Dynamics of Social Influence on New Employees' Use of Volitional IS: m-EHR Case in Hospital Setting

Completed Research Paper

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Abstract

It is widely recognized that user resistance to Information Systems (IS) is particularly high in hospitals. In this regard, the future of mobile Electronic Health Record (m-EHR) systems is highly in question, mainly because their usage is not mandatory. Aiming to provide insights on how best to promote the use of m-EHR in hospitals, we investigate the effect of social influences on m-EHR usage by new doctors who recently began working at a hospital. Drawing upon the concept of organizational socialization and social influences, we hypothesize that coworkers' m-EHR usage is positively associated with one by new doctors, and the strength of this association varies by the coworkers' type of usage, by the hierarchical rankings of coworkers, and by the stage of socialization process in which the new doctors are situated. Our analyses using longitudinal m-EHR usage data (595,914 logs of 737 doctors) generally support our hypotheses.

Keywords: Healthcare Information Systems, Social influences, New employee, IS, adoption/usage, Mobile Electronic Health Records, Volitional IS, Organizational socialization

Introduction

Despite significant investment in new information systems (IS), new systems are often underutilized (Cragg and King 1993; Iacovou, Benbasat, and Dexter 1995; FINK 1998). The healthcare sector, which has invested in various types of IS, such as electronic health records (EHR), mobile-based EHR (m-EHR) systems, and patient portals, is no exception. Among them, m-EHR is a relatively new system that has been adopted by many hospitals in recent years to improve the quality of patient care and the work efficiency of doctors with busy medical schedules (Ventola 2014; D'Ambrosio et al. 2015). It is a smartphone application that helps doctors monitor patients' vital signs, manage their schedules, research pharmaceutical information, and communicate with other medical professionals (Ventola 2014; D'Ambrosio et al. 2015; Malhotra and Galletta 2005). Despite the potential benefits of m-EHR, several studies have reported low rates of m-EHR usage (Kim et al. 2016; Wu, Li, and Fu 2011). Some research attributes this failure to the fact that the use of m-EHR is not mandated (Wu, Li, and Fu 2011). Due to doctors' busy schedules and the volitional feature of m-EHR, doctors often receive insufficient training, resulting in underutilization of m-EHR. Instituting policies such as mandating usage of m-EHR would not be an ideal solution, because the level of resistance to mandated IS is very high in hospitals (Kane and Labianca 2011).

In this study, we aim to provide insights on ways to promote the use of m-EHR in hospitals. In particular, we examine the role of social influences by coworkers. Given that doctors share strong relationships built on strong teamwork and apprentice relationships, we expect that social influence by coworkers will serve as a viable alternative to formal training to promote m-EHR. More specifically, we investigate the effect of social influences on doctors who recently began working at a hospital (we use the term "new doctor" to refer to any doctor who joins a hospital as a new employee, regardless of his or her experience). This approach allows us to examine the dynamics of social influences, as new members of an organizational environment undergo various social interactions that change over time. Drawing upon the concept of organizational socialization and social influences, we hypothesize that coworkers can influence the m-EHR use by new doctors. We also hypothesize that the strength of their influence varies by the coworkers' type of usage (general vs. function-specific) and by the hierarchical rankings of coworkers (higher-ranking, similar-ranking, lower-ranking). Some doctors use a variety of functions available in m-EHR (i.e., general), while others use only a few functions (i.e., function-specific). Also, doctors in different hierarchical rankings (professors, fellows, residents, interns) have different roles and responsibilities. Because the behaviors of coworkers with different usage patterns and hierarchical rankings will shape different images and beliefs towards m-EHR, we expect that they will exert influences through different mechanisms that result in different consequences. We also examine the changes in their influences at the different stages of socialization process in which the new doctors are situated.

Based on the assumption that a doctor's actual m-EHR usage represents his or her attitudes and beliefs toward m-EHR, we tested our hypothesis using longitudinal m-EHR usage data on 156 new doctors who joined a major research hospital in South Korea in 2015. We analyzed the usage of m-EHR by new doctors and their coworkers who cared for at least one patient in common in a given month. The panel regression analysis results of the 80,159 log data of the new doctors during the eleven-month period, combined with 515,755 log data of 581 existing doctors, generally support our hypotheses. Our results show that a 1% increase in the average m-EHR usage by coworkers is associated with a 0.232% increase in a new doctor's m-EHR use, and the magnitude of the association decreases over time by 0.009% each month. Also, the association between new doctors and coworkers in their m-EHR use is stronger when coworkers explore and use various features of m-EHR rather than when they use only a few specific features of the system. However, this difference decreases over time. Last, the associations of m-EHR use between new doctors and their coworkers are statistically significant regardless of coworkers' hierarchical rankings. However, the magnitudes of association do not change over time, failing to support our hypothesis.

Our study contributes to the IS adoption and use literature by providing several unique perspectives. First, we apply the concept of social influences and examine different types of social influences on the use of a new technology. In particular, we consider the usage patterns and hierarchical rankings of coworkers and examine changes in these influences over time. To the best of our knowledge, prior literature on social influences have not accounted for potential dynamics in social influence and different usage patterns of referent others (Wang, Meister, and Gray 2013; Karahanna, Straub, and Chervany 1999). In this regard, our finding provides new insights on social influence in these dimensions.

Second, we extend prior IS adoption and use studies by exploring ways to promote the use of m-EHR, which is voluntary in hospitals. Prior studies have typically examined traditional IS, for which use is mandatory with a few exceptions (Maruping and Magni 2015; Teo, Wei, and Benbasat 2003; Sasidharan et al. 2011). The healthcare IS studies also tended to focus on traditional EHR or patient portals for which usage is mandatory. As a result, m-EHR has received relatively less attention, despite its potential benefits.

Third, our study examines the use of m-EHR by new members in an organization, a group that has not been exclusively examined in prior studies. A hospital is an ideal setting to investigate IS usage for new members in an organization, because there is a large influx of new members in different hierarchical ranks every year, due to the inherent nature of the medical education system (i.e., trainee doctors in a residency or internship program stay with a hospital for about one to four years). In settings where the employee turnover rate is high, it is difficult to provide efficient technical training on IS systems. We believe that our results provide valuable insights that can be extended beyond major hospitals and are applicable to other organizations where employee turnover rates are relatively high.

Last, from the managerial perspective, our study provides important practical implications that can help in designing a technical training program for m-EHR for new doctors who join hospitals. Our results highlight the important role of coworkers and emphasize the need for informal interactions and discussion among doctors. We believe the implications of our study will help hospitals increase the return on their investment in m-EHR with regard to monetary terms as well as quality of care.

