2014 47th Hawaii International Conference on System Science

The Role of Disseminative Capacity in HIT Adoption: An Empirical Analysis

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Abstract

Health information technology (HIT) has the potential to significantly reduce medical errors, streamline clinical processes, contain healthcare costs, and ultimately improve the quality of healthcare. Yet, the adoption of HIT among hospitals in the United States has been rather slow. This work synthesizes the theories on social networks and knowledge transfer by introducing the notion of a disseminative capacity *to study HIT adoption. We argue that members within a socioeconomic system possess both absorptive and disseminative capacities that influence knowledge transfer among them. Accordingly, a research framework is proposed, in which the absorptive capacity of a potential adopter and the disseminative capacity of connected adopters act as two key determinants, and these two capacities substitute for each other in affecting HIT adoption. Using a large panel dataset covering adoption decisions of over 5,000 hospitals across a 13-year horizon, we find strong support for our hypotheses derived from this framework.*

Keywords: *HIT adoption, healthcare, knowledge transfer, absorptive capacity, disseminative capacity, social networks, empirical analysis.*

1. Introduction

Currently, the United States spends \$2.7 trillion annually on healthcare alone, which is about 18% of the country's GDP—the highest in the world, in absolute as well as in relative terms. According to the World Health Organization, the per capita expenditure on healthcare continues to grow as well, and the current level of more than \$8,500 is also the highest in the world; at the same time, however, the quality of care is towards the bottom when compared to other developed nations [17].

Among the major challenges facing it, the healthcare sector lacks effective mechanisms to coordinate patient care, share relevant information, and monitor compliance with guidelines [28]. An effective way to meet these challenges could be deploying health information technology (HIT) that reduces medical errors, streamlines clinical processes, contains healthcare costs, and improves overall quality of healthcare. Recognizing the benefits of HIT, in 2009, President Obama committed incentives worth \$20 billion to computerize all medical records [21]. However, many providers in the US have been rather slow in adopting HIT [13]. According to the Healthcare Information and Management Systems Society (HIMSS), as of the first quarter of 2013, roughly one in eight providers is still without a Clinical Data Repository (CDR) system—the most basic building block of Electronic Health Records (EHR). Further, a large fraction of providers that now have a CDR system has not implemented other advanced systems, such as Computerized Physician Order Entry (CPOE) or Clinical Decision Support System (CDSS). In addition, many providers are still unable to implement a sharable EHR system that is critical to not only ensuring high quality service for patients but also controlling bulging healthcare costs by holding providers accountable for unnecessary or ineffective treatments. The potential loss due to a lack of HIT exceeds \$80 billion each year [11].

Given the purported benefits of HIT and its woefully inadequate adoption, it is of much practical significance that we understand what enables rapid diffusion of such technologies or systems. In fact, academic researchers have already taken up this important question of technology diffusion, tackling it from primarily two different angles. On one hand, some researchers have employed the *knowledge transfer* theory to study the underlying diffusion mechanism. This theory focuses on how information relating to a new technology flows from current adopters to potential ones, influencing their decisions to adopt. On the other hand, more recently, researchers have also started employing the *social network* approach, which recognizes that current and potential adopters are embedded in a web of relations, and the network structure determines how the

978-1-4799-2504-9/14 \$31.00 © 2014 IEEE
DOI 10.1109/HICSS.2014.509

actions of one actor in the network influences others. However, there is a notable disconnect between these two streams. The knowledge transfer literature does not consider the role of social networks, and the social network literature overlooks the issue of knowledge transfer. Thus, neither explicitly models or investigates knowledge transfer in a network setting. This is the gap we seek to fill.

We study the diffusion of HIT, empirically, using a large dataset obtained from the HIMSS database. We carefully examine the adoption of CDR, a technology that has been diffusing gradually over the last decade and has now reached a large majority of all kinds of providers. Its gradual diffusion over a decade-long period, along with its uneven adoption rates across different provider networks, affords us a natural setting and a rich panel dataset that are necessary for a thorough empirical investigation. Indeed, our sample includes 38,506 observations for 5,171 hospitals across 13 years (1998–2010).

