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"Doctors Do Too Little Technology": A Longitudinal Field Study of an Electronic Healthcare System Implementation

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With the strong ongoing push toward investment in and deployment of electronic healthcare (e-healthcare) systems, understanding the factors that drive the use of such systems and the consequences of using such systems is of scientific and practical significance. Elaborate training in new e-healthcare systems is not a luxury that is typically available to healthcare professionals—i.e., doctors, paraprofessionals (e.g., nurses) and administrative personnel—because of the 24×7 nature and criticality of operations of healthcare organizations, especially hospitals, thus making peer interactions and support a key driver of or barrier to such e-healthcare system use. Against this backdrop, using social networks as a theoretical lens, this paper presents a nomological network related to e-healthcare system use. A longitudinal study of an e-healthcare system implementation, with data gathered from doctors, paraprofessionals, administrative personnel, patients, and usage logs lent support to the hypotheses that: (1) ingroup and outgroup ties to doctors negatively affect use in all user groups; (2) ingroup and outgroup ties to paraprofessionals and administrative personnel positively affect use in both those groups, but have no effect on doctors' use; and (3) use contributes positively to patient satisfaction mediated by healthcare quality variables—i.e., technical quality, communication, interpersonal interactions, and time spent. This work contributes to the theory and practice related to the success of e-healthcare system use in particular, and information systems in general.

Key words: IT diffusion and adoption; healthcare and IT
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Introduction

> "We perform assessments on all new residents when they enter the facility. Although we will get their hospital orders at that time, currently, it takes 24 to 48 hours to get the patient's [complete] records. This is a fragile, medically compromised patient population that would benefit most from electronically linked information networks," said Patricia Kolling, chief compliance officer at BEI, one of the largest nursing home chains in the U.S.

The cost of health care is about a fifth of the U.S. GDP and close to that for OECD countries (PricewaterhouseCoopers 2005) and is on the rise. Electronic healthcare (e-healthcare) systems have been touted as a key solution to several problems that plague the healthcare industry, with enormous benefits expected for all parties in the healthcare industry—ranging from hospitals to suppliers to patients (PricewaterhouseCoopers 1999, 2005). The implementation of e-healthcare systems is expected to reduce costs and errors and seamlessly integrate patient data, thus providing better health care at a lower cost (PricewaterhouseCoopers 1999, 2005). The U.S. government, for instance, aims to make all medical records electronic and standardized by 2014, thus creating enormous pressure to implement e-healthcare systems rapidly. In the United States, $77 billion could be saved annually by properly implementing and adopting e-healthcare systems (Hillestad et al. 2005). A key barrier to success of such systems is the availability of adequate training and support (PricewaterhouseCoopers 1999). Typically, e-healthcare systems are inflicted on healthcare professionals with little or no training or process change support, thus resulting in adoption taking much longer than expected and benefits not being realized for a long time (PricewaterhouseCoopers 1999, 2005). In light of this, it is estimated that only between a fourth or a third of all doctors use technology solutions available to them, and less than 5% use all the powerful features available in these solutions. Most physicians often rely on paper records that are frequently incorrect or outdated (e.g., O'Brien 2008). Even in healthcare organizations that have successfully deployed healthcare systems, it is often the case that caregivers and administrative personnel frequently do not use the system as intended—i.e., at the time of interaction with the patient—instead, data are entered into the system at a later time. This greatly undermines the benefits of the system at the point of care and major touchpoints with patients. In sum, there is an underutilization and/or abandonment of e-healthcare systems. Thus, understanding the factors influencing success of e-healthcare systems is of great practical significance.

IS researchers have long studied technology in health care, with much of the emphasis being at the macrolevel, ranging from policy issues and challenges (e.g., Currie and Guah 2007) to challenges in small physician practices (e.g., Reardon and Davidson 2007) to firm-level outcomes, such as profitability (e.g., Devaraj and Kohli 2000) and compliance to standards (e.g., Davidson and Chiasson 2005), to quality of care at the level of the hospital (e.g., Devaraj and Kohli 2000) and the group (e.g., Kane and Alavi 2008). Some research at the individual level has found that doctors have typically not embraced e-healthcare systems and preferred to use paper records (e.g., Anderson 1997, O'Brien 2008). This is important because firm-level benefits are ultimately garnered when individuals in critical roles in healthcare organizations embrace and use implemented systems and, if such individual use occurs, contributes to positive outcomes. More recent work has focused on the design of healthcare systems (e.g., Johnson et al. 2008) and their impacts on various aspects of quality of care (e.g., Matheny et al. 2007). There has also been work on user acceptance and usability (e.g., Klein 2007), a topic that has been researched extensively in the broader IS context as well (see Venkatesh et al. 2007). Despite the great interest in e-healthcare system implementations, a recent review suggests that the work in this area is largely atheoretical and based on retrospective accounts and data from the same source for all aspects of the model, thus rendering prior work to be somewhat limited in terms of richness and scientific rigor (see Overtveit et al. 2007). Against the backdrop of these gaps, there is a need for more theory-driven investigations of the underlying phenomenon of use and impacts of e-healthcare systems.

We use social network theory as the lens to further our understanding of e-healthcare system use and its impacts. Social network theory is particularly appropriate for reasons largely related to its focus on interpersonal interactions and their relationships to behaviors and outcomes (Borgatti and Foster 2003, Brass and Labianca 1999, Labianca and Brass 2006). First, given the critical and 24×7 nature of operations in healthcare organizations, especially hospitals, there is little or no time for traditional training (PricewaterhouseCoopers 1999, 2005), thus making interactions with peers and colleagues and learning on the job important in these organizations. Second, in most cases, the knowledge necessary to complete work activities is specialized and spread across many individuals. Third, healthcare professionals rely on each other to learn not only about medical practices, but also about technology (Davidson and Chiasson 2005). Finally, because communication is at the heart of health care, there is a need for research to examine how interactions among various groups of healthcare professionals and the consequences of such interactions (see Kaplan et al. 2007) influence outcomes of interest.

Among the different types of networks, e.g., advice, friendship, and information (Borgatti 2005), we focus on advice networks, particularly advice seeking, because during the implementation of a new e-healthcare system, healthcare professionals are more likely to seek knowledge related to the system in order to use it for work activities. The advice provided by healthcare professionals is bound by their educational backgrounds and professional cultures. Such acculturation is likely to contribute to the development of healthcare professionals' cognitive schema, which would play a significant role in affecting individuals' decision-making (see Labianca et al. 2000). Likewise, healthcare professionals who receive advice will interpret and apply such advice based on their educational backgrounds and professional cultures. Thus, we incorporate advice seeking and acculturation into our theorizing in order to better understand e-healthcare system use and its impacts.

In the quest for the ultimate dependent variable of interest, we turned to the broad literature on IS success and work on e-healthcare systems. The IS success model of DeLone and McLean (2003) has identified examples of critical metrics of success. System use is one such metric, and has been the focus of much work at the individual level studying technology implementations (see Venkatesh et al. 2003). Beyond system use, the IS success model calls for a study of net benefits and/or broader personal and organizational outcomes of interest. In the context of health care, one such metric is patient satisfaction—in fact, recent work has suggested that patient satisfaction is key because it is not only an important metric to healthcare providers in its own right but also is key to insurance companies as a consequence of quality of care (Kohli and Piontek 2007). Therefore, research explaining patient satisfaction is particularly important in the domain of health care and technology. Given the important role of system use in driving implementation outcomes, the objectives of this work are to:

(i) develop a nomological network around e-healthcare system use by doctors, paraprofessionals, and administrative personnel—specifically, we develop a model that draws from social network theory and identify predictors of e-healthcare system use, and link such system use to patient satisfaction; and

(ii) empirically validate the model in a longitudinal field study conducted in a hospital, with data gathered from healthcare professionals and patients.

This work is expected to contribute to research in several ways. First, it enriches our understanding of e-healthcare system success by linking the network position to patient satisfaction mediated by use and the proximal impacts of use, thus adding not only to individual-level work on e-healthcare system success (e.g., Klein 2007) but also complementing macrolevel work on this topic (e.g., Devaraj and Kohli 2000). Second, this work complements research on e-healthcare system success by leveraging acculturation of different groups of healthcare professionals and linking advice networks to key outcomes in the context of e-healthcare systems. Finally, this work adds to the body of knowledge related to IS success (DeLone and McLean 2003, Rai et al. 2002). Specifically, this work responds to continuing calls in prior research to extend the nomological network related to IS implementation beyond the technocentric outcomes that are typically studied in IS research (see Venkatesh et al. 2007).

Background: Social Networks

Prior social networks research suggests that network position influences behavior and performance outcomes (e.g., Borgatti and Foster 2003, Lin 2001). Lin (2001), citing four reasons grounded in social capital, namely information, influence, social credentials, and reinforcement, suggest that individuals who are more embedded in social networks are more likely to perform particular target behaviors. An individual's network position is typically conceptualized as *network centrality*, which describes how well connected an individual is within the network (Borgatti 2005). We adopt an egocentric conceptualization of advice network centrality, referring to an individual's interaction with others in an organizational unit to get advice. The greater the centrality, the more likely an individual has access to the information they need to resolve work-related problems (see Burkhardt and Brass 1990). Network centrality can drive the performance of the "appropriate" behaviors guided by access to resources, such as advice, information and knowledge, and the performance of behaviors can have positive performance impacts (Borgatti and Foster 2003, Lin 2001; for examples, see Bolino et al. 2002). Network centrality also yields benefits simply by virtue of position and topology of the network without a focal individual necessarily having to perform any behaviors (see Borgatti and Foster 2003 for a discussion). Prior research indicates that employee network centrality plays an important role in influencing access to important resources, such as advice, information, and knowledge, and applying such resources in completing one's job may greatly improve one's job performance (Brass 1984, Sparrowe et al. 2001). Taken together, the core idea is that centrality contributes positively to performance both directly and by leading to the performance of a key behavior or set of behaviors that in turn drive performance outcomes.

When seeking advice, they will be exposed to various ideas, concepts, knowledge, and views of other people that may in turn shape their own views toward, and knowledge of, the new system, making them react to the system in different ways. Thus, the extent to which they are connected to others in an advice network will play an important role in driving system-related behaviors, such as system use. Practitioner literature suggests that the use of e-healthcare systems should result in performance benefits. Drawing from social networks research, we would expect network position of users to result in direct performance benefits.

