*Protection	-0.031	0.019	0.099	0.045	0.025	0.075
	ED*Richness	-0.038	0.017	0.024	0.080	0.022	0.001
	ED*Reach	0.012	0.009	0.199	-0.016	0.012	0.189

ES: Inventors' expertise specialization within the primary class
ED: Inventors' expertise diversity across classes
MD Exp: Firm j's technological experience in medical device innovation
ReviewTime: Number of days since the application Date to the issue date
Inventor: Number of inventors for patent i
Class: Number of technological classes for patent i
Site: Number of sites sample for firm j in year t

An additional robustness test we conducted is to assess the effect of interaction between ES and ED on the broadening and deepening of knowledge capital. As shown in Table 4.14, we observe significant interaction effects between ES and ED to impact KB (γ_{ED*ES} = 0.004, p < 0.1) and KD (γ_{ED*ES} = 0.014, p < 0.01). Figure 4.10 demonstrates that ES and ED is complementary with each other to both broaden and deepen knowledge capital. After controlling for the interaction effects between ES and ED, results remain consistent with the main analysis results.

Table 4.14. HLM Results with ES*ED

		KB			KD		
		Coeff.	S.E.	P	Coeff.	S.E.	P
Constant		0.770	0.048	0.000	0.487	0.058	0.000
L1 CVs	Inventor	0.001	0.001	0.196	-0.003	0.001	0.018
	Class	0.033	0.004	0.000	0.121	0.006	0.000
	ReviewTime	0.000	0.000	0.000	0.000	0.000	0.055
L2 CVs	Site	-0.001	0.002	0.581	0.001	0.003	0.645
	MD Exp	0.000	0.000	0.564	0.000	0.000	0.160
	DYear1	-0.003	0.007	0.629	0.001	0.009	0.904
	DYear2	-0.005	0.011	0.640	0.008	0.015	0.577
	DYear3	-0.020	0.019	0.302	0.040	0.025	0.119
	R&D	-0.475	0.380	0.219	0.636	0.473	0.187
	PPE	-0.002	0.091	0.983	0.045	0.107	0.677
	ROA	-0.005	0.058	0.933	-0.031	0.076	0.689
	Firm Size	0.000	0.000	0.484	0.000	0.001	0.504
	Firm Age	0.000	0.001	0.766	0.000	0.001	0.957
	ERP	-0.001	0.035	0.970	-0.017	0.045	0.710
IV	ES	-0.184	0.027	0.000	0.271	0.036	0.000
	ED	0.017	0.003	0.000	-0.016	0.004	0.000
IV^2	ES^2	-0.002	0.002	0.383	-0.018	0.002	0.000
	ED^2	-0.003	0.001	0.002	0.005	0.001	0.000
IV*IV	ES*ED	0.004	0.002	0.068	0.014	0.003	0.000
M	Protection	-0.024	0.045	0.592	-0.016	0.058	0.780
	Richness	0.005	0.055	0.930	0.068	0.071	0.346
	Reach	0.030	0.022	0.173	0.005	0.028	0.859
IV*M	ES*DYear1	0.007	0.027	0.807	0.072	0.036	0.046
	ES*DYear2	0.045	0.032	0.158	0.059	0.042	0.157
	ES*DYear3	0.152	0.053	0.005	0.077	0.070	0.271
	ES*Protection	-0.153	0.194	0.431	0.438	0.257	0.089
	ES*Richness	0.473	0.152	0.002	0.295	0.202	0.143
	ES*Reach	0.164	0.093	0.078	-0.088	0.123	0.475
	ED*DYear1	0.000	0.003	0.941	0.000	0.004	0.997
	ED*DYear2	-0.004	0.003	0.270	0.004	0.005	0.352
	ED*DYear3	-0.013	0.006	0.023	0.020	0.008	0.009
	ED*Protection	-0.033	0.019	0.089	0.046	0.026	0.071
	ED*Richness	-0.039	0.017	0.020	0.078	0.022	0.001
	ED*Reach	0.013	0.010	0.159	-0.012	0.013	0.360