Technology adoption has ties to knowledge transfer [27]—a process through which an adopter (knowledge sender) transmits pertinent information, such as information relating to risks and benefits of a new technology, to a potential adopter (knowledge receiver). Since providers within the same integrated healthcare delivery system (IHDS) establish formal and information communication channels, such as meetings, forums, and councils to exchange information among them [24], the issue of knowledge transfer in a network setting is particularly relevant in the context of HIT adoption. The existing literature on knowledge transfer argues that knowledge receivers typically differ in their *absorptive capacity* [15]. Organizations with higher absorptive capacity are able to quickly identify and recognize the value of external knowledge and information and are, therefore, more likely to easily absorb and assimilate such knowledge and information; as a result, they are also likely to adopt a new technology sooner. We do consider the role of this absorptive capacity in HIT adoption, but also go beyond and introduce the concept of a *disseminative capacity*—a construct *critical to extending the existing theory on knowledge transfer to a network setting*. Specifically, we define the disseminative capacity of a current adopter as its ability to transfer knowledge to potential adopters in the same provider network and thereby influence their decisions to adopt HIT. Put simply, in a network setting, the absorptive capacity of an organization affects its own decision to adopt information technology, but its disseminative capacity potentially affects the decisions of those connected to it.

An important contribution of this research is that it extends the knowledge transfer perspective to a network setting in a way that allows one to *go beyond the usual dyadic nature of analysis and to study the adoption decisions of providers within the web of relations in a provider network*. It reveals several important insights. First, we posit and find significant empirical support that absorptive and disseminative capacities both play a major role in the adoption of new information technologies. In other words, knowledge transfer in provider networks indeed plays a significant role in inducing HIT adoption, and that the adoption decision of a provider cannot be studied in isolation. Second, our empirical analysis lends evidence that these two capacities—absorptive and disseminative—actually substitute for each other in affecting HIT adoption, that is, the disseminative capacity plays a more significant role for providers that have a lower absorptive capacity. These insights have important implications for healthcare organizations and provider networks, as well as for governments and public policy institutions.

2. Theoretical Background

Technology and innovation are important vehicles that enable transformation of business processes, enhance firm productivity, and facilitate collaboration and transactions across organizational boundaries [29]. Quick adoption and assimilation of technology and innovation are important for firms to gain competitive advantages and achieve business success.

Two theoretical perspectives have received increasing attention: the *social network* approach and the *knowledge transfer* theory. In the social network literature, social actors are embedded in their social contexts and relations, which could either facilitate or derail economic exchanges and decision making [4]. In particular, scholars have investigated how social networks affect technology adoption in the healthcare industry. They have discovered that hospitals become more likely to adopt total quality management with increased number of previous adoptions [37], and that hospitals in alliances with physicians are more likely to adopt new imaging technologies [18].

Although the social network approach to technology adoption is becoming popular lately, the influence of knowledge transfer on the spread of innovation has a longer tradition. Knowledge transfer has been defined as the process through which the knowledge state of one social actor is affected by that of another [2]. Although knowledge transfer can take on various forms, such as personnel movement, training, association, and alliance, the end result, in essence, is that knowledge is passed on from the source to the destination [33]. More importantly, it has been observed that technology adoption is an information-intensive endeavor, which is essentially a process of knowledge transfer from current to potential adopters [27].

A key concept in the literature on knowledge transfer is that of absorptive capacity, which refers to an actor's ability to identify, absorb, assimilate, and exploit external information and knowledge to gain a competitive advantage [7, 15]. Early literature argues that innovation success is positively related to a favorable receptivity towards technology, and technology suppliers can facilitate learning and adoption by lowering knowledge barriers for potential adopters [3]. Several other studies have expanded and enriched the learning perspective to technology adoption by focusing on the ability of an organization to overcome hurdles in order to adopt and assimilate technology successfully [25]. Moreover, realizing that organizational efforts in deploying and managing technology yield strikingly different results, Boynton et al. [5] argue that the absorptive capacity of an organization is truly the underlying force beneath successful adoption and deployment of new technologies.