Research Context – m-EHR in Hospitals

It is widely recognized that user resistance to IS is particularly high in healthcare settings (Kane and Labianca 2011). This high level of resistance is not because doctors do not understand the potential benefits of IS in healthcare (e.g., lowering treatment costs, medical errors, and improving overall efficiency and quality) (Venkatesh, Zhang, and Sykes 2011; Kane and Labianca 2011). Rather, doctors are concerned about changes that may be brought with the new systems, particularly whether the new systems will fundamentally alter traditional medical practice and routines (Venkatesh, Zhang, and Sykes 2011; Anderson 1997). Moreover, doctors often feel that their power and authority are threatened, because they believe that the new system will undermine their professional identity that they have built through patient interactions for years; they may fear that their unfamiliarity with a new system may make them look inexperienced (Pratt, Rockmann, and Kaufmann 2006; Venkatesh, Zhang, and Sykes 2011). Thus, doctors tend to hold negative attitudes about new systems, resulting in low usage (Venkatesh, Zhang, and Sykes 2011; Kane and Labianca 2011). In addition, doctors' extremely busy schedules make implementing wide usage of IS even more difficult. Doctors in academic hospitals care for patients, participate in conferences, and conduct teaching sessions (Zerubavel 1979). Therefore, scheduling technical training on new systems, which is often not considered as critical for patient care, is very challenging.

Regarding the resistant due to the fear of losing authority, m-EHR is expected to take a different path, because it is one of volitional IS's, meaning that the use of m-EHR is not mandatory. Volitional systems are different from traditional systems, such as EHR, of which use is mandatory (Malhotra and Galletta 2005). Traditional EHR is used mainly for fundamental medical practices, such as ordering medicines and recording information in patient charts. On the other hand, m-EHR systems in many hospitals assist doctors as a supplementary channel to obtain non-critical information. For example, doctors can use m-EHR to monitor a patient's vital signs, manage their schedules, search for pharmaceutical information, and communicate with other medical professionals (Ventola 2014; D'Ambrosio et al. 2015; Malhotra and Galletta 2005). Often, the use of m-EHR does not force doctors to change their traditional medical practices, allowing them to maintain their sense of power and authority. Therefore, it is expected that the resistance level toward m-EHR among doctors is less problematic. The critical question becomes instead how to promote voluntary use of m-EHR among doctors. Before tackling this question, we provide a review of prior literature that investigated the factors affecting new IS adoption and usage in the following section.

Literature Review

The adoption and usage of new technologies is one of the most extensively studied topics in IS research. Prior research has been conducted at both the firm and the individual levels. At the firm level, researchers have investigated the antecedents of the adoption and use of various organization-wide information systems, such as electronic data integration (EDI) (Chwelos, Benbasat, and Dexter 2001; Zhu et al. 2006), smart card–based payment systems (Plouffe, Hulland, and Vandenbosch 2001), and enterprise resource planning (ERP) systems (Huigang Liang et al. 2007). At the individual level, there are three broad streams of research: (1) utility-oriented models, (2) network-based models, and (3) social influence models. Most studies in utility-oriented models have adopted and extended the Technology Acceptance Model (TAM), which mainly considers individual traits, such as perceived ease of use and perceived usefulness by a potential user, as key drivers for use intentions of new technology (Venkatesh et al. 2003; Venkatesh, Thong, and Xu 2012; Venkatesh and Davis 2000). Network-based studies demonstrate how the structural characteristics of an individual in his or her social network (e.g., degree or betweenness centrality) affect his or her own or peers' IS adoption and use (Venkatesh, Zhang, and Sykes 2011; Sasidharan et al. 2011; Lynn Wu 2013). The last stream of research investigates pressure/influences by others on an individual's IS adoption and use. Studies in this research stream build on various theoretical concepts, such as herd behavior (Heshan Sun 2013), network externality (Wattal, Racherla, and Mandviwalla 2010), and social influences (Sussman and Siegal 2003; Karahanna, Straub, and Chervany 1999; Wang, Meister, and Gray 2013; Malhotra and Galletta 2005).

From the review of literature about IS adoption and related studies in healthcare IS, we identified three main areas to which our study can contribute. First, compared with the utility-oriented and network-based IS adoption and usage studies, our knowledge about social influence on IS usage is still limited. In particular, prior IS research that investigated social influences on IS usage tended to examine only one specific type of social influence in each study, mainly emphasizing explicit/implicit social pressure by others. However, studies in marketing and communication, where the concept of social influence has been extensively studied, emphasize the multifaceted nature of social influences and argue that various aspects of social influences need to be considered together from a broader perspective (Deutsch and Gerard 1955; Burnkrant and Cousineau 1975; Karahanna, Straub, and Chervany 1999). A few recent studies have started to look at this issue (Wang, Meister, and Gray 2013; Malhotra and Galletta 2005), and our study builds on this research stream.

Second, while the question of how to motivate the use of volitional IS has gained recent attention (Malhotra and Galletta 2005; Wu, Li, and Fu 2011), to the best of our knowledge, there has been no empirical study on this agenda in a hospital setting where the negative attitude toward IS is particularly high. Our study is the first to empirically examine the use of m-EHR in the medical field.

Third, to the best of our knowledge, there has been no study investigating the effect of social influences on a new member's IS use during the process of adjusting to an organization. A new member of an organization goes through dynamic socialization processes during the adjustment period, and the social influences on a new member's IS adoption and use are likely to be different from the ones on existing members. Considering the increasing workforce mobility in many industries (Kambourov and Manovskii 2008), it is an important question but has not yet been investigated.

Last, prior studies conducted in the context of social influence in hospitals have considered doctors as a homogeneous group exerting power on other groups such as paraprofessionals (i.e., nurses) (Venkatesh, Zhang, and Sykes 2011; Kane and Labianca 2011). However, in a big research hospital, a doctor group consists of several classes—attending professionals, fellow doctors, resident doctors, and intern doctors. Doctors in a higher rank exert a strong, top-down power to doctors in the lower ranks (Diefenbach and Sillince 2011). Therefore, our study provides unique insight on the social influences among doctors.

Theory and Hypothesis Development

Organizational Socialization and Social Influence

Organizational socialization refers to a new member's adjustment process through which an outsider of an organization becomes an insider (Charles 1981; Louis 1980; Feldman 1976; Bauer et al. 2007). Prior research suggests that organizational socialization consists of four phases: anticipatory, encounter, change/acquisition, and (behavioral) outcome (Charles 1981; Louis 1980; Feldman 1976; Bauer et al. 2007). Two phases in the middle, the encounter and the change/acquisition phases, are considered adaptation phases, while the first (anticipatory) and the last (behavioral outcome) are generally considered antecedent and outcome phases (Bauer et al. 2007). This current research focuses on the two middle phases of the adjustment process, because our goal is to demonstrate how new members are socially influenced during the period when they are becoming insiders. In the encounter phase, new members start defining their roles in the new working team, learning task-related skills and organizational norms, and forming new relationships with existing members (Feldman 1976; Charles 1981; Louis 1980). During the acquisition phase, they master their new tasks, begin to fully understand the organization's norms and their expected roles, and establish relationships with existing members (Feldman 1976; Charles 1981; Louis 1980; Bauer et al. 2007). Upon joining a new organization, a new member starts interacting with various groups of referent others through verbal and nonverbal communication, and consciously and unconsciously observes and learns their behaviors(Morrison 1993; Miller and Jablin 1991; Louis 1980). Social influence results from these social interactions that shape an individual's attitudes, beliefs, and behaviors.