L1 CVs: control variables at the innovation activity level (i.e., patent-firm-year level)
L2 CVs: control variables at the firm context level (i.e., firm-year level)
IV: independent variables
M: Moderators
ES: Inventors' expertise specialization within the primary class
ED: Inventors' expertise diversity across classes
Inventor: Number of inventors for patent i
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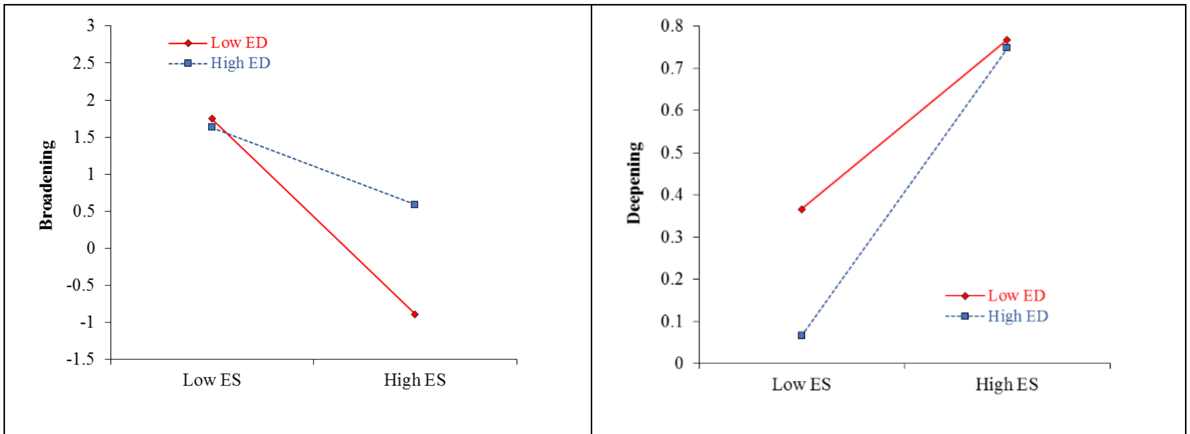

a. ES*ED→KB **b. ES*ED→KD**

Figure 4.10. Moderation Effects of ED on ES→KB and ES→KD

4.5 Discussion

4.5.1 Theoretical Contributions

Scholars who work on organizational learning and innovation have a core interest in understanding the mechanisms through which firm develop innovation. Theories and constructs surrounding innovation development are complex and span many levels of analysis. Whereas most research in this vein has been conducted at the firm level (Almeida and Kogut 1999, Wadhwa and Kotha 2006; Miller et al. 2007), we contribute to this stream of research by examining the conversion from inventor team expertise to knowledge capital at a more granular level, the patent level. Our findings enrich the discussions on the tension between the breadth and depth of innovation activities (Kuhn 1962; Leahey and Reikowsky 2008) by scrutinizing the technological profiles of patent innovation.

Although both deep and broad knowledge capital can lead to impactful innovation, the generation of these two structures of knowledge capital entail fairly different challenges and require different properties of inventor team expertise

(Rosenkopf and Nerkar 2001, Gupta et al. 2006). Our results provide patent-level evidence that specialized expertise may hinder the broadening of knowledge capital, while diverse expertise may impede the deepening of knowledge capital. More interestingly, we find significant curvilinear relationships between inventor team design and knowledge capital generation, indicating that (1) diverse expertise initially increases knowledge broadening, whereas the relationship turns negative as the level of diversity further increases; (2) diverse expertise decreases, yet specialized expertise increases, knowledge deepening, whereas the marginal strengths of these relationships decrease as the level of diversity or specialization increases.

In addition, this study enriches the structural empowerment literature by conceptualizing digital capabilities as a strategic enabler to foster empowerment climate and facilitate innovation development. Following the guidelines by Hong et al. (2013), we theorize digital capabilities in the innovation development context, and identify three context-specific dimensions (i.e., Reach, Richness, and Protection) to represent the core constructs. This contextualization approach allows us to differentiate effects of each dimension of the overall construct and develop a more nuanced understanding on the role of IT in the context of innovation development. In particular, we identify the digital capability of protection as an important dimension for innovation development. In contrary to the existing knowledge that IT-enabled protection prevents loss of value, our findings suggest that, a protective and secured digital environment fosters an open and collaborative climate and enhances the effectiveness of conversion from inventor team expertise into broad and deep knowledge capital.

Digital capabilities for innovation development are complex not only in conceptualization, but also in operationalization. From a methodological standpoint, our study contributes to IS research by introducing a comprehensive development and empirical measurement of the three-dimensional Innovation Development Digital Capabilities using secondary data sources. The use of CI data on the actual implementation of IT in organization establishments to operationalize digital capabilities offers a fairly novel but very useful methodology with the potential for greater application in the IS research.

This study also contributes to the literature on IT business value in the context of innovation development. Making use of IT to produce intangible returns is critical to firms' long-term success. Prior research has established a link between firm-level IT investment on innovation productivity. Not only R&D-related IT but also general infrastructure IT have been found to facilitate different innovation processes including knowledge management, innovation production, and inter-organizational coordination (Kleis et al. 2012; Joshi et al. 2010). Our study brings the unit of analysis down to the innovation activity level and provides more granular evidence on the role of IT in innovation development. At the patent level, our results illustrates that IT alone does not optimize the generation of knowledge capital; rather, IT can help enhance the effectiveness of conversion from inventor team expertise into broad and deep knowledge capital. In general, our findings correspond with the literature that much of the business values of IT stem from its complementarities with organizational resources in various forms (Barua et al. 1995; Powell and Dent-Micallef 1997; Chi et al. 2010). In particular, we demonstrated that digital capabilities may empower inventor teams to complement or substitute inventor team expertise to develop broad and deep knowledge capital and facilitate knowledge production in terms of patent innovation. In other words, digital capabilities may amplify the positive effects and mitigate the adverse effects of inventor team expertise on the broadening and deepening of knowledge capital.