However, a closer examination of the literature above reveals a clear gap between these two theories of technology adoption. The social network approach suggests that information channeled through the network can facilitate technology adoption, but it does not explicitly model the process of knowledge transfer from current adopters to potential ones. On the other hand, though the knowledge transfer approach admits that innovation diffusion is a process of mutual understanding and information exchange between current and potential adopters [27], it typically focuses on dyadic relationships, neglecting the web of network relations between these two groups of actors. This is because the current literature on knowledge transfer predominately focuses on the capacity of receivers to absorb and assimilate technology, with little attention paid to the capacity of current adopters to transfer useful information about a technology to potential adopters connected to them. By introducing the concept of a *disseminative capacity*, in this study, we build a unified research framework that bridges this discernible gap and provides new insights into the diffusion of HIT.

3. Hypotheses

Our research framework seeks to capture the process of knowledge transfer in a network setting. The impact of the absorptive capacity of a potential adopter on HIT adoption is modeled by Hypothesis 1, whereas Hypothesis 2 considers the impact of the disseminative capacity. The potential substitutability between these two capacities is modeled by Hypothesis 3. Theoretical underpinnings of these hypotheses are discussed in this section.

3.1. Absorptive Capacity

The concept of absorptive capacity was originally developed to study how organizations or firms can effectively identify, absorb, assimilate, and exploit external information to gain competitive advantages [7]. As suggested in the knowledge-based view of competitive advantages, the survival and prosperity of social actors essentially lie in their capacity to acquire information and create knowledge. Therefore, developing organizational capabilities by sharing and integrating different aspects from a variety of knowledge bases is an important source of competitive advantage [36].

Absorptive capacity has been examined from various angles, such as an actor's receptivity to technological changes, the ability to use external knowledge, and the capacity to learn and solve problems [10, 22]. However, it is most often operationalized as the actor's existing knowledge stock [7]. Adoption researchers have quickly come to realize that the concept of absorptive capacity offers a promising theoretical lens for research on technology adoption and deployment [5], potentially because it "nicely captures the notion that... (actors) differ in their ability to develop relevant knowledge bases, recognize valuable external information, and make appropriate decisions in adopting technology" [29].

At the organizational level, absorptive capacity typically refers to an organization's capability to effectively locate, acquire, and use external information and knowledge, which enables them to analyze, process, interpret, and understand stocks and flows of knowledge [15]. Organizations with higher absorptive capacity are able to quickly identify and recognize the value of external information and are, therefore, more likely to easily absorb and assimilate such information so as to reinforce, complement, or refocus their knowledge base. The end result from this process is a faster adoption of new technologies. Formally, we hypothesize:

HYPOTHESIS 1 **(H1)**. *The higher the absorptive capacity, the earlier a potential adopter will adopt HIT.*

3.2. Disseminative Capacity

The social network theory suggests that social actors are not atomic or isolated, as they are constantly interacting with others within the network. Through this process, knowledge held by one actor can potentially be disseminated to another within its ego network, often leading to a better performance by both. Recent research demonstrates that inter-firm knowledge sharing is indeed one of the possible sources of supernormal profits generated in an exchange relationship that cannot be generated by firms in isolation [10], and that knowledge sharing among firms can promote competitive advantages rather than hindering competitiveness [9].

Of course, sharing of knowledge could be intentional as well as unintentional. There are several reasons for a social actor to intentionally disseminate knowledge to others. First, one may have useful knowledge about a technology that exhibits positive network effects, where the value of the technology to an adopter increases as the technology becomes more widely adopted [19]. Second, an organization may intentionally disseminate knowledge in order to encourage recipients to contribute to the knowledge pool, which, in turn, can be exploited by the sender to further improve its capability and competitiveness [38]. Third, firms may deliberately disseminate technologies in the hope of creating an industry standard or a dominant design [32].