Researchers have tried to distinguish different types of social influences, and several categorizations have been suggested. For example, Kelman (1958) identifies three types of social influence mechanisms: compliance, identification, and internalization (Malhotra and Galletta 2005; Wang, Meister, and Gray 2013; Kelman 1958). Compliance is when individuals behave in a certain way because of perceived pressure by others, often in order to gain rewards or avoid punishment. Identification leads individuals to intentionally mimic observed behaviors of referent others in order to appear similar to and establish a good relationship with them. Internalization is when individuals incorporate others' opinions and show similar behaviors in accordance with those opinions.

Another research stream categorizes social influences into normative versus informational influences. Normative influence is similar to compliance-based influence, referring to the case when one tries to conform to the expectations of others in order to realize reward or avoid punishment (Deutsch and Gerard 1955; Burnkrant and Cousineau 1975). As the desire to get a sense of belonging to a group is also an important source of normative influence, identification-based influence can also be considered a part of normative influence (Burnkrant and Cousineau 1975). On the other hand, informational influence refers to the case when one accepts information obtained from others as evidence of reality (Deutsch and Gerard 1955). It is similar to internalization-based influence and is often observed as a result of information-seeking behaviors (Burnkrant and Cousineau 1975). Normative and informational social influences are often considered as the outcome of the three processes described earlier—compliance, identification, and internalization (Burnkrant and Cousineau 1975). As we try to explain the changes in usage with the concept of socialization processes, in the rest of this study, we will use Kelman's (1958) notations.

Uncertainty and New Doctors to Hospitals

New members of an organization encounter uncertainty and unpredictability in their new working environments (Van Maanen and Schein 1977; Miller and Jablin 1991). Like new members of any other organizations, doctors who join a new hospital encounter various types of uncertainty. As mentioned, we use the term "new doctor" to refer to any doctor who joins a new hospital, regardless of his or her medical experience. Therefore, a new doctor can be a highly experienced doctor. In this regard, it is important to distinguish uncertainty associated with medical knowledge and skills (i.e., knowledge used for medical decision making) from uncertainty about new roles and tasks for a doctor who is new to a specific hospital (e.g., how to use a system to monitor a patient's vital signs). Doctors experience medical uncertainty because medicine is inherently uncertain, and it is hard to fully master medical knowledge and skills (Fox

1957; Timmermans and Angell 2001; Gerrity et al. 1992). On the other hand, uncertainty due to a new environment can be resolved relatively quickly. New doctors should adapt to new hospitals regardless of their depth of medical knowledge and experience levels, because each hospital is unique, and new doctors are more familiar with the specific tasks and roles that they performed at their previous hospitals. Several studies have pointed out that even highly experienced doctors can encounter uncertainty about their roles and tasks in a new environment due to lack of adequate supports and guidelines (Gerrity et al. 1992; Brown, Chapman, and Graham 2007; Bowen 1998). Also, although organizations attempt to provide appropriate support and guidelines, new doctors often perceive a lack of information relevant to them (Jablin 1984; Miller and Jablin 1991). Thus, new doctors seek to resolve unmet needs from social sources through interpersonal and feedback processes and interaction (Miller and Jablin 1991; Katz 1980). In hospitals, unmet needs for information for new doctors may include technological skills, because hospitals often do not consider technology training as a high priority for new doctors. Thus, new doctors often seek information on m-EHR from their social sources. However, their dependency on social sources will decrease over time as they gain the needed information about their roles and tasks (Morrison 1993; Miller and Jablin 1991).

Hypothesis Development

Based on the social influence perspective, we expect that compliance-based influence will be relatively small because the use of m-EHR is not mandatory and not considered a part of evaluation. Even if there is implicit pressure to use m-EHR, overwhelmed new doctors may not have the mental capacity to consider this implicit norm during the initial stage of the organizational socialization process. On the other hand, we expect that the effect of identification and internalization will be strong, particularly during the initial stage of the organizational socialization process. Confronting high uncertainty during the initial stage of organizational socialization, new members tend to seek information to reduce uncertainty by relying on their social sources (Miller and Jablin 1991; Morrison 1993; Berger and Calabrese 1975). One way to reduce uncertainty is simply to mimic others' behavior. This identification mechanism may lead new doctors to increase the use of m-EHR if their coworkers extensively use m-EHR. Another way for new doctors to reduce uncertainty is to make their working environment predictable, understandable, and controllable (Saks and Ashforth 1997; Berger and Calabrese 1975; Bauer et al. 2007). In this regard, a new doctor may consider m-EHR as a tool to reduce uncertainty about new roles and tasks during the early phase. However, high motivation to use a new technology is a necessary but not sufficient condition for actual use. Being aware of the benefits of a new technology, a doctor may be motivated to use the technology but cannot, simply because he or she does not know how to use it effectively in the actual working environment (Wang, Meister, and Gray 2013). Therefore, a new member who is surrounded by coworkers who extensively use m-EHR is likely to have more opportunities to learn from his or her coworkers how to use m-EHR and get practical tips and know-how.

H1: A new doctor's m-EHR use is influenced by the m-EHR use of his or her coworkers.

As new doctors spend more time in their new hospital, they master their new roles and tasks (Charles 1981; Louis 1980; Feldman 1976; Bauer et al. 2007). The decrease in uncertainty will reduce the incentive for new doctors to copy others' behavior, as they act more proactively based on their own judgment. Also, they are likely to have accumulated sufficient expertise to effectively explore the necessary functions of m-EHR (Maruping and Magni 2015). Therefore, their reliance on social sources to seek technical information about m-EHR will decrease (Berger and Calabrese 1975; Morrison 1993; Miller and Jablin 1991).

H2: The effect of coworkers' m-EHR use on a new doctor's m-EHR use decreases over time.