Model Development

The baseline model builds on prior social networks research that network position will foster behavior—here, e-healthcare system use—and performance—here, quality of care and patient satisfaction. Our proposed model expands on the baseline model by theorizing that ingroup ties and outgroup ties will have positive or negative effects, depending on professional group—i.e., doctors versus paraprofessionals versus administrative personnel. With regard to consequences of e-healthcare system use, we will make the case that e-healthcare system use will positively influence various quality of care metrics that will in turn positively influence overall patient satisfaction.

Construct Definitions

In the healthcare context, the distinctions across different *professional groups* are critical in the understanding of the impacts of centrality on e-healthcare system use. We organize the professionals into three categories: doctors, paraprofessionals (e.g., nurses, doctor's assistants) and administrative personnel. The first category—i.e., doctors—comprises those who have MD degrees and are the primary healthcare providers making decisions regarding patient care. Such a categorization based on possessing a medical degree is consistent with much prior work on this topic (e.g., Kane and Alavi 2008, Pratt et al. 2006). The second category—i.e., paraprofessionals—primarily consists of nurses, doctors' assistants, and technicians, and are those who are in direct or indirect care-giving support roles to doctors and hold a professional certificate/license endorsing their ability to play a support role in caregiving. The third category—i.e., administrative personnel—comprises those not involved in caregiving but who provide support activities related to care, such as billing, credit, and insurance.

We argue that individuals' centralities in different professional groups and the extent to which those individuals' networks cut across the different professional groups are related to e-healthcare system use and performance. Building on the definition of centrality, an ingroup tie is a connection to an individual who is in the same professional group, and an outgroup tie is a connection to an individual who is in a different professional group. Consequently, *ingroup centrality* is how well connected an individual is in his or her own professional group, and *outgroup centrality* is how well connected an individual is in each of the other professional groups. For instance, a doctor's connectedness to other doctors represents ingroup centrality, and a doctor's connectedness to paraprofessionals represents outgroup centrality (to paraprofessionals).

The study of system use has a rich history in IS research at the individual level (see DeLone and McLean 2003, Venkatesh et al. 2003). *E-healthcare system use* is defined as the interaction a user has with the newly installed technological system. We conceptualize use as duration, frequency, and/or intensity of use (e.g., Venkatesh et al. 2008).

Patient satisfaction is defined as the extent to which a patient, or the patient's authorized decision maker, is pleased with the overall medical care received (Hays et al. 1987, Zeithaml et al. 1990). While patient satisfaction is an important ultimate dependent variable, research in health care has noted that quality is a key determinant of satisfaction (Hays et al. 1987; Ware et al. 1976a, b, 1983; Ware and Snyder 1975). Research on *quality of care* has varied greatly and has primarily been driven by a variety of instruments that are available in practice (see American Physical Therapy Association 1995 for a collection of instruments used in a variety of hospitals). The patient satisfaction questionnaire III (e.g., Hays et al. 1987; Ware et al. 1976a, b, Ware et al. 1983), which is widely deployed in practice, is based on extensive field work. They employed a grounded theory approach to identify the core elements of quality of health care that drive overall patient satisfaction. They identify six determinants of patient satisfaction: technical quality, communication, interpersonal interactions, time spent, financial aspects, and access/availability/convenience, whose definitions are adapted from Ware et al. (1976a, b, 1983) and Hays et al. (1987). Technical quality is the patient's assessment of each healthcare professional's competence in handling specific aspects of care and administrative handling; communication is defined as the extent to which the patient perceives that he or she has received sufficient information about the care in the hospital, care after they leave the hospital, and administrative matters from each healthcare professional; interpersonal interactions is defined as a patient's perceptions of empathy and friendliness of each healthcare professional; time spent is defined as the extent to which the patient perceives that each healthcare professional has spent sufficient time with the patient; financial aspects are defined as the patient's assessment of the hospital's handling of various money-related matters; and access/availability/convenience is the patient perceptions about various logistical aspects related to the hospital, its location, and organization. As we discuss later, we use the first four metrics as being direct consequences of e-healthcare system use and use the other two as control variables in predicting patient satisfaction.

Baseline Model

Based on the earlier discussion about social networks, we present a baseline model. An employee who is more central in a network is likely to have access to more resources (e.g., Ahuja et al. 2003, Cross and Cummings 2004), such as information about a new system. Such ties will help users deal with questions and challenges related to using the new system (e.g., Jensen and Aanestad 2007). To resolve such problems, they are likely to seek advice from their coworkers. Also, connections to different groups of users, i.e., doctors, paraprofessionals, and administrative personnel, may expose central individuals to a variety of views and knowledge related to the new system. By reflecting the connectedness of an individual, in this context, network centrality is the extent to which an individual can obtain *information* about system features, procedural details, and activities in the new process; *knowledge,* such as tips and tricks, shortcuts, and details related to the integration of the process and software; and other tangible *resources*, such as training resources, manuals, and tutorials, that can greatly help with using the system (Sykes et al. 2009). Beyond the instrumental support described above, those who provide advice often provide social support. Advisors are frequently listeners who can empathize and/or sympathize with a focal individual. Such empathy and sympathy can drive behavior—here, e-healthcare system use (Loewenstein and Small 2007).

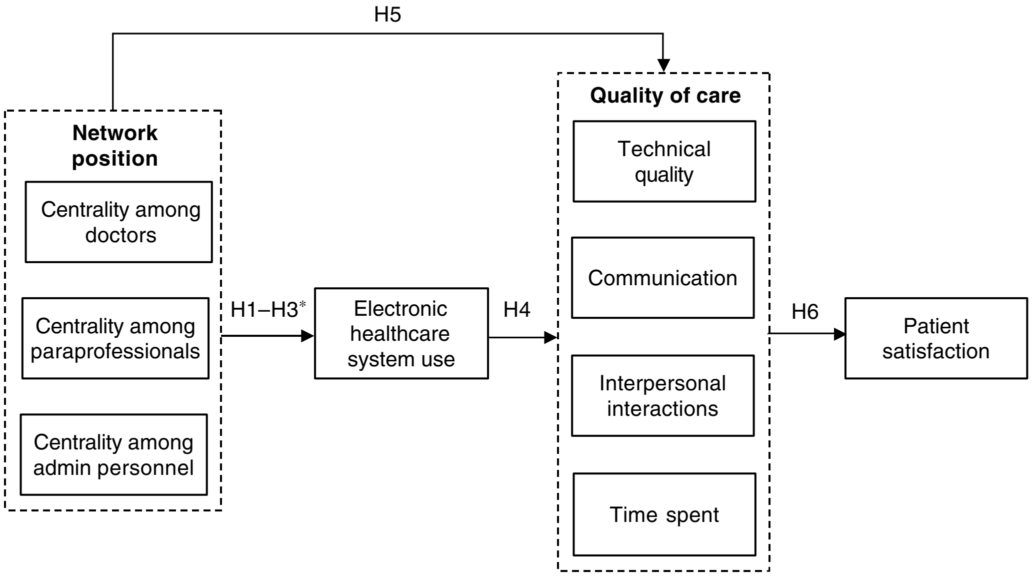
Beyond the well-established general behavior to performance relationship, prior work, mostly based on anecdotal evidence, has suggested that e-healthcare system use can contribute positively to overall patient satisfaction (see Kohli and Piontek 2007). Several mechanisms are cited in the trade press for such an effect—e.g., e-healthcare systems reduce costs and errors (e.g., Anderson 1997, Jensen and Aanestad 2007). As noted earlier, despite limited systematic empirical evidence, patient satisfaction is emerging as a critical metric that reflects quality and value of care (Kohli and Piontek 2007). Beyond the use-performance relationship, network centrality itself can yield direct performance benefits given that central individuals are more likely to gain access to resources, such as advice and social support unrelated to the system, that contribute positively to their performance (Sparrowe et al. 2001). Thus, in keeping with prior social network theory, our baseline model suggests that the relationship between network position and performance will be partially mediated by behavior.

Doctor, Paraprofessionals, and Administrative Personnel: Roles and Acculturation

Acculturation of Doctors. Doctors, paraprofessionals, and administrative personnel) have different educational backgrounds and professional cultures that play a key role in shaping their predispositions toward technologies in the workplace. Doctors have a strong sense of professional identity that revolves around their education and medical practices. This identity is formed early in their career (Freidson 1988, Pratt et al. 2006). Doctors also tend to have a high level of professional commitment tied to treating patients and clinical practices even as they progress through their career and evolve into other roles, such as a physician executive (e.g., Hoff 2001). The doctor-patient relationship is one of the most special and hinges on a strong sense of mutual trust and loyalty (Vaughan and Higgs 1995) and practices related to interacting with patients are ingrained into doctors' professional identity from the earliest days of their training (Pratt et al. 2006). Furthermore, doctors view autonomy and power as a cornerstone of their profession (e.g., Blumenthal 1994). The implementation of e-healthcare systems has been seen as something that changes traditional medical practice, lowers the autonomy that doctors have in constructing patient records, and requires doctors to fundamentally alter the way they organize their thought processes about patient care (Anderson 1997). Moreover, the introduction of any new technology, e.g., an e-healthcare system, can change the original power structure that traditionally favors central doctors through the redistribution of information that confers power on their possessors (see Burkhardt and Brass 1990, Doolin 2004), the disruption of occupational roles (Black et al. 2004), and power transfer in the forms of hospital management possibly being able to usurp doctors' power and integrate the power into administrative personnel (Doolin 2004). For fear of losing their autonomy and power, central doctors in an advice network can be expected to develop negative views towards a new e-healthcare system.