Knowledge dissemination may also be unintentional. Unintentional dissemination can occur under several circumstances. For example, a current adopter may influence potential ones, unintentionally, through association, shadowing or externships, and joint problem-solving [10]. Knowledge could also be unintentionally disseminated through employee mobility or turnover—employee migration can bring knowledge and expertise of product lines to the hiring firms and, therefore, can increase chances of their market entry [2]. Similarly, new firms often recruit employees from established firms to overcome resource constraints, triggering unintentional knowledge transfer. Finally, the existence of social relationships among employees from two or more organizations can also lead to unintentional sharing of confidential knowledge across organizational boundaries.

In this study, we define the disseminative capacity as the ability of current adopters to efficiently and effectively pass on information about a technology to a potential adopter, either intentionally or unintentionally. Essential to understanding the mechanism of dissemination is the network connectivity between current and potential adopters. The level of dissemination from a current adopter to a potential one depends on two factors: (i) the ability of the current adopter to influence the potential adopter, and (ii) whether there exists a connection between them. Viewed this way, the aggregate disseminative capacity a potential adopter is exposed to is the sum of the individual disseminative capacities of all the adopters in its ego network.

By introducing the notion of disseminative capacity, we essentially assert that the process of knowledge transfer has to be considered within the network comprising both current and potential adopters [4], and that each potential adopter is subject to knowledge dissemination from all its connected peers when contemplating adoption of a new technology. This way, we go beyond the dyadic analysis typically used in the knowledge transfer literature and extend it by incorporating the connectivity within a network. In our network setting, the process of knowledge transfer for a focal hospital is influenced by its own absorptive capacity related to the technology as well as the combined disseminative capacity of the connected adopters.

We argue that the disseminative capacity plays a positive role in facilitating technology adoption. Studies show that influences from senders, as well as the knowledge of the subject matter they possess, are critical to successful knowledge transfer [16]. As noted by Rogers [27], technology adoption is essentially the process of communication and knowledge transfer. If current adopters do not have sufficient ability to transfer relevant information about a technology to potential adopters, the speed with which the technology spreads will be greatly reduced. Therefore, if current adopters are highly effective in imparting knowledge about the technology or influencing a potential adopter to use the technology, they will be able to change the potential adopter's perception of the new technology, ultimately inducing its adoption. Thus, we propose the following hypothesis:

Hypothesis 2 **(H2)**. *The higher the disseminative capacity of its connected peers, the earlier a potential adopter will adopt HIT.*

3.3. Combined Influence of Absorptive and Disseminative Capacities

Literature has revealed that, when social actors face influences from multiple sources, these influences do not simply add up. For example, firms often substitute resource acquisition for innovation as a way to gain competitive advantage, or apply a capacity-building strategy as a substitute for resource picking to generate economic return [23]. Examples also abound where two influences complement each other. For example, R&D investment and network connectivity have been found to complement each other in facilitating firm innovation and performance [35]. Quite often, the substitution effect reflects a loss in value due to redundant influences from multiple resources [31]. The complementarity effect, in contrast, arises from the fact that multiple resources are potential enablers of each other.

In our context, the relevant question then is how effective the disseminative capacity will turn out to be if a social actor already possesses a high absorptive capacity. We argue that the two capacities are substitutes for each other in terms of their marginal effects. In the process of technology adoption, if a potential adopter can recognize the importance and benefits of a new technology, and if it, by itself, has the ability to effectively understand and absorb the technology, then it is more likely to actively explore and apply the new technology on its own, even when situated in an environment that is not so favorable [e.g., 27]. When few other actors have adopted the new technology, the potential adopter does not have many outside sources to consult or learn from, and it is not affected as much by the adoption decisions of its peers. Under this circumstance, the ability and discretion of the potential adopter play a crucial role in its adoption decision. Thus, a potential adopter with a stronger absorptive capacity can adopt the new technology without much intervention and help from peers. Viewed differently, the marginal effect of a potential adopter's absorptive capacity on technology adoption is likely to increase as the current adopters' disseminative capacities decrease.