Next, we consider two different types of usage patterns of coworkers. Some doctors may explore and use various features of m-EHR. We refer to this as general usage. On the other hand, other doctors may use only a few features of m-EHR, but use them extensively. We refer to this as function-specific usage. In a patient care setting, a patient is treated by doctors with different expertise, and each doctor performs a specific role depending on his or her expertise and affiliated department (Pratt, Rockmann, and Kaufmann 2006; Zerubavel 1979). For example, a cancer patient is typically treated by a team of surgeons, oncologists, and anesthetists. In this regard, doctors who show function-specific usage patterns may have expertise on specific features of m-EHR that can be irrelevant to a new doctor in understanding and performing his or her new roles and tasks (Maruping and Magni 2015). On the other hand, if coworkers show general usage patterns, it is more likely that at least some features may be relevant to new members. The more often new members are exposed to the relevant features of m-EHR by coworkers, the more they will increase their use of m-EHR.

H3: Doctors with general usage patterns have greater influence on the usage of m-EHR for new members than doctors with function-specific usage.

Social influences may operate differently based on the hierarchical power relationship between new doctors and existing doctors. Wang, Meister, and Gray (2013) investigate different social influences of superiors, peers, and subordinates in the context of knowledge management system (KMS) use in consulting firms. We expect that similar arguments can apply to the use of m-EHR in hospitals, with a few notable differences.

First, we hypothesize that the effect of higher-ranking doctors on the m-EHR use of a new doctor is strong, based on the prior IS research that has shown that an individual's IS use is significantly influenced by higher-ranking members in the same organization (Wang, Meister, and Gray 2013; Venkatesh, Zhang, and Sykes 2011; Kane and Labianca 2011). First, higher-ranking members are important sources of information for newcomers (Morrison 1993), and thus their positive view on a new system can lead lower-ranking members to shape a positive belief (i.e., internalization) (Wang, Meister, and Gray 2013). Second, while m-EHR use is not mandatory, extensive use of m-EHR by an evaluator may exert unintended, implicit pressure on new doctors. Higher-ranking doctors are often in the position to directly and/or indirectly evaluate the performance of doctors, and the desire to get a better evaluation motivates one's behavior to conform to the evaluator's expectations (i.e., compliance) (Magee and Galinsky 2008). Third, one's desire to get a sense of belonging to a group forces him or her to assimilate and behave according to the existing group's common goals and beliefs, which are often shaped by higher-ranking members (i.e., identification) (Burnkrant and Cousineau 1975). We expect that, while m-EHR use is not mandatory and not part of evaluation, the compliance and identification effects can still be strong in hospitals, professional organizations that are explicitly institutionalized in a hierarchical structure, and where power is exercised in a top-down way (Diefenbach and Sillince 2011; Magee and Galinsky 2008; Ackroyd and Muzio 2007). Under these circumstances, social influence on lower-ranking members' behaviors to conform to higher-ranking members' expectations is very strong (Magee and Galinsky 2008). For these reasons, the use of m-EHR by higher-ranking members will encourage new doctors to explore m-EHR.

In addition, we hypothesize that this effect strengthens as the new member's socialization process proceeds. Prior literature suggests that compliance- and identification-based influence require that group members undergo socialization, because these influences operate well when members trust one another (Deutsch and Gerard 1955). Thus, the effect of social influence on new doctors is relatively weaker at first, but grows as they gain trust in existing doctors.

H4A: **The influence of higher-ranking doctors on m-EHR use of new doctors is statistically significant.**

H4B: The influence of higher-ranking doctors increases over time.

New doctors seek technical information that can help them perform their tasks more effectively (Bandura 1969; Morrison 1993). They are likely to learn this type of information from their peers who are in a similar rank, because similar-ranking doctors share many common aspects in terms of expertise and experience (Morrison 1993; Comer 1991). Because of the similarities, new doctors are likely to consider information from similar-ranking doctors more useful and trustable, reinforcing the internalization effect (Moschis 1976). We also expect a strong identification-based influence of similar-ranking doctors, because one tends to compare him- or herself with similar others (Jaccard, Blanton, and Dodge 2005).

We expect that the influence of similar-ranking doctors on a new doctor will increase as the new doctor resolves initial uncertainties and adapts to the new hospital. Over time, new doctors tend to spend more time with similar-ranking doctors, as they become familiar with new environment and build personal bonds with similar others. Therefore, we expect these informal relationships with similar-ranking coworkers to reinforce the identification- as well as internalization-based influences discussed above (Jenkins 2000), increasing the magnitude of these influences.

H5A: The influence of similar-ranking doctors on m-EHR use of new doctors is statistically significant.

H5B: The influence of similar-ranking doctors increases over time.

It is unlikely that compliance-based or identification-based influence is exerted from lower-ranking doctors because of the nature of the hierarchical structure in hospitals. However, internalization-based influences can still be effective. To resolve high uncertainty during the earlier phase of the socialization process, new doctors may extend information sources to lower-ranking doctors who have more experience with the hospital. With medical knowledge, doctors are reluctant to ask lower-ranking doctors for advice and information because medical knowledge represents hierarchical power (Diefenbach and Sillince 2011; Magee and Galinsky 2008; Ackroyd and Muzio 2007). Technical knowledge, however, such as how to use m-EHR systems, is not related to hierarchical power or authority. In fact, a lower-ranking doctor's use of m-EHR can encourage a higher-ranking doctor's use by increasing the awareness of benefits and shaping a good image of the technology (Wang, Meister, and Gray 2013). However, we expect that this internalization-based influence will decrease over time, as new doctors become familiar with m-EHR and are able to make their own judgment. Moreover, their reliance on lower-ranking doctors as information sources will decrease, as their peers (i.e., similar-ranking doctors with similar medical experience and knowledge) can replace their roles, as discussed earlier.

H6A: The influence of lower-ranking doctors on a new doctor's m-EHR use is statistically significant.

H6B: The influence of lower-ranking doctors decreases over time.

Empirical Design

Data

Our research site is the largest hospital in South Korea. This hospital provides an ideal environment for testing social influence on new doctors' m-EHR usage mainly for two reasons. First, the size of the hospital is large enough that there is an ample number of new doctors. Second, the hospital introduced m-EHR in 2010, so existing doctors have accumulated sufficient knowledge and established group norms about the m-EHR application.