Supporting Roles of Paraprofessionals and Administrative Personnel. The main task of paraprofessionals is to assist doctors. The training of paraprofessionals thus centers around supporting doctors and delivering secondary care. Considering the supporting role they play, they typically understand their relative power and autonomy. In contrast to doctors, paraprofessionals will have more positive views towards the implementation of a new system and are more likely to use it. For example, studies indicate that the strength of a new e-healthcare system is in its ability to help create and store well-documented nursing notes (Jensen and Aanestad 2007) that create a better overview of each patient and ease the work processes for paraprofessionals such that they could spend more time on patient care instead of on administrative tasks (e.g., Jensen and Aanestad 2007). Whereas doctors are generally unwilling to change their traditional practice and use a new e-healthcare system, paraprofessionals tend to more readily accept and use a new e-healthcare system (Anderson 1997). Another reason paraprofessionals develop more favorable views toward a new system than doctors do is that whereas doctors do not consider the implementation of a new system as a way to improve patient treatment, paraprofessionals are likely to perceive such a system as an effective tool for facilitating coordination with other healthcare groups, another important role of paraprofessionals in addition to their bedside responsibilities (Jensen and Aanestad 2007). Finally, whereas the introduction of a new e-healthcare system may jeopardize the unique power of doctors (Bhattacherjee and Hikmet 2007, Doolin 2004, Frideson 1985, Malvey 1981), paraprofessionals will be less affected because they do not possess such unique power before the implementation of a new e-healthcare system and, therefore, they do not have as much to lose. Instead, the implementation of a new system might empower paraprofessionals due

Figure 1 Research Model



*Moderated by group membership.

to other groups' increased reliance on paraprofessionals (Pisano et al. 2001).

The last group of e-healthcare systems' users is administrative personnel. This group not only supports doctors so that they can deliver better-quality health care, but also coordinates external and internal activities to optimize hospital management. For example, if doctors require specific medical equipment, they need to coordinate with the doctors and the suppliers of the equipment. They need to coordinate and manage doctors' and paraprofessionals' schedules to optimize healthcare operation. In order to do so, they must monitor and/or administer the work of doctors and paraprofessionals. They generally have a favorable view toward adoption and use of a new e-healthcare system because such systems can help them monitor and administer the work of doctors and paraprofessionals (Doolin 2004). Furthermore, much monitoring and administration helps administrative personnel better control doctors and make them more responsible for their own actions (Doolin 2004). Prior research has suggested that computerized physician order entry (CPOE) systems could support clinical management practices in coping with institutionally triggered change in the organizational environment (Davidson and Chismar 2007). To respond to institutional changes in markets or regulatory pressures in the organizational environment, such as the pressure exerted by regulatory agencies, insurers, and large firms (Bodenheimer 1999), administrative personnel, especially those at the top of the hierarchy, would be more likely to adopt and use new systems (Greenwood and Hinings 1996, Scott 2001). Other administrative personnel, i.e., those not at the top of the hierarchy, are likely to obey policies and decisions made by top management, and thus are likely to actively use, and influence others to use, the new system.

Proposed Model

Figure 1 shows the proposed model. The model relates network position in different professional groups to quality of care via e-healthcare system use. Quality of care in turn predicts patient satisfaction. The model further presents that the relationship between network position and system use will be moderated by group membership, with the interactions proposed being shown in Table 1.

Impact of Ties to Doctors on E-Healthcare System Use. Contrary to much prior social networks research, in the context of doctors, we argue that both ingroup ties within doctors and outgroup ties to doctors will have a negative effect on e-healthcare system use. We have discussed the benefits associated with centrality as being able to access different resources. In this context, central doctors are those who interact a great deal with doctors for advice, information, and knowledge related to performing their work. As noted earlier, doctors are likely to develop negative views towards the new system because it could pose a threat to their autonomy and power (Bhattacherjee and Hikmet 2007, Jensen and Aanestad 2007), which have been viewed as the cornerstone of their profession (e.g., Blumenthal 1994). Such negative views are likely to prevent central doctors from actively seeking knowledge to resolve system-related problems, resulting in less or ineffective use of the system. Even when central doctors seek advice from other doctors about

Table 1 Effects of Ties on System Use

	Ties to:		
Ties from:	Doctors	Paraprofessionals	Admin personnel
Doctors	H1A: Negative effect on use	H2A: No effect on use	H3A: No effect on use
Paraprofessionals	H1B: Negative effect on use	H2B: Positive effect on use	H3B: Positive effect on use
Admin personnel	H1C: Negative effect on use	H2C: Positive effect on use	H3C: Positive effect on use

the new system, they are likely to get negative comments about the system, thus reinforcing their original negative views towards the system. We thus expect doctors who are better connected to other doctors to resist using the system and to continue to engage in traditional practices. Although social capital generally tends to foster new behavior through information and resource access, there is evidence that it can create maladaptive situations, foster undesirable behaviors, and inhibit behaviors (see Gargiulo and Benassi 1999, Portes and Landolt 1996, Portes 1998). We expect that to be the case here, where there is a desire for and commitment to the status quo, such that more ingroup ties within doctors will negatively influence e-healthcare system use. In contrast, noncentral doctors, i.e., doctors who are on the periphery of the network, will be less influenced by other doctors because of their limited interactions with other doctors. They are thus less likely to be submerged in a sea of negative views towards the new system. Consequently, at least to some extent, they are more likely to explore and use the new system. Also, noncentral doctors could see the new system as a way to acquire power and status within the network, a benefit that using the new system potentially confers (Burkhardt and Brass 1990). Thus, we hypothesize as follows.

Hypothesis 1A (H1A). *Ingroup ties will negatively influence doctors' e-healthcare system use.*

The negative effects observed in the case of ingroup ties to doctors are also expected to apply in the case of outgroup ties that paraprofessionals and administrative personnel have to doctors. When being asked by paraprofessionals or administrative personnel for advice related to how to better use the system, doctors are less likely to provide useful advice due to their limited use and knowledge about the system. They could even persuade those paraprofessionals and administrative personnel not to use the system. Those with many outgroup ties to doctors are more likely to be influenced by doctors and develop similar negative views towards the new system via negative comments about the system and how it interrupts traditional medical practices. Doctors are at the top of the clinical hierarchy (Kaplan et al. 2007, Melia 1987), and those lower down the hierarchy have greater dependence on doctors for their workflow and activities. In contrast, paraprofessionals and administrative personnel with fewer outgroup ties to doctors are likely to explore and use the new system. Thus, we hypothesize as follows.

Hypothesis 1B (H1B). *Outgroup ties to doctors will negatively influence system use among paraprofessionals.*

Hypothesis 1C (H1C). *Outgroup ties to doctors will negatively influence system use among administrative personnel.*

Impact of Ties to Paraprofessionals and Administrative Personnel on E-Healthcare System Use. Doctors' ties to outgroup members—i.e., paraprofessionals and administrative personnel—are not expected to have an effect on their own system use. This is an important null effect to recognize. Doctors, as previously discussed, due to their commitment to traditional medical practices and professional identity, are not likely to be open to input and influence from other groups, particularly those groups over whom they preside in the clinical hierarchy and view as supporting to their role. The acculturation of doctors prevents them from seeking and acting upon advice from paraprofessionals and administrative personnel. Even though doctors can be well connected to paraprofessionals who could be the sources of knowledge about the new system, they are less likely to seek knowledge from paraprofessionals because seeking knowledge reveals their ignorance (see Borgatti and Cross 2003, Lee 1997). Admitting their ignorance to people of lower status could tarnish their reputation or image, which could pose a threat to doctors' authority, which they are strongly motivated to protect (Ferris et al. 1994, Lee 1997). Furthermore, studies have indicated that doctors have to rely more on information provided by paraprofessionals after the implementation of a new e-healthcare system (Pisano et al. 2001). To minimize seeking knowledge from people of lower status, they are likely to act against a change that could subvert such authority (e.g., Black et al. 2004).

Doctors value their autonomy and are not likely to depend on administrative personnel for system-related advice. The reason is that doctors are likely to perceive the implementation of a new system as empowering to administrative personnel while reducing their own autonomy (Jensen and Aanestad 2007).

As noted earlier, e-healthcare systems can be used to help monitor and scrutinize doctors' activities in hospitals (Doolin 2004). By implementing a new system, hospital management can reduce doctors' power and integrate power into the organizational decision-making process. Thus, a new system poses a direct threat to both doctors' autonomous roles, such as being the only entity that can determine modes of treatment (Bhattacherjee and Hikmet 2007, Frideson 1985), and strong economic bargaining position in the hospital, such as having direct access to the policy-making governing board without having to go through the chief executive officer in the hospital (Malvey 1981). Doctors are more likely to form negative perceptions of a system when they perceive it as a control mechanism and a threat to their autonomy (Bhattacherjee and Hikmet 2007, Jensen and Aanestad 2007). Consequently, doctors are less likely to seek advice from administrative personnel who assume the role of deploying the control mechanism, i.e., the new system. Prior research suggests that such political barriers between doctors and administrators must be resolved in order for effective knowledge exchange between these two groups of users that could lead to the strategic application and use of the new system (Kim and Michelman 1990). We thus suggest that there will be little or no effect of outgroup ties on doctors' e-healthcare system use.

In contrast to our discussion thus far, we expect both ingroup and outgroup ties will have a favorable effect in the context of paraprofessionals and administrative personnel. As noted earlier, the acculturation of paraprofessionals and administrative personnel makes them more likely to view the new system favorably because the new system is likely to benefit them. Paraprofessionals or administrative personnel who have high ingroup centrality are those who are well connected to paraprofessionals or administrative personnel, respectively, and hence are more likely to be affected by others' positive views toward the system, which will be further reinforced when seeking knowledge from others within these groups. In addition, such individuals enjoy a broad array of benefits and opportunities unavailable to those on the periphery of the network (Sykes et al. 2009), such as a better access to knowledge. This could be critical in an e-healthcare system implementation where the formal training sessions are not effective in providing the knowledge necessary, but rather much of the learning occurs in the community of practice, such as the advice network (Jensen and Aanestad 2007). Being central within the ingroup advice network of paraprofessionals or administrative personnel will result in more assistance from peers and the super-users (Jensen and Aanestad 2007). Given that ingroup paraprofessionals or administrative personnel are likely to get help to resolve problems in using the new system, such individuals are more likely to use it.