Furthermore, when the absorptive capacity of a potential adopter is not sufficiently high to fully realize the benefits of a new technology, strong disseminative capacities of technology-adopting peers are likely to be more effective in communicating the benefits of the new technology and converting a potential adopter to an adopter. Put another way, the marginal effect of current adopters' disseminative capacities on technology adoption increases as the potential adopter's absorptive capacity decreases. This implies that, although both capacities can positively induce adoption, an increased exposure to both can potentially create more redundant and possibly conflicting influences, thereby reducing their individual marginal effects. Hence, we posit:

HYPOTHESIS 3 **(H3)**. *The absorptive and disseminative capacities substitute for each other in influencing HIT adoption.*

4. Dataset and Variables

Health information technology (HIT) consists of a diverse set of technologies used for delivering healthcare and managing health information used by patients, providers, and insurers/payers. Broadly speaking, HIT falls into two main categories: HIT for diagnosis/treatment such as magnetic resonance imaging (MRI), and transactional HIT such as electronic health records (EHR). While the first category improves the quality of medical services, the second primarily improves the coordination and sharing of medical information across parties involved in the healthcare service chain. The foundation of EHR is the clinical data repository (CDR) system, a real-time transaction processing database that merges data from a variety of clinical sources to present a consolidated view of every patient's clinical history. In this study, we examine the adoption of CDR by hospitals in the Unites States.

4.1. Dataset

To investigate our research questions, we use the Healthcare Information and Management Systems Society (HIMSS) database. The HIMSS database is the largest and the most up-to-date HIT adoption and investment database in the US. It provides extensive information on HIT adoption by healthcare providers across the nation. This database is available from the HIMSS Foundation.[1] We have obtained a data panel on the adoption of CDR during the thirteen-year time period from 1998 to 2010. Many types of healthcare providers are included in the dataset, such as ambulatory, home health, hospital, and sub-acute providers. We restrict our analysis only to hospitals (also called acute healthcare providers). Our final sample includes 38,506 observations for 5,171 hospitals.

It is possible that several hospitals in our final sample belong to a single integrated healthcare delivery system (IHDS). Hospitals within the same IHDS establish both formal and information communication channels, such as meetings, forums, and councils to exchange information among them [24]. Thus, they are essentially connected with one another. In the HIMSS database, each hospital is assigned a unique identifier, which we used to match data records and construct the data panel. Our sample includes, as potential adopters, those hospitals that had not adopted a CDR system by 1998. We then tracked their adoption decisions till 2010. Once a hospital adopted, we no longer considered it a potential adopter for later years.

[1] To access the database, please point your browser to `http://apps.himss.org/foundation/histdata.asp`.

4.2. Variables

The dependent variable in this study is a binary variable indicating whether or not a hospital adopts CDR in the observation year. There are eight different CDR adoption statuses available in the dataset. Among them, in this study, we consider the following four as an adoption: (i) *live and operational*, (ii) *installation in process*, (iii) *contracted/not yet installed*, and (iv) *to be replaced*. The remaining four—*not automated*, *not reported*, *not yet contracted*, and *service not provided*—are considered as non-adoption. There are two key independent variables in this study, the absorptive capacity ($ACAP$) and the disseminative capacity ($DCAP$). We now discuss how these two, as well as other independent variables, are operationalized in this study.

$ACAP$: As discussed earlier, $ACAP$ represents the ability to absorb and assimilate external information, and is mostly conceptualized as the organizational learning capability [22]. Learning is best characterized as cumulative and path-dependent, since assimilating new knowledge requires related prior knowledge. In essence, "if external information is closely related to ongoing activity, then external information is readily assimilated" [7]; that technology adoption is affected by the degree to which the new technology is related to the pre-existing stock of knowledge is also evident from the fact that personal computers diffused more rapidly among firms who had prior experience with mainframes or minicomputers. In this study, we use the current stock of HIT as a proxy for $ACAP$, because it is consistent with these ideas. First, it is cumulative and path-dependent. Second, it is representative of the stock of knowledge that is related to the new technology (CDR). Finally, it embodies ongoing activities that can facilitate assimilation of relevant external information. Specifically, to represent the stock of HIT, we count all the HIT applications other than CDR, which have already been adopted by the focal hospital; the use of counts of related technology applications for such purposes is indeed widespread [15].