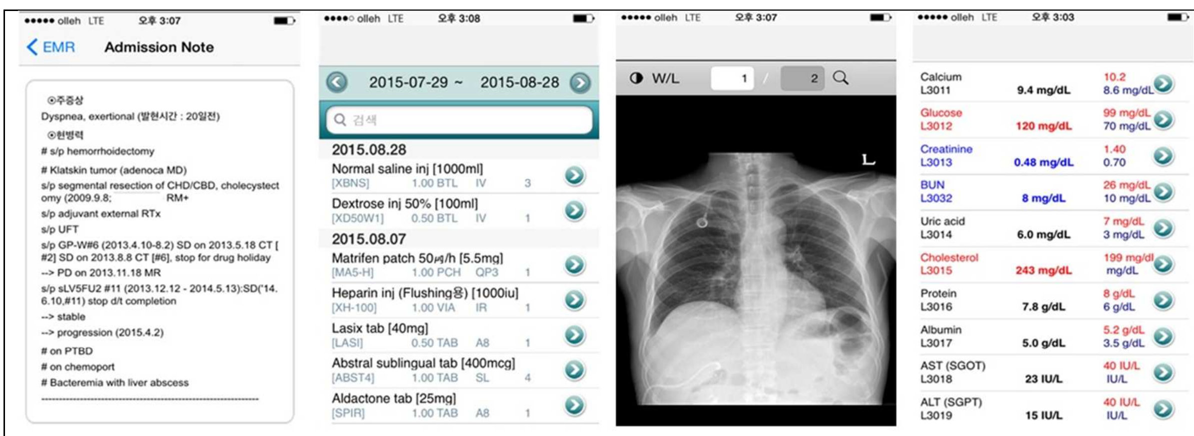


Figure 1. Snapshot of mAMIS

We collected reported usage logs of a mobile-based application, "mAMIS" (see Figure 1), which is used by medical staff members (e.g., doctors, nurses, administrators). mAMIS does not have features that allow medical staff to record patients' history or medicine orders. Rather, medical staff use this application for browsing and searching information on inpatients for fourteen functions, including medicine order history, medical test results, Picture Archiving and Communication System (PACS), medical dictionary, and diagnostic results. Doctors often preset the patients for whom they will receive information via m-EHR using PC-based EHR systems due to the limited search capability and screen size of m-EHR. It allows doctors to easily browse information for their own patients.

Following our theoretical framework, we focused on the 156 new doctors—45 interns, 26 residents, 81 fellow doctors, and 4 attending doctors (i.e., professors)—who joined the hospital in February 2015. We analyzed their log data that were reported during the eleven-month period from February 2015 to December 2015, based on the assumption that this is a typical length of time for a new member to settle down in a new organization (Louis 1980). The total number of observations is 80,159. To examine the social influence of existing doctors, we also collected log data of 581 existing doctors during the same period. The number of logs they reported is 515,755.

To match a doctor to coworkers, we took a finer granular approach than the one in the prior studies that defined coworkers as members based on their position within the organizational structure—for example, doctors in the same working groups (Wang, Meister, and Gray 2013). In hospitals, doctors often work with experts with different specialties, although they are affiliated with a different department (Zerubavel 1979). For instance, as mentioned before, the team treating a cancer patient includes surgeons, oncologists, and anesthetists. Also, trainee doctors learn diverse knowledge from medical experts in different fields by rotating departments every three months. Thus, we match doctors who care for at least one common patient by using the patient identification key. For instance, if a resident doctor requests information on a patient numbered 0001 in the m-EHR and an attending doctor requests information on the same patient, we considered these doctors to be coworkers for the purposes of this study.

Measurement

	Variable	Description
Dependent variable	USAGE	Log-transformed count of monthly logs of a new doctor
Explanatory variables	SOCIAL	Log-transformed average count of monthly logs of the doctors who were seeing the same patients
	GEN	Log-transformed average count of monthly logs of the doctors who were seeing the same patients and in the general usage group
	FUN	Log-transformed average count of monthly logs of the doctors who were seeing the same patient and in the functional-specific user group
	HIGHER	Log-transformed average count of monthly logs of the doctors who were seeing the same patient and in the higher ranks in the hierarchy
	SIMILAR	Log-transformed average count of monthly logs of the doctors who were seeing the same patient and in the same rank in the hierarchy
	LOWER	Log-transformed average count of monthly logs of the doctors who were seeing the same patient and in lower ranks in the hierarchy
	TIME	The number of months since March (i.e., 1 to 10)
Clustering analysis	N_FUN	Normalized number of functions used during a given month
	CONCENT	The Herfindahl index indicating the usage concentration in specific functions ($\sum_{i=1}^{14} C_i^2$) (i = menu, C = the number of logs in menu$_i$ / the total number of logs)

Table 1. Description of Variables

For our dependent variable, we constructed a variable USAGE to represent the use of m-EHR, determined by counting the number of logs a doctor makes through m-EHR in each month, an approach consistent with prior research (Wang, Meister, and Gray 2013). To construct the independent variables that represent social influences of coworkers, we used coworkers' actual usage, based on the assumption that a referent other's usage represents his or her attitudes toward and beliefs about the application (Malhotra and Galletta 2005; Wang, Meister, and Gray 2013).

We categorized coworkers' usage patterns into general usage and function-specific usage. To measure the degree of specific usage (or the degree of general usage) of m-EHR, we considered two factors—the breadth (N_FUN) and concentration (CONCENT) of usage. The breadth of usage refers to the number of functions explored by a doctor in a month. Its value ranges between 1 and 14, because the application has 14 menus. This measure captures the variety of functions used by doctors, but does not account for the variances in the amount of usage of each function. Thus, we supplemented the measure of usage patterns with the usage concentration. Usage concentration is often conceptualized as the degree of how a set of certain contents is regularly utilized among various choices (Jung, Kim, and Chan-Olmsted 2014). We followed this approach and operationalized it by employing the Herfindahl index, which has been widely used in IS research as a measure of concentration (Yim 2003; Picard 1988). The value of this index ranges between 0 and 1, and a higher value indicates a high concentration level. The index is calculated using the number of logs a doctor made in each function ($\sum_{i=1}^{14} C_i^2$) (i = menu, C = the number of logs in menu_i / the total number of logs).

To categorize doctors into two groups, we employed a K-means clustering algorithm (Hartigan and Wong 1979), which clusters data into homogeneous subgroups by making each observation belong to the cluster with the smallest intra-cluster distance and the largest inter-cluster distance. We normalized the scales of N_FUN to prevent potential bias due to different scales between N_FUN and CONCENT (Shmueli, Patel, and Bruce 2010). The clustering analysis result reveals the usage pattern of each doctor in each month—either general usage or function-specific usage. Then, we calculated the average count of monthly logs of the coworkers (i.e., the existing doctors who were seeing the same patient as a new doctor in a given month) in the general user group (GEN) and in the function-specific user group (FUN).

We also constructed three variables to represent m-EHR use by doctors of different hierarchical ranks. We categorized coworkers into three subgroups—higher-ranking, similar-ranking, and lower-ranking for each new doctor. We define higher-ranking doctors of a new doctor as those who care for the same patients as the new doctor and are in higher ranks. For instance, for a new doctor at the rank of fellow, attending doctors who were seeing the same patient as him or her were considered higher-ranking coworkers. Likewise, for a new doctor at the rank of resident, fellow and attending doctors who were seeing the same patient as her were categorized as higher-ranking coworkers. We calculated the average log count of m-EHR use by higher-ranking coworkers to construct the variable HIGHER. We use similar approaches to construct the other two variables, SIMILAR and LOWER. For a doctor at the rank of fellow, similar-ranking coworkers would be other fellow doctors, and lower-ranking doctors would be resident and intern doctors, given that they are seeing the same patients. We calculated the average log count of m-EHR use by similar-ranking and lower-ranking doctors, using the variables SIMILAR and LOWER, respectively.