In both cases, because of the complexity and interdependence that is created by a new e-healthcare system, there will be benefits to being well connected to both groups. Paraprofessionals who are better connected within the group are more likely to be able to resolve problems, get assistance on features applicable to them, and learn how to adapt their old work practices to the new system context. Furthermore, paraprofessionals who are better connected to administrative personnel will be able to work on aspects of the system that will be at the nexus of patient care and administration. By having stronger ties to administrative personnel, paraprofessionals are likely to better understand their own new workflows as well as the jobs of administrative personnel and how the system fits into their (administrative personnel) workflow. Taken together, both ingroup ties to other paraprofessionals and outgroup ties to administrative personnel will contribute positively to system use among paraprofessionals. Likewise, from the perspective of administrative personnel, ties within the group and outside the group to paraprofessionals will be positively related to system use because they will help administrators to more easily solve problems related to the system. Thus, we hypothesize as follows.

Hypothesis 2A (H2A). *Outgroup ties to paraprofessionals will not influence e-healthcare system use among doctors.*

Hypothesis 2B (H2B). *Ingroup ties will positively influence e-healthcare system use among paraprofessionals.*

Hypothesis 2C (H2C). *Outgroup ties to paraprofessionals will positively influence e-healthcare system use among administrative personnel.*

Hypothesis 3A (H3A). *Outgroup ties to administrative personnel will not influence e-healthcare system use among doctors.*

Hypothesis 3B (H3B). *Outgroup ties to administrative personnel will positively influence e-healthcare system use among paraprofessionals.*

Hypothesis 3C (H3C). *Ingroup ties will positively influence e-healthcare system use among administrative personnel.*

Impacts of System Use on Quality of Care. There have been extensive discussions in the trade press about the various positive impacts that e-healthcare systems can provide (e.g., Anderson 1997, PricewaterhouseCoopers 2005). Much of this has centered around improved quality of care, with a particular emphasis on reducing errors (e.g., Anderson 1997). Based on the documented empirical evidence and the reason that using e-healthcare systems will allow doctors and paraprofessionals to provide better care, we expect a positive relationship between use and quality of care. The primary reasons why e-healthcare systems will be helpful in improving technical quality is that there will be better and more complete access to patient information. This will allow doctors and paraprofessionals to provide the most relevant care (e.g., tests and advice) rather than engaging in exploratory testing and creating redundancy in tests. In terms of administration, the availability of accurate and complete information with the e-healthcare system will allow for greater accuracy in billing and other administrative formalities. Thus, we hypothesize as follows.

Hypothesis 4A (H4A). *Electronic healthcare system use will positively influence technical quality.*

Communication, interpersonal interactions, and time spent with patients will all be favorably affected as a result of e-healthcare system use. For doctors and paraprofessionals, the availability of more accurate and complete patient case information will mean that they will be able to provide the relevant information about their thought process and treatment plans to patients. It will require them to spend less time studying this information after talking with the patient in order to arrive at treatment plans. With more accurate and complete information available prior to and at the point of care, care givers will be less subject to piecemeal information that can typically result in altering the course of treatment plans. Given the availability of better information about a patient at the point of care and more efficient assessment of each case, doctors and paraprofessionals can spend more time and be friendlier in their interactions with patients as the time pressures (per patient) can be expected to reduce somewhat. Recall that communication relates to information provided to the patient and interpersonal aspects relate to concern and friendliness toward the patient. We note that the effectiveness benefits of the e-healthcare system will essentially allow for both types of benefits to be garnered. Likewise, for administrative personnel, the accurate and timely information available from an e-healthcare system will free up time they would otherwise have to use to collate all records and discern various billing and follow-up matters. This will make available more time to better interact with patients and/or authorized decision makers. Thus, we hypothesize as follows.

Hypothesis 4B (H4B). *Electronic healthcare system use will positively influence communication with patients.*

Hypothesis 4C (H4C). *Electronic healthcare system use will positively influence interpersonal interactions with patients.*

Hypothesis 4D (H4D). *Electronic healthcare system use will positively influence time spent with patients.*

Impacts of Network Centrality on Quality of Care. The effect of network centrality on quality of care will be partially mediated by system use. Prior work argues that an employee's network centrality plays an important role in affecting access to key resources, i.e., information, knowledge, or work-related advice, which in turn serves as a key mechanism contributing positively to job performance (Brass 1984, Sparrowe et al. 2001). In this context, central individuals can be doctors, paraprofessionals, or administrative personnel who have a large number of ties to other doctors, paraprofessionals, or administrative personnel in an advice network. The more ties they have, the more sources from which they could seek knowledge or advice to improve quality of care. For example, central doctors in a doctors' advice network are likely to obtain more advice or knowledge from other doctors about how to deal with a difficult medical case, including treatment plans, similar cases, and ongoing medical trials. When they get advice from other doctors, they can compare cases handled by others with their own and synthesize and evaluate different sources of advice to make a better decision. Likewise, central paraprofessionals can get advice from doctors or paraprofessionals such that they would have knowledge about how to deliver better service to patients. Finally, administrative personnel can get advice from doctors and paraprofessionals to remove ineffective procedures, resulting in better care. Consequently, such central individuals are likely to perform better than less-central individuals. Thus, we hypothesize as follows.

Hypothesis 5 (H5). *Network centrality will positively influence quality-of-care metrics—i.e., technical quality, communication, interpersonal interactions, and time spent.*

Impact of Quality of Care on Patient Satisfaction. There is evidence that quality and the proximal determinants of satisfaction hinge upon context. Specific attributes of quality related to the service context have been related to customer satisfaction in a variety of industries (see Ostrom and Iacobucci 1995, Zeithaml et al. 1990). In the healthcare context, building on prior research on quality of care and patient satisfaction, four key metrics of quality of care—i.e., technical quality, communication, interpersonal aspects, and time spent—that are expected to be influenced by e-healthcare system use will in turn positively influence patient satisfaction. The general rationale, albeit at the level of the hospital, for the effects of each of these metrics on overall patient satisfaction has been developed in prior work (e.g., American Physical Therapy Association 1995; Hays et al. 1987; Marquis et al. 1983; Ware et al. 1976a, b, 1983). The rationale at the level of each patient and at the level of each individual caregiver or administrative staff member is that receiving the right treatment at an affordable price will be important in driving satisfaction. This is akin to the effects of accuracy of product or service delivery on customer satisfaction (see Zeithaml et al. 1990). The healthcare context, even more so than many other service situations, requires intensive interactions between the client and service personnel and hinges on the empathy and sympathy of these personnel. Communication, interpersonal aspects, and time spent are key to patient perceptions of such interactions. For instance, communication, which incorporates patient education, will be seen by patients as being key to their care when they are at the hospital and even when they leave the hospital (e.g., home care). When doctors, paraprofessionals, and administrative personnel are rated highly on each of those three components, it contributes to a greater level of satisfaction. Thus, we hypothesize as follows.

Hypothesis 6 (H6). *Quality-of-care metrics—i.e., technical quality, communication, interpersonal interactions, and time spent—will positively influence*

Method

Context and System

Our study was conducted in the context of an implementation of an IT-based enterprise-wide healthcare solution, which we term E-HealthSys to maintain confidentiality, in a private hospital. The hospital provided a complete range of healthcare services to patients. The hospital had about 800 beds and boasted a medium-sized emergency care operation. The hospital had on its staff just under 250 doctors, with about 20% of them being contracted on an as-needed basis. These contracted doctors were typically at the hospital on one or two days of the week, depending on the workload. There were about three times as many paraprofessionals working at the hospital across various shifts. Finally, a little over 200 administrative staff members were involved in the running the hospital.

E-HealthSys was designed to support all aspects of patient care, including patient health information, health records, treatment plans, billing, and follow-up. In that sense, this system is typical of those that hospitals are currently implementing in an effort to modernize operations and become more effective and efficient. The system was developed by a leading vendor and was customized to fit the needs of the specific hospital over a six-month period before the training. Some doctors, paraprofessionals, and administrative personnel were interviewed by the vendor in the process of customizing the system.

Participants

The participants were doctors, paraprofessionals, and administrative personnel at the hospital and patients who received care at the hospital (and/or closest relative or friend authorized to make decisions on behalf of the patients—hereinafter, "authorized decision maker"). Overall, of the 1,348 possible respondents (244 doctors, 894 paraprofessionals, and 210 administrative personnel), 1,120 respondents provided responses, which was above the threshold of 80% that is recommended for primary social network studies (Wasserman and Faust 1994). Within the different user groups, we found the response rate to be highest among administrative personnel ($n = 190$), followed by paraprofessionals ($n = 770$), and lowest among doctors ($n = 160$). To assess nonresponse bias, we compared the respondent and nonrespondent demographic profiles. We found that the profiles were comparable and statistically equivalent, with one exception—i.e., among doctors, more of the nonrespondents were contracted doctors who were only at the hospital part time, which was not seen as a major threat because their expected use of the solution and role in the advice network was expected to be more minimal compared to those doctors employed full time at the hospital. We used only the usable responses to construct the advice network matrices (e.g., 160×160 in the sample of doctors; $1,120 \times 1,120$ in the entire sample) and in the all data analyses.

All patients received a survey to assess their satisfaction with the care and administration at the hospital. Although the exact number of surveys mailed was not shared with us, a total of 8,440 patient and/or authorized decision-maker responses were received. Each doctor and paraprofessional had, on average, about 40 and 60 responses, respectively. Each administrative staff member had, on average, about 65 responses.

Procedure

The study was conducted in conjunction with the implementation of E-HealthSys at the hospital. The timeline for the major activities and data collected is shown in Table 2. There was strong support for E-HealthSys from the top management, and this was reflected in their interest in collecting data from their employees. The researchers provided input into the questionnaire that was being administered by the hospital. The hospital retained a market research firm to assist with the data collection to ensure that the employees were comfortable with sharing information honestly and also to ensure the privacy and confidentiality of employee responses.