$DCAP$: In our model, $DCAP$ represents the ability of knowledge senders to efficiently and effectively impart knowledge to receivers. Of course, two actors must be connected for the knowledge transfer to take place. In our context, this means that two hospitals must be in the same IHDS to share information about a technology. We first capture this by defining the following variable:

$$I_{ij} = \begin{cases} 1, \text{ if } i \text{ and } j \text{ are in the same IHDS, } i \text{ has} \\ \qquad \text{adopted CDR, and } j \text{ has not,} \\ 0, \text{ otherwise} \end{cases}$$

Next, we measure the $DCAP$ of a CDR-adopting hospital (a current adopter) based on its HIT stock that is common with the focal hospital (a potential adopter). Research in the social network theory suggests that social actors within a network do not always exert the same level of influence and can, therefore, be classified in accordance with their influence in the network [30]. Hospitals with a large number of common HIT applications accumulate similar stocks of knowledge, procedures, and rules, which allow them to effectively share information about a new technology [22]. Therefore, if a CDR-adopter hospital shares more common HIT stock with the focal hospital, the former would also possess a higher disseminative capacity and potentially exert a much stronger influence on the latter to adopt. Using this logic, we code $DCAP$ in the following manner. For every pair of hospitals i and j, we denote as μ_{ij} the number of HIT applications that are common between the two hospitals. Then, the $DCAP$ of hospital i—as it influences hospital j—is simply $\mu_{ij} I_{ij}$. Consequently, a focal hospital j is exposed to a total $DCAP$ of $\sum_i \mu_{ij} I_{ij}$.

This operationalization of $DCAP$ is consistent with our earlier observation that knowledge transfer can be intentional or unintentional. For example, a current adopter with a similar stock of HIT might already have a level of business synergy with a potential adopter in terms of patient information sharing and collaborative workflows, which can be further enhanced if the potential adopter also adopts the new technology. Likewise, when an employee migrates from a current adopter to a potential one with a similar stock of HIT, the knowledge he carries tends to be more relevant to the potential adopter.

Similarity: Hospitals are of various types, where each type represents a different business scope in which a hospital operates.[2] The variable business scope *similarity*, written as ϕ_j, is used to measure how the CDR-adopting hospitals within the same IHDS are similar in their business scopes when compared to a focal hospital j. For every pair of hospitals i and j, we define:

$$\psi_{ij} = \begin{cases} 1, \text{ if } i \text{ and } j \text{ are of the same type,} \\ 0, \text{ otherwise} \end{cases}$$

[2] Our dataset contains thirteen different types of hospitals; they are: (i) academic, (ii) cardiology, (iii) critical access, (iv) eye, ear, nose, & throat, (v) general medical, (vi) general medical & surgical, (vii) long term acute, (viii) oncology, (ix) orthopedic, (x) other specialty, (xi) pediatric, (xii) pediatric & women's health, and (xiii) women's health.

Furthermore, for a focal hospital j, let $N_j = \sum_i I_{ij}$ be the total number of CDR-adopting hospitals in the same IHDS. Then, for hospital j, the similarity is calculated as:

$$\phi_j = \begin{cases} \frac{\sum_i \psi_{ij} I_{ij}}{N_j}, & \text{if } N_j > 0, \\ 0, & \text{otherwise} \end{cases}$$

Base: Technology adoption is often influenced by social contagion attributable to instituitional isomorphism or normative pressure—as well as network effects—whereby every adopter impacts the decision of a potential adopter uniformly [1, 6, 34, 39]. To control for the contagion effect, we use the variable *base*, which is the total number of CDR-adopting hospitals in j's IHDS. Thus, the *base* for a focal hospital j is simply N_j defined above.

Other Regressors: The variable *time* is the calendar year of an observation minus 1998. Consistent with prior literature, we also control for hospital *size* and *age* in this study [1, 37]. The size of a hospital is measured by the number of beds in the hospital, and its age is measured as the time span (in years) since its inception to the observation year. In addition, we control for the *type* of a hospital since prior literature suggests that HIT adoption rates differ substantially across various types of hospitals [11]. A summary of all variables is provided in Table 1.