To indicate a new doctor's progression in regard to organizational socialization, we use the number of months since the new doctor joined the hospital and denote it as TIME.

Model

To test our hypotheses, we employed a fixed-effect panel regression model to control for the individual and organizational (i.e., department) heterogeneity, which is controlled in individual intercept terms in the fixed-effect model (Hill, Griffiths, and Lim 2011). We use the Driscoll and Kraay robustness standard error to estimate our fixed effect model (Driscoll and Kraay 1998).

Our model specification is designed as follows. We examine a doctor's m-EHR usage, $\text{USAGE}_{it,}$ as a function of his or her coworkers' average usage (GEN, FUN, HIGHER, SIMILAR, LOWER) in various forms along with the progression of organizational socialization (TIME). We also included a lag variable of USAGE, USAGE_{it-1}, which is a doctor's m-EHR usage in the previous month, following prior research

(Wang, Meister, and Gray 2013). In addition, we include the interaction terms between coworkers' average usage and TIME.

$$Usage_{\,it} = \beta_1 Usage_{it-1} + \beta_2 Soc_{it} + \beta_{14} Time_{it} + \sum Individual_i + e_{it}$$

$$Usage_{\,it} = \beta_1 Usage_{it-1} + \beta_2 Soc_{it} + \beta_5 Soc_{it} * Time_{it} + \beta_{14} Time_{it} + \sum Individual_i + e_{it}$$

$$Usage_{\,it} = \beta_1 Usage_{it-1} + \beta_3 Gen_{it} + \beta_4 Fun_{it} + \beta_{14} Time_{it} + \sum Individual_i + e_{it}$$

$$Usage_{\,it} = \beta_1 Usage_{it-1} + \beta_3 Gen_{it} + \beta_4 Fun_{it} + \beta_6 Gen_{it} * Time_{it} + \beta_7 Fun_{it} * Time_{it} + \beta_{14} Time_{it} + \sum Individual_i + e_{it}$$

$$Usage_{\,it} = \beta_1 Usage_{it-1} + \beta_8 High_{it} + \beta_9 Similar_{it} + \beta_{10} Low_{it} + \beta_{11} High_{it} * Time_{it} + \beta_{12} Similar_{it} * Time_{it} + \beta_{13} Lower_{it} * Time_{it} + \beta_{14} Time_{it} + \sum Individual_i + e_{it}$$

Results

Data Description

Table 3 provides descriptive statistics of our data. Among a total of 737 doctors, 156 doctors are newcomers. Most doctors spend a year completing their internship in South Korea, so 100% of intern doctors are newcomers. The average usage is the highest among resident doctors, followed by professors and fellows. The usage level is lowest among interns. This low usage level may be attributed to the fact that all interns are newcomers.

	Number of doctors	Newcomers (%)	Mean of usage count(SD)	Mean of age(SD)	% of males
Interns	45	45 (100%)	172.6 (332.43)	28.22 (2.25)	44.44%
Residents	272	26 (27.9%)	968.6 (2095.281)	30.46 (2.68)	50%
Fellows	174	81 (46.6%)	773.0 (1183.85)	34.57 (2.15)	60.34%
Professors	246	4 (1.6%)	773.1 (1573.72)	47.52 (8.52)	80.08%
Total	737	156 (28.0%)	808.6 (1676.86)	36.99 (9.33)	62.41%

Table 2. Descriptive Statistics

Clustering Analysis: General vs. Function-Specific Users

Table 3 shows the results of clustering analysis and descriptive statistics of the two variables used for the analysis, N_FUN and CONCENT. Among 737 doctors in our sample, some did not use m-EHR at all in certain months, so we have a total of 4,631 observations of 737 doctors for 10 months. Using a k-mean clustering algorithm, we categorized each doctor's usage pattern in every month into two clusters. We refer to the cluster with the higher mean of CONCENT and the lower mean of N_FUN as the function-specific usage, while the other is referred to as the general usage. Out of 4,631 observations, 3,522 observations are classified into the general-usage category, and 1,109 observations are classified as function-specific usage. The t-test result shows that the difference between the two groups is statistically significant at the 1% level.

	No. Observations	Mean (CONCENT)	Mean (N_FUN)
Total	4,631	0.3375	0.4774
General usage	3,405	0.240	0.595
Function-specific usage	1,226	0.608	0.152
t-test[1,2]	-	-53.285***	100.64***

1. The t-test results are for the null hypothesis H_0: Mean of general users = Mean of function-specific users.
2. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3. The results of K-means clustering

Summary Statistics

We constructed the variables described in the previous section, and our final sample for the panel regression analysis consists of 765 observations of 156 new doctors who joined the hospital in 2015. Table 4 provides the summary statistics of key variables.

			Correlation Matrix						
Variable	Mean	Std.d	(1)	(2)	(3)	(4)	(5)	(6)	(7)
USAGE(1)	3.746	1.431	1						
GEN(2)	3.699	2.982	0.615	1					
FUN(3)	3.707	2.914	0.406	0.287	1				
HIGH(4)	0.534	1.291	0.567	0.770	0.316	1			
SIMILAR(5)	2.851	2.793	0.462	0.420	0.360	0.378	1		
LOW(6)	1.304	2.315	0.464	0.617	0.245	0.314	0.303	1	
TIME(7)	2.218	2.99	0.092	0.086	0.028	0.079	0.084	0.071	1

Table 4. Summary Statistics and Correlation Matrix of Key Variables

Fixed-Effect Panel Regression Results

Table 5 provides the fixed-effect panel regression results.

In Model I, the coefficient of the main variable, SOCIAL, is positive and statistically significant at the 1% significance level. A 1% increase in the average use of m-EHR by coworkers is associated with a 0.232% increase in a new doctor's m-EHR use. It supports our Hypothesis 1, which suggests that a new doctor's m-EHR use is influenced by the m-EHR use of his or her coworkers.

In Model II, we examine whether the effect of social influences changes over time. The LR test result comparing Model I and Model II shows that the inclusion of the time effect significantly improves the model fit at the 5% significance level. The coefficients of both main variables, SOCIAL and TIME, and the interaction term, SOCIAL × TIME, are statistically significant at the 5% significance level, supporting Hypothesis 2. The coefficient of the interaction term indicates that one additional month in the new hospital decreases the effect of SOCIAL by 0.009. For example, while a 1% increase in the average use of m-EHR by coworkers is associated with a 0.268% increase in a new doctor's use of m-EHR in the first month (TIME = 1), the effect decreases to 0.187% in the tenth month (TIME = 10). Figure 2(a) shows the effects of SOCIAL as a function of TIME.