As can be seen in Figure 1 (model diagram shown earlier), one of the key aspects of our research design is the three distinct sources used in the data collection: (1) individual-level and social network data from employees; (2) use data from system logs; and (3) patient satisfaction and related data from patients

Table 2 Data Collection Timeline

T0: Pretraining	T1: Month 1	T2: Months 2–3	T3: Months 4–12
Archival measures of preimplementation quality of care from patient surveys.	Training takes place over a 1-month period, with several sessions available.	E-HealthSys is installed and available on all computers.	Change management support is measured at the end of month 6.
	Survey to collect individual-level variables and social network data.		Use is averaged over this period.
			Archival measures of post-implementation quality of care from patient surveys.

and/or authorized decision makers. Several training sessions were offered over the month before the availability of the system. Management mandated that within a month all employees had to attend one session tailored to their user group, and consistent with this, almost everyone attended a session, although some of the contracted doctors could not fit this into their schedule. The training sessions were tailored to the needs of the specific user groups—i.e., doctors, paraprofessionals, and administrative personnel. Anyone was welcome to attend any session or multiple sessions. Each training session spanned approximately 4 hours, and employees could attend as many sessions as they desired. The number of participants in any session was capped at 25 to facilitate small class sizes. Several sessions were run in parallel, and given the around-the-clock nature of a hospital, sessions were offered 16 hours a day. In order to accommodate this hectic training schedule, at times during the month the hospital ran at less than 100% capacity and postponed some nonemergency hospitalization visits or referred them to their sister hospital about 30 miles away. Given the sheer number of training sessions, especially in parallel, it was impossible to eliminate trainer variability, but because the trainers followed a specific script, biases were minimized. Also, trainer dummy variables were not significant, thus further minimizing potential biases. Pertinent to our study, as can be seen from Table 2, we gathered pretraining data about patient satisfaction, which was a control variable. Immediately following the training, in conjunction with the organization's survey, individual-level and social network data were gathered. Immediately after completion of their training session, doctors, paraprofessionals, and administrative personnel filled out a survey that was used to gather individual-level variables and social network data.

After the training sessions were completed, E-HealthSys was made available on desktop computers, laptop computers, and handheld tablet computers throughout the hospital. Internet access was available throughout the hospital and was often necessary to access data. Approximately two months was deemed the learning phase by the management. During this period, the vendor and upper management held three weekly town hall meetings to get feedback from users. Fixes and changes were effected during this period. The next nine months to the end of the first year of deployment was considered the period of evaluation by management, at the end of which they were to take stock of the system and decide on possible course corrections. During this nine-month period, no major changes were made to the system. Also, during this period, on-call problems (bugs reported and time taken to fix the bugs) were tracked. It was estimated that approximately 80 man hours were dedicated to addressing problems in the first month and that number was down to fewer than 40 hours in the second month and fewer than 5 hours by the third month, thus suggesting that the technical aspects of the implementation were reasonably well executed.

We gathered use data from e-healthcare system logs over this nine-month period. Although we continued to gather use data, we sought to explain use during this phase of the implementation—i.e., termed the shakedown phase—because it can make or break a system (see Morris and Venkatesh 2010). During this period, the system was available to provide patient care and handle follow-up administrative care. About a week following each patient's hospital visit, a survey was mailed to them to collect data on the care they received. One follow-up survey was sent two weeks after the initial survey, and one follow-up phone call was made another two weeks later in order to enhance the response rate. In cases where patients were unable to participate, authorized decision makers were sought to fill out the survey.

Measures

The appendix lists the items from the survey that were used in this paper.

Survey of Health-Care Professionals. Various individual-level variables were measured primarily for use as control variables. The social network data, focused on advice networks, were gathered using a roster-based approach that is consistent with much prior research on social networks (see Borgatti and Foster 2003, Wasserman and Faust 1994). Given the number of employees, the survey spanned several pages. Employees were given the option to fill out the survey online or on paper. Respondents were asked to identify from which of the listed individuals (from a list of all doctors, paraprofessionals, and administrative personnel in the hospital) they received work-related advice (on a 7-point scale). Consistent with prior research, as noted earlier, we used only the usable responses.

In order to capture true advice ties and not incidental contact, we then dichotomized the responses, with responses of 4 or greater being considered a tie. This point was deemed appropriate because it represented getting advice at least once a week from an individual and is consistent with prior social networks research (e.g., Cross and Cummings 2004). An individual's network position was operationalized as degree centrality because it represents the number of direct ties an individual has in the network (Borgatti 2005) because degree centrality relates well to the underlying theoretical mechanisms that we have elucidated. The more direct ties, the more access to advice a person has from these ties and the more likely the person's views and behaviors will be based on such advice (Erickson 1988, McCarty et al. 2007). We adapted our measure from the E–I index (Krackhardt and Stern 1988) that presents a ratio of external and internal ties, but by capturing and retaining both ingroup and outgroup direct ties separately, we used absolute values of both types of ties, rather than just a ratio. E was calculated using outgroup degree centrality and I was calculated using ingroup degree centrality. UCINET 6.29 (Borgatti et al. 2002) was used to construct the network matrices for the computation of overall centrality and each of the ingroup and outgroup centralities. Ingroup degree centrality for each user was calculated based on the subnetwork comprising only members of a particular user group—e.g., doctors only. Two outgroup network degree centrality scores were calculated for each user by including the particular user as a member of each of the other two user group subnetworks—e.g., each doctor as a member of the subnetwork of all paraprofessionals and each doctor as a member of the subnetwork of all administrative personnel.[1]

[1] Density, the proportion of ties present divided by total ties possible, for the whole network as well as within each group was also calculated. Within the entire network (all three groups), the density was 11.7%. The doctor group had a density of 13.9%, within the paraprofessional group had a density of 4.3%, and the administrative personnel group had a density of 14.2%.

Professional group membership was coded using two dummy variables: Groupvar1, which was coded as 1 for doctors, and Groupvar2, which was coded as 1 for paraprofessionals. These two dummy variables were used to test the two-way interactions.

Archival Logs of Electronic Healthcare System Use. E-HealthSys use was measured using archival system logs. For each user, the following use data were extracted from the system logs: duration, number of features used, and frequency of use of each feature (see Venkatesh et al. 2008). As a security feature, the system automatically logged out idle users after a specified period of time (5 minutes), thus minimizing possible inflation of use for those who were logged in but not actively using the system. These three archival measures were used as formative indicators representing e-healthcare system use.

Survey of Patients. Overall patient satisfaction and key metrics of quality that are modeled as mediators of the use-satisfaction relationship, i.e., technical quality, communication, interpersonal interactions, and time spent, were measured by adapting the Patient Satisfaction Questionnaire III (PSQ III). One of the key differences in the way this particular hospital used these four quality indicators in the PSQ III was to gather data about each doctor, paraprofessional, and administrative team that dealt with a patient. In the case of doctors and paraprofessionals, the patient and/or authorized decision maker responded to various questions based on their experiences with each doctor or paraprofessional. In the case of administrative personnel, frequently, patients or their authorized decision makers may never have come into contact with any administrative staff member. Further, for each patient, as in the case of the doctors and paraprofessionals who handled their care, several administrative personnel were likely involved in processing various details of their case—e.g., billing, accounts receivable, insurance, credit. Given the minimal patient and/or authorized decision-maker interaction with most of these staff members, they rated their interactions with an administrative team. Corresponding to a particular patient, the same score was then assigned to all members of the administrative team that processed a patient's case.

We collected the performance data, i.e., four quality-of-care metrics and patient satisfaction, from the multiple patients or authorized decision makers with whom the medical professionals had dealt over a period of time. We did not collect data from the same patient over multiple periods of time, and some performance data were collected before the system use data were collected. To alleviate potential biases that could be introduced by this timing of measurement, we operationalized the different quality-of-care metrics and patient satisfaction as formative constructs that include both mean ratings and consistency, i.e., based on the standard deviation of all ratings received by each healthcare professional. The mean rating was the overall average for each employee—i.e., doctor, paraprofessional, and administrative staff member. The consistency was calculated as −1 multiplied by the standard deviation of the several ratings for each employee. For instance, if a doctor received ratings from 50 patients or authorized decision makers, the mean and standard deviation were computed, with the former referring to the overall rating and the latter (sign reversed) referring to the consistency. A positive impact of use would mean higher overall ratings and higher consistency (low standard deviations).[2]

In addition, two quality metrics that were part of the PSQ III were retained as is and included in the survey as control variables: financial aspects and access/availability/convenience. However, these were gathered separate from any specific doctor, paraprofessional, or administrative team and hinged largely on decisions made by hospital management. The scores received were similarly averaged across all patient ratings for each healthcare professional. Both the overall rating and consistency scores were calculated to develop the formative scales used as control variables.

Control Variables. In predicting system use, technical quality, communication, interpersonal interactions, time spent, and patient satisfaction, the corresponding preimplementation measures were used as control variables. To rule out the possibility that doctors' resistance emerged from poor implementation of the system, we control for training attendance, training satisfaction, and change management support. Training related factors, i.e., training attendance and training satisfaction, were controlled because it is a critical and common intervention for successful system implementations. Change management support is also a key factor that fosters successful system implementation. Training attendance was obtained from the archives of the hospital. Three items each were created to measure training satisfaction and change management support. Also, as mentioned in the section related to patient surveys, two additional postimplementation quality metrics that are part of the PSQ III were used as control variables for overall patient satisfaction: financial aspects and access/availability/convenience (Hays et al. 1987). Various individual-level control variables, i.e., gender, age, conscientiousness, were also included. Also, preimplementation job satisfaction (Janssen 2001) and job performance, along with perceived usefulness and perceived ease of use (Klein 2007, Venkatesh et al. 2003) of the E-HealthSys were used as control variables.

Results

LISREL 8.7, a covariance-based structural equation modeling technique (Joreskog and Sorbom 1996) was used to analyze the data. We first checked for outliers, multivariate normality, and multicollinearity and found no problems or violations of our assumptions, using maximum likelihood as an estimation method. Next, measurement properties of constructs were analyzed by using confirmatory factor analysis (CFA), which includes the estimation of internal consistency (reliability) and the convergent and discriminant validity of the construct.

We used five different indices to assess model fit. These indices are the χ^2 statistic, the root mean square error of approximation (RMSEA), the comparative fit index (CFI), the nonnormed fit index (NNFI), and the standardized root mean square residual (SRMR). The model is deemed to be a good fit when the χ^2 statistic indicates that the null hypothesis of the covariance matrix equality is not rejected, RMSEA is 0.06 or lower, CFI is 0.95 or higher, NNFI is 0.95 or higher, and SRMR is 0.08 or lower. Our final CFA model indicated good model fit ($\chi^2 = 82.4$, df $= 70$, $p > 0.10$; RMSEA $= 0.041$, CFI $= 0.99$; NNFI $= 0.99$, SRMR $= 0.028$). Reliability was assessed using composite reliability. It has been suggested that a value of 0.70 or greater indicates adequate reliability (Fornell and Larcker 1981). Reliabilities of all constructs are reported in Table 3, and they were all above 0.70, thus indicating good reliability and internal consistency. Table 3 also reports the means and standard deviations. The correlations were in the patterns expected. E-HealthSys use and various proximal indicators of quality were correlated with patient satisfaction. The various control variables were correlated modestly with the dependent variables of interest.