Table 1. Definition of Variables

Variable	Definition
Dependent Variable	
Adoption of CDR	Indicator variable for CDR adoption. It is 1 if the focal hospital adopts CDR in the observation year and 0 otherwise
Independent Variables	
ACAP	Total number of HITs adopted by the focal hospital (divided by 100)
DCAP	Total number of HITs that are common between the focal hospital and its technology adopting peers in the same IHDS (divided by 100)
Similarity	Business scope similarity between the focal hospital and its technology adopting peers in the same IHDS
Base	Total number of technology adopting peers of the focal hospital in the same IHDS (divided by 100)
Time	Observation year minus 1998
Size	Total number of beds available in the focal hospital (divided by 100)
Age	Time span in years since the inception of the focal hospital to the observation year (divided by 10)
Type	Dummy variables for hospital types; there are 13 hospital types and, therefore, 12 dummies

5. Estimation

We use a logit model to express the probability of CDR adoption by a focal hospital i as:

$$\Pr[Y_i = 1|\boldsymbol{X}_i] = \Pr[\boldsymbol{X}_i'\boldsymbol{\beta} + \epsilon_i > 0],$$

where Y_i represents the binary adoption decision, $\boldsymbol{X}_i$ are the regressors, and ϵ_i is the i.i.d. normal error. This is better represented with a latent variable, Y_i^*, as:

$$Y_i^* = \boldsymbol{X}_i'\boldsymbol{\beta} + \epsilon_i; \quad Y_i = 1\left[Y_i^* > 0\right]. \tag{1}$$

The motivation for this model choice is as follows. The dataset used in this study is best described as *time-to-event data*, with the adoption of CDR representing the event of interest. To study this event, we need to use *duration analysis*, which could be either continuous or discrete [12]. Here, we must employ a discrete model since the observations are one year apart. When a discrete duration model is used with panel data, it becomes equivalent to a logit model [14]. To explicitly account for the simultaneity issue in examining network influence, we take advantage of our panel dataset and employ the independent variables in one time period to predict the adoption of CDR in the following one [26]. By doing so, we explicitly specify that the decision to adopt CDR at time t is determined by the state of network interactions at time $(t-1)$, and not vice versa. In other words, the regression model in (1) is better expressed as:

$$Y_{i,t}^* = \boldsymbol{X}_{i,t-1}'\boldsymbol{\beta} + \epsilon_{i,t}; \quad Y_{i,t} = 1\left[Y_{i,t}^* > 0\right]. \tag{2}$$

In essence, the resulting model is a *spatial discrete choice lag model*, where adoptions in previous years influence current and future adoptions; such models are particularly suitable for studying technology adoption "across different individual establishment locations in different geographic areas" [20].

In order to test our hypotheses, we apply incremental regression strategy using (2) . The results are presented in Table 2. Model 1 represents the baseline and lists estimation results without the absorptive and disseminative capacities. This model controls for *time*, as well as *size* and *age* of hospitals. The coefficient of *time* is estimated to be both significant and positive, implying that the hospitals in our sample were gradually becoming more open to using CDR for reasons other than those studied in

Table 2. Estimation Results

Independent Variable	Model 1	Model 2	Model 3
ACAP		2.794***	4.461***
		(0.411)	(0.435)
DCAP		0.224***	0.722***
		(0.019)	(0.054)
ACAP×DCAP			-0.882***
			(0.090)
Similarity	0.230	0.336*	0.428**
	(0.178)	(0.181)	(0.187)
Base	6.726***	3.897***	3.156***
	(0.364)	(0.440)	(0.505)
Time	0.192***	0.049**	0.078***
	(0.023)	(0.023)	(0.024)
Size	0.081***	0.024	0.039
	(0.031)	(0.033)	(0.035)
Age	0.093***	0.114***	0.128***
	(0.016)	(0.017)	(0.019)
Log likelihood	-7266.569	-6891.692	-6823.943

NOTE: $N = 38,506$. Estimated coefficients and their associated standard errors (in parentheses) are listed for each model. Our independent variables also include 12 dummy controls for the *hospital type*. For brevity, the coefficients of these dummy variables are not shown. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

this work. Absent this control variable, any analysis of the influence of the adopters would become systematically biased. The coefficients of *size* and *age* are also positive and significant. This is expected, as we anticipate larger and more mature hospitals to adopt a new technology sooner [1]. The positive and significant coefficient of *base* is also expected [1], and it does reveal a strong contagion effect—as more hospitals in an IHDS adopt CDR, they tend to induce other hospitals in their network to adopt as well. Thus, the results from Model 1 are consistent with our basic understanding of the research context and, hence, are also reflective of the integrity of the dataset and its appropriateness for our purpose.