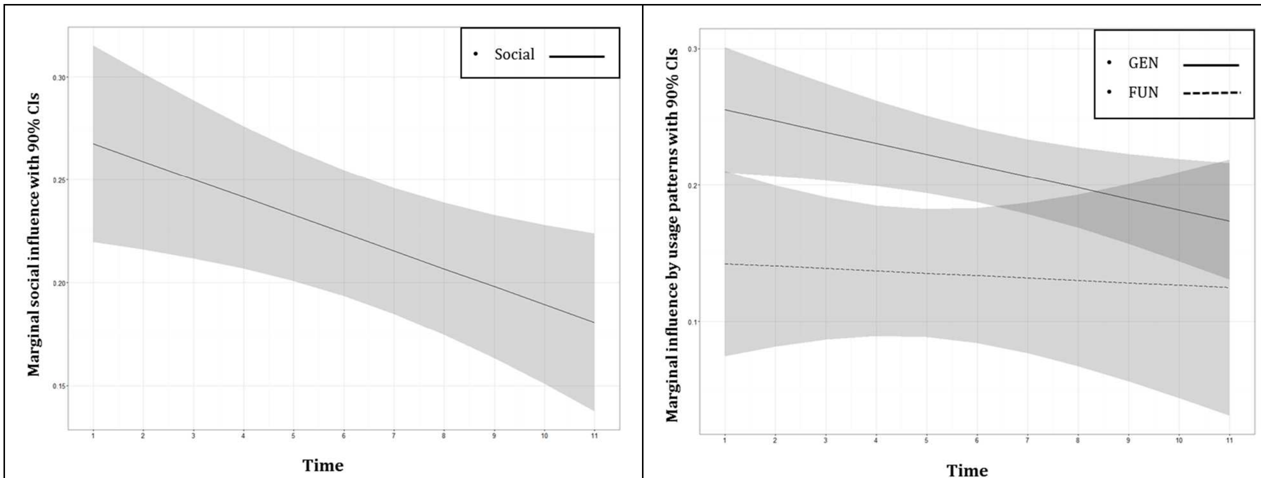
In Model III, we examine the effect of coworkers by their usage patterns. The LR test of comparing Model I and Model III supports the differences of effects between two groups; general vs. function-specific patterns (p-value < 0.001). The coefficients of two main variables, GEN and FUN, are statistically significant at the 1% significance level. A 1% increase in m-EHR use by general users and function-specific users is associated with increases of 0.221% and 0.138% in new doctors' use of m-EHR, respectively. The T-test result indicates that the coefficient of GEN is statistically greater than the one of FUN at the 1% significance level (T = 2.28, p-value < 0.05). This result is consistent with Hypothesis 3, showing that the influence by general users on the m-EHR use of new doctors is greater than the one by function-specific users.

Model IV examines whether the decrease in social influence over time varies by the usage patterns of coworkers. The effects of all main variables hold their statistical significance at the 1% significance level. The coefficient of the interaction term, GEN × TIME, is negative and statistically significant at the 10% level. This result indicates that one additional month in the new hospital decreases the effect of GEN by 0.008. For example, while a 1% increase in the average use of m-EHR by general users is associated with a 0.255% increase in new doctors' use of m-EHR in the first month (TIME = 1), the effect decreases to 0.183% in the tenth month (TIME = 10). On the other hand, the coefficient of FUN × TIME is not statistically significant. Figure 2(b) shows the changes of the effects of GEN and FUN as a function of TIME. We observe that the difference between GEN and FUN decreases over time, and after seven months, the difference becomes statistically insignificant.

Dependent variables: User's usage count during a month					
Variables	Model I	Model II	Model III	Model IV	Model V
SOCIAL	0.232 *** (0.022)	0.277 *** (0.032)			
GEN			0.221 *** (0.019)	0.263 *** (0.031)	
FUN			0.138 *** (0.031)	0.144 *** (0.047)	
SOCIAL * TIME		-0.009 ** (0.004)			
GEN * TIME				-0.008 * (0.004)	
FUN * TIME				-0.002 (0.008)	
HIGH					0.163 *** (0.013)
SIMILAR					0.067 ** (0.034)
LOW					0.128 *** (0.032)
HIGH × TIME					0.001 (0.003)
SIMILAR × TIME					0.005 (0.004)
LOW × TIME					-0.006 (0.004)
P_USAGE	0.043 (0.030)	0.040 (0.029)	0.039 (0.029)	0.036 (0.027)	0.025 (0.024)
TIME	-0.007 (0.015)	0.026 (0.024)	-0.005 (0.014)	0.026 (0.022)	-0.010 (0.013)
Adj. R^2	0.234	0.237	0.247	0.250	0.243
F-statistic	84.89 ***	64.80 ***	68.88 ***	55.17 ***	33.69 ***
N_obs.	765	765	765	765	765
N_doctors	156	156	156	156	156
All variables are log transformed except the TIME variable. Fixed-effect panel regression results. Robust standard errors are in parentheses. * significant at <10%; ** significant at <5%; *** significant at <1%					

Table 5. Summary Statistics and Correlation Matrix

Model V tests whether the effects of social influences vary by the hierarchical rankings of coworkers (Hypotheses 4A, 5A, and 6A). It also shows whether these influences change over time. The effects of both higher- and lower-ranking doctors are statistically significant at the 1% significance level, and the effect of similar-ranking doctors is statistically significant at the 5% significance level. A 1% increase in the m-EHR use by higher-, similar-, and lower-ranking doctors is associated with increases of 0.163%, 0.067%, and 0.128%, respectively, in new doctors' m-EHR use. However, the coefficients of all interaction terms are statistically insignificant, failing to support Hypotheses 4B, 5B, and 6B.



(a) (b)

Figure 2. Graphs for Interaction Effects

Discussion

Our study provides several important findings that support our hypotheses. First, Hypotheses 1 and 2 are supported by our results that provide evidence that there exist strong social influences by coworkers on a new doctor's m-EHR usage during his or her adjustment process to a new organization. The results also provide evidence that the effect of social influence on a new doctor's m-EHR use decreases over time. The decrease in the magnitude of social influences is noteworthy. Prior studies, focusing on compliance- or identification-based social influences, have argued that social influences are stronger when a user has built social relationships with and holds shared trust with referent others (Deutsch and Gerard 1955; Burnkrant and Cousineau 1975). This argument suggests that social influences may increase over time for a new doctor as he or she goes through the organizational socialization process. However, our results imply that compliance- or identification-based social influences are not dominant mechanisms for the use of m-EHR, suggesting strong internalization-based influences because the use of m-EHR is voluntary.