We examined convergent validity by calculating average variance extracted (AVE) for each construct. All AVE values were above the recommended 0.50, and item loadings were high (>0.70) and significant, thus indicating good convergent validity of the scales. For satisfactory discriminant validity, the squared correlations between constructs should be greater than

[2] Several hundreds of factor analyses were run using the employee data, and after aggregating the data for all employees. Factor analyses were not run if the sample size for any given employee was too small. The loadings and cross loadings followed the expected pattern, with loadings being >0.70 and cross loadings being <0.35 in the aggregate data set. In the individual employee data sets, the pattern was less clean, with about 10% of the employee data sets having loadings less than 0.70 and cross loadings greater than 0.35. However, some of these analyses were run on relatively small samples, thus rendering this issue to be less of a concern, especially given that the overall factor analysis produced an acceptable structure. The Cronbach alpha of all scales was greater than 0.75 in the aggregate data set and greater than 0.70 in almost all employee data sets.

the AVEs. In Table 3, AVEs are shown on the diagonal, and the off-diagonal elements show the correlations. In all cases, the AVE of a variable is greater than the squared correlation of that variable with all other variables, thus indicating satisfactory discriminant validity.

Structural Model Tests

In order to test our hypotheses, a series of model tests were conducted. First, we tested the baseline model to understand how well prior social network theory would predict E-HealthSys use and consequent patient satisfaction. We then tested the proposed model. Specifically, we tested the overall model for the entire data set. Based on the latent variable values estimated for this model, we tested three models, one for each of the professional groups to better understand the results in each group.

We first tested the baseline model of patient satisfaction. These results are shown in Tables 4(a) and 4(b). E-HealthSys use was predicted by the control variables. As expected, overall centrality also pos-

Table 3 Descriptive Statistics, Correlations, ICRs, and AVEs

	Reliab.	Mean	SD	1	2	3	4	5	6	7	8	9	10	11	12	13
1. Gender (1: men)	NA	NA	NA	NA												
2. Age	NA	44.20	15.20	0.04	NA											
3. Organization tenure	NA	13.84	7.75	0.17**	0.28***	NA										
4. Conscientiousness	0.75	6.07	0.46	0.07	0.04	0.03	0.75									
5. Perceived usefulness	0.88	4.08	1.22	0.14*	−0.17**	0.03	0.03	0.85								
6. Perceived ease of use	0.84	3.95	1.55	0.15*	−0.19**	−0.13*	0.05	0.16**	0.80							
7. Pre-impl. job satisfaction	0.81	5.55	1.04	−0.13*	0.13*	0.08	0.02	0.08	0.03	0.74						
8. Pre-impl. job performance	NA	6.89	1.17	0.08	0.19**	−0.19***	0.07	−0.12*	0.05	0.22***	NA					
9. Pre-impl. technical quality	0.72	4.66	1.08	0.04	0.16*	0.16**	0.03	0.03	0.06	0.12*	0.19**	0.70				
10. Pre-impl. communication	0.74	4.49	1.12	0.02	0.10	0.17**	0.04	0.04	0.06	0.15**	0.20***	0.32***	0.70			
11. Pre-impl. interpersonal interactions	0.71	4.51	1.07	0.05	0.12*	0.16**	0.03	0.03	0.06	0.14*	0.22***	0.31***	0.55***	0.71		
12. Pre-impl. time spent	0.70	3.68	1.01	0.05	0.08	0.19**	0.02	0.02	0.05	0.14*	0.20***	0.25***	0.25***	0.24***	0.71	
13. Pre-impl. patient satisfaction	0.77	4.48	1.26	0.08	0.10	0.16**	0.08	0.10	0.02	0.15**	0.22***	0.29***	0.30***	0.29***	0.27***	0.70
14. Training attendance (0: no)	NA	0.87	0.04	−0.15*	0.07	0.02	0.13*	0.04	0.05	0.03	0.04	0.15*	0.17**	0.15*	0.15*	0.21***
15. Training satisfaction	0.91	4.80	1.01	0.10	−0.08	−0.07	0.10	0.12*	0.13*	0.02	0.02	0.18**	0.19**	0.17**	0.14*	0.17**
16. Change management support	0.92	3.75	0.87	−0.16*	−0.04	−0.05	0.07	0.14*	0.12*	0.07	0.05	0.22***	0.20***	0.20***	0.13*	0.14*
17. Centrality (overall)	NA	130.03	62.80	0.09	0.17**	0.07	0.02	−0.13*	0.16**	0.19**	0.07	0.19**	0.15*	0.16**	0.17**	0.24***
18. Centrality among doctors	NA	22.12	13.43	−0.14*	0.14*	0.16**	0.07	−0.15**	0.06	0.12*	0.19**	0.26***	0.20***	0.21***	0.19**	0.14*
19. Centrality among paraprofessionals	NA	33.41	15.43	−0.19**	0.13*	0.19**	0.02	−0.13*	0.13*	0.08	0.23**	0.26***	0.21***	0.20***	0.20***	0.15*
20. Centrality among admin.	NA	26.50	10.93	−0.05	0.13*	0.15**	0.05	−0.12*	0.15*	0.09	0.13*	0.22***	0.21***	0.22***	0.20***	0.08
21. Groupvar1 (1: doctors)	NA	NA	NA	0.24***	0.04	0.02	0.05	0.02	0.04	0.08	0.04	0.08	0.04	0.03	−0.02	0.07
22. Groupvar2 (1: paraprofessionals)	NA	NA	NA	−0.29***	0.08	0.05	0.06	0.00	0.02	0.10	0.02	0.07	0.04	0.02	0.04	0.10
23. Electronic healthcare system use	NA	25.12	14.80	0.04	−0.21***	−0.22***	0.05	0.20***	0.17**	−0.25***	−0.28***	−0.12*	−0.13*	−0.14*	−0.10	0.31***
24. Post-impl. technical quality	0.72	5.04	0.80	0.05	0.17**	0.17**	0.02	0.13*	0.12*	0.13*	0.17**	0.21***	0.16**	0.17**	0.15**	0.28***
25. Post-impl. communication	0.74	5.17	0.94	0.07	0.10	0.19***	0.08	0.17**	0.14*	0.15**	0.18**	0.17**	0.22***	0.25***	0.20***	0.25***
26. Post-impl. interpersonal interactions	0.73	4.90	0.92	0.10	0.14*	0.20***	0.04	0.19**	0.13*	0.16**	0.20***	0.18**	0.25***	0.23***	0.17**	0.25***
27. Post-impl. time spent	0.78	4.31	1.03	0.07	0.12*	0.20***	0.02	0.13*	0.12*	0.17**	0.18**	0.22***	0.20***	0.20***	0.24***	0.26***
28. Post-impl. financial aspects	0.77	4.51	1.34	0.02	0.04	0.05	0.01	0.02	0.04	0.03	0.02	0.01	0.12*	0.13*	0.14*	0.17**
29. Post-impl. acc/avail/conv	0.70	4.38	1.38	0.03	0.02	0.08	0.04	0.05	0.02	0.08	0.04	0.09	0.14*	0.15**	0.16**	0.19**
30. Post-impl. patient satisfaction	0.79	5.23	0.91	0.05	0.08	0.20***	0.10	0.19**	0.17**	0.19**	0.30***	0.17**	0.19**	0.17**	0.15*	0.28***

Table 3 Continued

	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30
14. Training attendance (0: no)	NA																
15. Training satisfaction	0.10	0.80															
16. Change management support	0.03	0.04	0.83														
17. Centrality (overall)	0.04	0.02	0.10	NA													
18. Centrality among doctors	0.10	0.05	0.08	0.18**	NA												
19. Centrality among paraprofessionals	0.08	0.04	0.02	0.20***	0.19**	NA											
20. Centrality among admin.	0.04	0.02	0.03	0.17**	0.15**	0.26***	NA										
21. Groupvar1 (1: doctors)	0.02	0.01	0.05	0.10	0.33***	0.15*	0.08	NA									
22. Groupvar2 (1: paraprofessionals)	0.10	0.04	0.08	0.11*	0.20***	0.40***	0.09	−0.15**	NA								
23. Electronic healthcare system use	0.07	0.19**	0.17**	0.15**	−0.37***	0.29***	0.33***	−0.33***	0.25***	NA							
24. Post-impl. technical quality	0.15*	0.15*	0.14*	0.17**	0.24***	0.26***	0.21***	0.13*	0.07	0.24***	0.71						
25. Post-impl. communication	0.12*	0.17**	0.14*	0.18**	0.20***	0.24***	0.20***	0.10	0.12*	0.22***	0.13*	0.74					
26. Post-impl. interpersonal interactions	0.14*	0.20***	0.17**	0.19**	0.21***	0.25***	0.21***	0.11	0.10	0.23***	0.14*	0.53***	0.76				
27. Post-impl. time spent	0.16*	0.12*	0.13*	0.20***	0.22***	0.21***	0.17**	0.05	0.08	0.21***	0.14*	0.15**	0.16**	0.70			
28. Post-impl. financial aspects	0.12*	0.04	0.02	0.04	0.02	0.05	0.10	0.02	0.04	0.13*	0.15*	0.22***	0.24***	0.18**	0.79		
29. Post-impl. acc/avail/conv	0.08	0.03	0.05	0.02	0.03	0.07	0.08	0.06	0.02	0.12*	0.19**	0.20***	0.21***	0.14*	0.13*	0.70	
30. Post-impl. patient satisfaction	0.20***	0.21***	0.21***	0.20***	0.25***	0.24***	0.28***	0.08	0.10	0.25***	0.28***	0.25***	0.28***	0.22***	0.14*	0.16**	0.78

$^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 001$.

itively influenced E-HealthSys use. Patient satisfaction was predicted by E-HealthSys use. Furthermore, as found in prior social networks research, centrality influenced patient satisfaction above and beyond the behavior—i.e., E-HealthSys use. The model of patient satisfaction, based on overall centrality and E-HealthSys use, predicted 37% of the variance in patient satisfaction, with both constructs contributing unique variance. In order to provide preliminary evidence for the role of the professional group, we examined the detailed results by user group. It was evident that overall centrality did not have the same effect on E-HealthSys use among all user groups. These results are shown in the interaction model in Table 4(a) and the results in Table 4(b). Among doctors, EHealthSys use had no effect, but among paraprofessionals and administrative personnel, it had a positive effect. Taken together, this suggests that there may be a differential role for centralities in different professional groups.