4.5.2 Practical Implications

This study also has important practical implications for innovation-oriented firms. First, our findings suggest the necessity to recognize the multi-dimensional digital capabilities as enabling valuable innovation development. Well-developed IT infrastructures that give rise to superior access to external knowledge, rich quality of organizational knowledge, and secure protection of innovation activities play a role in facilitating development of broad and deep knowledge capital and generating impactful innovation. Managers need to focus on the identified aspects of digital capabilities as important levers for innovation development. Appropriate allocations of IT investment along the *Reach*, *Richness*, and *Protection* dimensions of digital capabilities would help firms reap the full benefits and strategic values of IT and obtain competitive advantages in innovation development.

Second, it is the combination of diverse and specialized inventor team expertise that leads to the broadening and deepening of knowledge capital, which generates patent innovation with high impacts. This study provides empirical evidence and insights into the complex relationship between inventor team expertise and the generation of knowledge capital. The diversity of inventor team expertise may amplify the positive impact of expertise specialization on knowledge deepening and mitigate the negative impact of expertise specialization on knowledge broadening. Thus, in order to generate impactful patents with broad and deep knowledge capital, firms may focus their attention on balancing the knowledge structure embedded in their inventor teams between expertise diversity and specialization.

Third, we provide pragmatic suggestions on how to leverage Innovation Development Digital Capabilities to effectively convert inventor team expertise into knowledge capital to generate highly impactful innovation. Specifically, we suggest that (1) firms with a protective digital environment would substitute the effects of expertise diversity to broaden the knowledge capital, as well as amplifying the benefits of expertise specialization and mitigating the adverse effects of expertise diversity on the deepening of knowledge capital; (2) firms that provide a digital environment supporting integration, representation and sharing of knowledge and facilitating automatic discovery of new insights would substitute the effects of expertise diversity to broaden the knowledge capital, as well as mitigating the adverse effects of expertise specialization on knowledge broadening and of expertise diversity on knowledge deepening; and (3) firms with a digital environment supporting connectivity and access to external knowledge would mitigate the adverse effect of expertise specialization on the broadening of knowledge capital. Our findings collectively suggest that firms should have a clear understanding on how people and IT complement each other in the process of innovation development.

4.5.3 Limitation and Future Research

We recognize some limitations of this study and identify directions for future research. First, this study undertook a small firm-level sample size by focusing on S&P 500 firms in the medical device sector. Future research may consider increasing the sample size by including medical device firms with different size, government structure or levels of performance, to strengthen the robustness of results.

Second, we restrict our focus to three dimensions of digital capabilities for innovation development, and their independent moderating effects to shape the effectiveness of conversion from inventor team expertise to knowledge capital. Future research may extend this theoretical model by incorporating other dimensions of digital capabilities in relevance with innovation development. In addition, future studies may generate more fruitful insights by looking at different combinations among the *Reach*, *Richness*, and *Protection* dimensions, and examining how various profiles of digital capabilities impact the innovation outcomes in different ways.

Third, IT that constitutes *Innovation Development Digital Capabilities* dimensions may change tremendously and rapidly over time. Some technologies may become obsolete while others emerge within a short period of time. Taking this issue into consideration, we took a further step to exclude relatively obsoleted technological in our *Reach* measures (e.g., low-speed Internet access technologies such as ISDN line, switched 56 line, and dial-up line) and conduct robustness analysis as shown in Table 10. Although we find highly consistent results in our analysis, future research is recommended to collect more information on a wider range of IT that support the functionalities of *Reach*, *Richness*, and *Protection*, and evaluate the robustness and generalizability of our measures.

4.6 Conclusion

Medical device innovation requires the development of deep knowledge within a technological domain and broad knowledge across multiple technological domains.

This market need has led firms to establish teams that are both specialized in certain knowledge domains and diverse in knowledge across multiple technological domains. In practice, however, firms often face a dilemma between broadening knowledge capital via inventor team diversity and deepening knowledge capital via inventor team specialization. We conceptualize *Innovation Development Digital Capabilities* into three dimensions: Reach, Richness, and Protection. Our study reveals that digital capabilities exhibit great potential in creating an empowerment climate that can enable inventors to access, exchange, and protect external and internal knowledge for innovation purposes. This IT-enabled empowering environment helps address the tension underlying the conversion of inventor team expertise into knowledge capital in a way that (i) the detrimental effects of expertise specialization on knowledge broadening and of expertise diversity on knowledge deepening are mitigated, and (ii) the positive effect of expertise specialization on knowledge deepening is amplified. In addition, we find that digital capabilities may also substitute expertise diversity for knowledge broadening.

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