Hypothesis 3 is also supported. The results show that, during the early stage of the organizational socialization process, coworkers who use m-EHR for general purposes have stronger influences on new doctors' use of m-EHR than coworkers who use m-EHR for specific functions. As discussed earlier, some specific functions of m-EHR might be irrelevant to new doctors, so the influence of function-specific users might vary by the relevance of the functions to new doctors. It is also worth noting that the difference between the influences by general users and the ones by function-specific users decreases over time. This might indicate that as new doctors become familiar with an m-EHR system, they no longer need to rely on coworkers to learn general features of m-EHR.

Hypotheses 4A, 5A, and 6A are supported. Our results show a strong influence by higher-ranking doctors on new doctors' use of m-EHR. This contrasts with the result reported by Wang, Meister, and Gray (2013), who failed to find a significant effect of higher-ranking employees on the use of knowledge management systems (KMS) by lower-ranking employees in a consulting firm. They suspected that the lack of physical proximity led to a lack of social influence by higher-ranking employees. In hospitals, the apprentice-based relationship between higher- and lower-ranking doctors is very strong, and they work closely together in physical proximity (Diefenbach and Sillince 2011). We believe that this vertical working structure in patient care practice contributes to our findings that support Hypothesis 4A.

Hypothesis 5A is also supported. We note that existing doctors in a similar rank as new doctors had relatively less influence on new doctors than both higher- and lower-ranking doctors. It might be because most new doctors are first-year resident doctors or first-year fellow doctors, and thus most similar-ranking doctors who are new doctors are also relatively new to the hospital. Therefore, new doctors in the earlier period of the adjustment process may not seek information from similar-ranking doctors who are also new to the m-EHR of the hospital. In addition, the apprentice-based working structure between higher- and lower-ranking doctors may contribute to their relatively greater influence on new doctors, because new doctors have less chance to interact with similar-ranking doctors.

Our result also supports Hypothesis 6A, which suggests the influences of lower-ranking doctors. The influences of lower-ranking members have been widely overlooked by prior research. Our study provides additional evidence for the argument raised by Wang, Meister, and Gray (2013) that show that lower-ranking organizational members can exert influences over their superiors through an internalization-based mechanism. Our finding is notable in that hospitals are regarded as an environment where hierarchical pressure is strong. We suspect that the fact that m-EHR use is voluntary is the main driver behind the social influences of lower-ranking doctors. Otherwise, concerns over losing authority might prevent new doctors from asking lower-ranking doctors about m-EHR, thus reducing the magnitude of the influences of the lower-ranking doctors.

However, we could not find any evidence that additional time in the new hospital increases or decreases the effect of any hierarchical group on the m-EHR use of new doctors, failing to support Hypotheses 4B, 5B, and 6B. This result may be due to the fact that both compliance- and identification-based influences are weak on the m-EHR use of new doctors. If compliance and identification were the underlying mechanisms for the social influence from other groups, we would have observed the increase in the influences over time, because these influences get stronger when members share established norms and trust (Deutsch and Gerard 1955). Therefore, failing to observe the increasing trend might serve as additional evidence that internalization-based mechanisms are the main driver behind the social influences of m-EHR use.

Our study is not free from limitations, which provide several opportunities for future research. First, our dataset may be subject to selection bias. Although the doctors in the hospital where we conducted our research are technically mobile-savvy, only about 60% of doctors in this hospital are using m-EHR. Because our original sample consisted of doctors who already adopted m-EHR, about 40% of the doctors were dropped from the sample. For future research, we are in the process of collecting additional data about the rest of the doctors in this hospital. We plan to analyze the factors that lead to volitional adoption of m-EHR, and determine whether there is a self-selection effect in social influences on m-EHR use. Second, we identified coworkers based on the common patient ID's of the information that doctors requested via m-EHR. Therefore, we were not able to identify coworkers who do not use m-EHR at all. We might have utilized the data from EMR, which is used by all doctors in the hospital, but the EMR log data were not available to us. Also, doctors may not have direct face-to-face interactions with each other, even though they are treating the same patient. This possibility may weaken our argument about social influences. Third, social influence is a multidimensional concept that can be operationalized in many different ways. Other approaches, such as a survey, may have allowed us to directly measure several dimensions of social influences and address our research question more directly. However, we did not directly measure the social influences and instead examined the effects of coworkers' usage, assuming that a doctor's usage represents his or her influence. While our approach allowed us to construct a panel dataset from an ample number of doctors, which would have been very challenging with a survey approach, we acknowledge the limitation of this approach. We plan to collect supplementary qualitative data through interviews to get more insights about our results. Fourth, we did not consider the possibility that higher-ranking doctors may let lower-ranking doctors search information on their behalf.[1] For instance, a professor may order a resident doctor to search the records for information on a specific patient during his or her rounds. Though our discussion with doctors in our research site indicates that the frequency of this occurrence is not high, it is plausible. Thus, we acknowledge this as a potential limitation of our study. Last, we simplified the hierarchical structure among doctors, categorizing coworkers into higher-ranking, similar-ranking, and lower-ranking doctors. However, the influences of other groups of different hierarchical rankings may be different by hierarchical distances. For example, the influences on intern doctors can be greater by attending doctors than by fellow doctors.

Despite these limitations, our study contributes to IS literature in several ways. First, our study is the first to apply the social influence theory to examine new employees' IS use. Our study builds on recent studies that provide theoretical discussion on the various potential mechanisms of social influences on the use of IS. By focusing on doctors who are new to a hospital, we show the changing dynamics of social influences over time, extending our current knowledge in this domain. Second, our findings also suggest that social influences work differently by the characteristics of IS of interest (i.e., mandatory vs. volitional), by the referent others' usage pattern (general vs. function-specific) and hierarchical rankings (higher-ranking, similar-ranking, lower-ranking), and/or the types of organization and work practices.

From a practical standpoint, our study provides several managerial guidelines for designing technical training programs to promote the use of new technologies in hospitals, especially the technologies of which use is not mandatory. As a volitional IS system, such as m-EHR, is usually considered a supplementary tool, hospitals may not put much effort in providing sufficient formal training for the system for new doctors. Our study suggests that social interactions with other doctors can be a good alternative informational source for new doctors to learn about m-EHR. In this regard, besides formal training, encouraging new doctors to spend sufficient time in informal interaction, discussion, and knowledge sharing with existing doctors about m-EHR might be an effective way to facilitate the use of m-EHR. Our result also advocates the importance of training key users, a strategy that has been recommended by prior research (Kane and Alavi 2008). These practical implications of our study might be useful for other professional organizations as well, where providing formal technical training is challenging due to busy schedules and high employee turnover rates.

[1] We thank an anonymous reviewer for pointing this out.

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