In Model 2, the two main regressors—$ACAP$ and $DCAP$—are introduced. Their coefficients are found to be positive and significant, implying that Hypotheses 1 and 2 are both supported. As a robustness check, we note that, even in this extended model, the coefficients of the control variables all have their expected signs and the contagion effect is significantly positive. Having established the importance of $DCAP$, we now test Hypothesis 3 that looks at the substitution effect between $ACAP$ and $DCAP$. This effect is captured in Model 3 by the interaction term $ACAP \times DCAP$. The coefficient of this interaction term is negative and significant, thereby providing support for Hypothesis 3 that $ACAP$ and $DCAP$ are, in fact, substitutes for each other. Of course, this does not imply that they offset each other; it only suggests that the marginal effect of one gets weaker as the other increases.

6. Conclusion

A major insight that emerges from this study is that the impact of knowledge flow—from the connected peers who have adopted a technology to potential adopters—can play a significant role in fostering diffusion. There are practical implications of this finding, as it suggests that a possible way of alleviating the problem of slow diffusion of HIT would be to encourage formation of new networks such as an IHDS. In fact, in recent years, the emphasis on the role of such networks has increased considerably. In a recent thought-provoking article in the New England Journal of Medicine, Crosson [8] argues that any movement away from the fee-for-service system, which simply incentivizes more consumption but not necessarily a better clinical outcome, would require integration of physicians from different specialties as well as hospitals to form new accountable systems of care. Also, the success stories of Mayo Clinic, the Geisinger Health System, and Kaiser Permanente have inspired some local governments to take initiatives to form and grow their own networks in order to better coordinate delivery of healthcare and improve accountability, both critical to bending the ever rising cost curve. An example of such state-initiated networks is the AccessCare network in North Carolina, which has now grown to a statewide network of over 300 primary care practices with 1,000 providers caring for over 260,000 Medicaid enrollees as of December 2010. Smaller states like Wyoming have also started joining the fray. Our finding about the role of the disseminative capacity is a clear indication that, in addition to serving the purposes for which they were set up, such networks can also serve as important vehicles of knowledge dissemination, providing the much needed boost to the rather slow process of HIT diffusion. It is also apparent that a lack of HIT adoption among independent providers, who do not participate in any integrated care network, can be partly addressed by incentivizing them to join a large network with a significant disseminative capacity. Doing so would not only improve the quality of patient care and reduce costs but would also promote the cause of HIT adoption, leading to even better quality of care and even lower costs.

Another important finding is that the dissemination process is more useful for providers with low absorptive capacities, that is, those who have little experience with technology and are, therefore, less likely to embrace a new technology on their own. According to our study, the key to helping these providers adopt a new technology turns out to be placing them in networks with adopters that have a similar structural mold in terms of their stocks of HIT. Thus, in years following the inception of a new beneficial technology, policymakers should pay particular attention towards encouraging providers to join networks that already have adopters with overlapping stocks of HIT.

Our study complements the emerging literature on social networks, as well as that on the knowledge transfer theory, by forging a relationship between the two. We distinguish between current and potential adopters and explicitly model the flow of knowledge along network connections from the former to the latter. This was an essential first step towards extending the knowledge transfer theory to network settings where actors are embedded in a multiplicity of connections. By taking this step, we have also paved the path for further research on the vexing issue of slow HIT adoption. For example, although we believe that IHDS networks represent a major channel for hospitals to communicate with each other, there are possibly other channels through which hospitals can share information. Our model may be applied to better understand the role and effectiveness of these additional communication channels.

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