We then proceeded to test the model presented in Figure 1. In the pooled model test that used interaction terms, we centered the variables that were used in the interactions to reduce potential multicollinearity and for ease of interpretation (Aiken and West 1991). Concerns regarding multicollinearity were eased to some extent, given that all variance inflation factors (VIFs) were below 5. We also conducted split-sample analyses, separately among doctors, paraprofessionals, and administrative personnel, respectively, in order to better understand the pattern of findings. Using the pooled data, we tested three models of E-HealthSys use: model 1 used only control variables as predictors; model 2 used centrality in different user groups as predictors; and model 3 used interaction terms also as predictors, and allowed us to better identify the differences in the importance of centralities within different user groups for predicting use. For the various quality-of-care dependent variables, we tested two models: model 1 used only control variables as predictors; and model 2 used centrality and E-HealthSys use as predictors. There was thus a one-to-one correspondence between models 1 and 2 of E-HealthSys use and quality of care. Because there were no moderators of the quality-of-care variables, we retained the same set of predictors for quality of care when testing model 3 of E-HealthSys use. These results are shown in Table 5. We also ana-

Table 4a Baseline Model

	Electronic healthcare system use ($n = 1{,}120$)			Patient satisfaction ($n = 1{,}120$)			
	Model 1	Model 2	Model 3	Model 1	Model 2a	Model 2b	Model 3
R^2	0.20	0.22	0.26	0.29	0.32	0.34	0.37
ΔR^2	0.20***	0.02*	0.04*	0.29***	0.02*	0.02*	0.03*
Control variables:							
Gender	0.01	0.02	0.00	0.05	0.04	0.04	0.03
Age	−0.14*	−0.03		0.13*	0.03	0.03	0.02
Organizational tenure	−0.14**	−0.01	−0.02	0.17**	0.13*	0.12*	0.08
Conscientiousness	0.02	0.02	0.00	0.03	0.02	0.02	0.01
Perceived usefulness	0.15*	0.13*	0.10				
Perceived ease of use	0.02	0.07	0.08				
Pre-impl. job satisfaction	−0.07	−0.06	−0.10	0.07	0.05	0.04	0.03
Pre-impl. job performance	−0.14*	−0.13*	−0.08	0.15*	0.15*	0.15*	0.13*
Pre-impl. patient satisfaction				0.30***	0.25***	0.26***	0.25***
Training attendance	0.05	0.02	0.01	0.07	0.03	0.04	0.03
Training satisfaction	0.12*	0.13*	0.06	0.15*	0.12*	0.12*	0.08
Change management support	0.16**	0.08	0.05	0.15*	0.12*	0.13*	0.11*
Main effects:							
Centrality (overall)		0.14*	0.07		0.16**		0.15*
Electronic healthcare system use						0.24***	0.23***
Interaction by user group:							
GroupVar1 (Others: 0; Doctors: 1)			−0.10				
GroupVar2 (Others: 0; Para-profs: 1)			0.05				
Centrality (overall) × GroupVar1			−0.15*				
Centrality (overall) × GroupVar2			0.08				

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

Table 4b Baseline Model: Predicting E-HealthSys Use Broken Down by User Group

	Doctors ($n = 160$)		Paraprofessionals ($n = 770$)		Administrative personnel ($n = 190$)	
	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
R^2	0.19	0.20	0.20	0.24	0.21	0.25
ΔR^2	0.19***	0.01	0.20***	0.04*	0.21***	0.04*
Control variables:						
Gender	0.02	0.01	0.05	0.00	0.08	0.03
Age	−0.16**	−0.04	−0.05	−0.03	−0.08	−0.12*
Organizational tenure	−0.12*	−0.09	−0.14*	−0.02	−0.20***	−0.13*
Conscientiousness	0.03	0.03	0.06	0.02	0.04	0.02
Perceived usefulness	0.15*	0.14*	0.16**	0.15*	0.21***	0.19**
Perceived ease of use	0.05	0.05	0.07	0.07	0.10	0.10
Pre-implementation job satisfaction	−0.04	−0.04	−0.19**	−0.17**	−0.13*	−0.14*
Pre-implementation job performance	−0.20***	−0.18**	−0.15*	−0.13*	−0.16**	−0.14*
Training attendance	0.05	0.02	0.07	0.06	0.05	0.04
Training satisfaction	0.12*	0.10	0.12*	0.12*	0.13*	0.10
Change management support	0.05	0.06	0.19**	0.13*	0.21***	0.15*
Main effect:						
Centrality (overall)		0.04		0.14*		0.12*

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

lyzed the data to predict E-HealthSys use for each of the three groups separately. In the split-sample analysis, model 1 uses only control variables as predictors and model 2 also uses the centralities as predictors. Note that model 3 is not applicable in the split-sample analysis—however, a comparison across user groups helped in understanding the pattern of results emerging from the testing of model 3 using

Table 5 **Structural Model Test for All Employees** ($n = 1{,}120$)

	Electronic healthcare system use			Technical quality		Communication		Interpersonal interactions		Time spent		Patient satisfaction	
	Model 1	Model 2	Model 3	Model 1	Model 2 (note 3)	Model 1	Model 2 (note 3)	Model 1	Model 2 (note 3)	Model 1	Model 2 (note 3)	Model 1	Model 2 (note 3)
R^2	0.20	0.30	0.51	0.15	0.34	0.15	0.28	0.15	0.28	0.16	0.28	0.29	0.53
ΔR^2	0.20***	0.10**	0.21***	0.15***	0.19***	0.15***	0.13**	0.15***	0.13**	0.16***	0.12**	0.29***	0.24***
Control variables:													
Gender	0.01	0.00	0.00	0.03	0.00	0.02	0.01	0.03	0.01	0.07	0.00	0.04	0.03
Age	−0.14*	−0.03	−0.03	0.02	0.01	0.02	0.01	0.02	0.01	0.03	0.02	0.12**	0.05
Organizational tenure	−0.14**	−0.02	−0.03	0.04	0.04	0.02	0.02	0.05	0.05	0.03	0.03	0.16**	0.05
Conscientiousness	0.02	0.01	0.00	0.03	0.01	0.00	0.00	0.03	0.01	0.05	0.05	0.03	0.01
Perceived usefulness	0.15*	0.13*	0.04										
Perceived ease of use	0.02	0.03	0.08										
Pre-implementation job satisfaction	−0.07	−0.04	−0.10	0.01	0.00	0.04	0.04	0.04	0.04	0.06	0.05	0.07	0.03
Pre-implementation job performance	−0.14*	−0.12*	−0.10	0.12*	0.05	0.13*	0.12*	0.13*	0.13*	0.20***	0.17**	0.15*	0.13*
Pre-implementation DV (see note 1)				0.24***	0.13*	0.26***	0.22***	0.28***	0.17**	0.28***	0.23***	0.28***	0.23***
Post-implementation financial aspects												0.15*	0.15*
Post-implementation acc/avail/conv												0.19**	0.13*
Training attendance	0.05	0.02	0.01	0.15*	0.04	0.10	0.04	0.02	0.01	0.05	0.01	0.04	0.02
Training satisfaction	0.12*	0.10	0.07	0.16**	0.08	0.02	0.02	0.06	0.04	0.02	0.02	0.13*	0.07
Change management support	0.16**	0.12*	0.07	0.14*	0.13*	0.11*	0.07	0.02	0.02	0.12*	0.05	0.13*	0.12*
Main effects:													
Centrality among doctors (C-DOC)		−0.21***	−0.15*		0.14*		0.14*		0.15*		0.13*		0.04
Centrality among para-profs (C-PAR)		0.14*	0.02		0.12*		0.08		0.10		0.04		0.08
Centrality among admin. (C-ADM)		0.13*	0.04		0.13*		0.06		0.04		0.16**		0.10
Electronic healthcare system use					0.21***		0.22***		0.25***		0.20***		0.12*
Post-implementation technical quality													0.20***
Post-implementation communication													0.21***
Post-implementation interpersonal interactions													0.12*
Post-implementation time spent													0.15*
Interaction effects:													
GroupVar1 (Others: 0; Doctors: 1)			−0.03										
GroupVar2 (Others: 0; Para-profs: 1)			0.04										
C-DOC × GroupVar1			−0.29***										
C-PAR × GroupVar1			−0.17**										
C-ADM × GroupVar1			−0.19***										
C-DOC × GroupVar2			0.24***										
C-PAR × GroupVar2			0.15*										
C-ADM × GroupVar2			0.16**										

Notes. In model 1, in each case, the preimplementation measure was used as a control variable. For instance, in predicting technical quality, preimplementation technical quality was used as control variable. Model 2 corresponds to both models 2 and 3 of electronic healthcare system use.

$^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

Table 6 Predicting Electronic Healthcare System Use: Analysis by User Group

	Doctors ($n = 160$)		Paraprofessionals ($n = 770$)		Administrative personnel ($n = 190$)	
	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
R^2	0.19	0.31	0.20	0.35	0.21	0.38
ΔR^2	0.19***	0.12**	0.20***	0.15***	0.21***	0.17***
Control variables:						
Gender	0.02	0.01	0.05	0.00	0.08	0.04
Age	−0.16**	−0.04	−0.05	−0.04	−0.08	−0.04
Organizational tenure	−0.12*	−0.04	−0.14*	−0.03	−0.20***	−0.10
Conscientiousness	0.03	0.03	0.06	0.03	0.04	0.03
Perceived usefulness	0.15*	0.13*	0.16**	0.13*	0.21***	0.17**
Perceived ease of use	0.05	0.04	0.07	0.06	0.10	0.08
Preimplementation job satisfaction	−0.04	−0.03	−0.19**	−0.17**	−0.13*	−0.12*
Preimplementation job performance	−0.20***	−0.17**	−0.15*	−0.14*	−0.16**	−0.13*
Training attendance	0.05	0.02	0.07	0.05	0.05	0.04
Training satisfaction	0.12*	0.08	0.12*	0.04	0.13*	0.08
Change management support	0.05	0.04	0.19**	0.12*	0.21***	0.14*
Main effects:						
Centrality among doctors		−0.28***		−0.16**		−0.21***
Centrality among paraprofessionals		0.03		0.14*		0.17**
Centrality among administrative personnel		0.01		0.13*		0.21***

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

the pooled data. Table 6 presents the results broken down by user group.[3]

As is evident from model 1 using the pooled data (Table 5), the control variables accounted for 20% of the variance in E-HealthSys use, with 6 of the 11 control variables being significant. Organizational tenure had a negative effect, suggesting that those who had been working at the hospital longer used E-HealthSys less. This is perhaps due to organizational tenure reflecting the extent to which employees were steeped in old practices and thus were more resistant to change. Both job satisfaction and job performance had negative effects on E-HealthSys use. This is likely due to the fact that those who were more satisfied with their jobs and/or high performers did not see a reason to change in that they were happy with old practices. Consistent with prior technology adoption research (see Venkatesh et al. 2007), perceived usefulness and perceived ease of use positively influenced e-healthcare system use. This pattern of effects among control variables was reflected when data from each user group were analyzed separately. Results of testing model 2 using the pooled data (Table 5) tested the main-effects hypotheses. Centrality among doctors had a negative effect on E-HealthSys use among all users, whereas centrality among paraprofessionals and administrative personnel contributed positively to E-HealthSys use. The main-effects model explained 30% of the variance in E-HealthSys use.

We tested our hypotheses, H1(A–C), H2(A–C), and H3(A–C), related to the proposed differential effects of different centralities among different user groups in two ways. First, we introduced the two dummy variables, GroupVar1 and GroupVar2, which represented group memebership. These results, shown in Table 5, relate to model 3 and used the pooled data. Second, we conducted split-sample analyses to better understand the pattern of effects that were emerging from the significant interaction terms. These results, shown in Table 6, relate to testing model 2, using data from each of the three user groups separately. We found that centrality in all user groups interacted with both dummy variables to influence E-HealthSys use. The model with interaction terms explained 51% of the variance in E-HealthSys use. GroupVar1 allows

[3] One possible concern related to the use, quality-of-care and patient satisfaction data are that given the timing of the data collection—i.e., over nine months—some of the dependent variable (e.g., patient satisfaction) data that were gathered may precede the independent variable (e.g., system use) data that were collected. To alleviate this concern, we used two approaches. The first was one that we have already described in modeling quality of care and patient satisfaction using both ratings and consistency. The greater the consistency, the less the data vary over time, thus lessening the concern about possible biases. However, this does not fully resolve the issue because the timing of measurement would not be in sync with the causal chain. In the second approach, we used different subsets of the data to conduct robustness checks. We used system-use data gathered in specific two- and three-month periods to predict quality of care and patient satisfaction collected in the same time period. This approach alleviates much of the time lag between when the various data were collected. We also used data gathered in specific two- and three-month periods to predict quality of care and patient satisfaction in the subsequent two- and three-month period. The results found in each of these cases were consistent with what we have already reported, thus alleviating concerns about biases associated with the timing of measurement.

for a comparison of the effects of different centralities among doctors versus others. GroupVar2 allows for a comparison of the effects of the different centralities among paraprofessionals versus others. These interaction terms taken together with the split-sample analyses shown in Table 6 help illustrate how different centralities play a role in different user groups. Centrality among doctors had a negative effect on all E-HealthSys use in all three user groups, thus supporting H1(A–C). Centrality among paraprofessionals had no effect on doctor's E-HealthSys use, but had a positive effect among paraprofessionals and administrative personnel's E-HealthSys use, thus supporting H2(A–C). Centrality among administrative personnel also had no effect on doctors' E-HealthSys use, but had a positive effect among paraprofessionals and administrative personnel, thus supporting H2(A–C). In terms of the outcome variables related to quality of care, E-HealthSys use had a positive effect on all four key metrics—i.e., technical quality, communication, interpersonal interactions, and time spent, thus supporting H4(A–D). With respect to the effect of centrality on quality-of-care metrics, we found that the effect of centrality among doctors was significant on all metrics, the effect of centrality among paraprofessionals was significant on technical quality, and the effect of centrality among administrative personnel was significant on both technical quality and time spent. Therefore, H5 was partially supported. In terms of predicting patient satisfaction, the two control variables, which were included consistent with prior research, i.e., financial aspects and access/availability/convenience, had positive effects on patient satisfaction. All the quality-of-care metrics had positive effects on patient satisfaction, thus supporting H6.

Discussion

Based on empirical evidence from a longitudinal field study in a hospital that implemented an e-healthcare system, we found support for a model that linked network position to e-healthcare system use ($R^2 = 0.51$), which in turn influenced patient satisfaction ($R^2 = 0.53$) mediated by key quality of care metrics. Given that our analyses controlled for various known predictors of the dependent variables and preimplementation levels of the dependent variables, we can conclude strong support for our nomological network related to e-healthcare system use. Whereas system use contributed positively to quality of care, ingroup ties among doctors had a negative effect on their system use and outgroup ties to doctors had a negative effect on paraprofessionals' and administrative personnel's system use.

Theoretical Contributions

This work makes key contributions to the different domains from which we draw. First, this work contributes to healthcare technology implementation. The nomological network proposed here complements and advances prior work in this domain that is largely at the macrolevel. Although it has long been documented that doctors resist e-healthcare systems, this work sheds light on the far-reaching impacts that their negative feelings toward technologies can have on other doctors, as well as on paraprofessionals and administrative personnel. We explain that, in large part, such negative effects can be attributed to doctors' acculturation and commitment to traditional medical practices that do not provide a key role for computer-based systems. We also noted that with doctors at the top of the clinical hierarchy, others (e.g., paraprofessionals) act in ways to preserve the hierarchy and defer to doctors' judgments. This is a key result given that e-healthcare system use has positive effects on various quality metrics that in turn influence patient satisfaction.

Related to the first point, our work reveals patterns of technology diffusion in the healthcare context. Prior social network research has shown that central individuals or opinion leaders play a critical role in affecting the diffusion of technology. When a technology is perceived as more advantageous, centrality is associated with more rapid diffusion, but when it is perceived as a risk, centrality impedes diffusion (Valente 1995). When seeking advice from other doctors about the system, central individuals are likely to receive more negative comments about the system, thus reinforcing or creating negative perceptions about the system. As a result, these central doctors are likely to impede the diffusion of the new system. In contrast, less-central individuals are likely exposed to fewer negative comments about the system. Thus, less-central individuals are more likely to adopt and use the new system. This pattern changes when paraprofessionals and administrative personnel seek advice or knowledge from other paraprofessionals and administrative personnel because these two groups of users are likely to develop positive perceptions of the system through these interactions. In this case, central paraprofessionals and administrative personnel are likely to receive more positive comments about the system, resulting in higher levels of system use.

A resource view helps further explicate the pattern of diffusion. Central doctors can access useful resources, e.g., advice, to improve job performance. They do not need to rely on the system to acquire resources. Given that less-central doctors do not have as many sources for advice, they may rely more on the system for resources. They may also want to use the system and become an expert on the same, because they will then likely be perceived as sources of help for system-related problems. When more people seek advice from them, they can become more central in the network (Burkhardt and Brass 1990). Thus, less-central doctors may support the diffusion of a new technology in order to gain access to more resources that are otherwise inaccessible due to their limited network connections.

This work contributes to the rich body of work on IS success. IS researchers have, for some time now, studied various types of impacts of system use at the individual level (see DeLone and McLean 2003) and macrolevel (e.g., Devaraj and Kohli 2000). Whereas at the macrolevel there has been a significant understanding of broader impacts of IT, such as the effects on profitability, at the individual-level less is known (Venkatesh et al. 2007). By providing a nomological network that incorporates both the determinants and consequences of e-healthcare system use, especially by including metrics of quality of care and patient satisfaction, this work complements and extends prior research on IS success. Specifically, this work not only leverages ideas underlying the IS success model, but also contextualizes the consequences of system use by developing arguments and providing empirical evidence about the consequences.

Leveraging the context to understand boundary conditions of prior theories has been identified as an important frontier for theory development in general (Johns 2006), as well as to generate insights for the domain of health care in particular (Chiasson and Davidson 2004, 2005). As noted earlier, social networks research has typically suggested that network position will lead to positive outcomes. Although we found modest support for this theoretical stand, we found more compelling evidence for the nuanced set of relationships presented in this paper. Network position can result in positive or negative effects on behavior, here e-healthcare system use, depending on the professional group, i.e., doctors versus paraprofessionals vs. administrative personnel.

There are several other avenues for future research. First, whereas a key strength of our research design is the multiple sources of data, future work should consider using objective metrics for quality of care, e.g., error rate, in conjunction with the perceptual metrics used in this work. Second, as noted at the outset, whereas recent research has emphasized design of e-healthcare systems, our theory and findings suggest the need to investigate the impacts of e-healthcare systems based on the alignment of the new systems with the traditional medical practices. Third, building on the earlier point, educational interventions in healthcare education settings should be studied. Fourth, our work emphasized the impacts of social networks both on e-healthcare system use and quality of care. A logical and important next step would be to understand how an e-healthcare system implementation changes the networks of each employee, especially given that newly implemented systems in a healthcare setting have been suggested to greatly change communication practices in healthcare organizations (Davidson 2000), social structures in healthcare organizations (Barley 1986, Davidson and Chismar 2007), and create greater interdependencies among workers and departments within the organization (Davidson and Chismar 2007). Finally, our theory development was anchored to social networks, future research can complement this by examining individualcentric theoretical perspectives and constructs such as personality and innovativeness.[4]

Practical Contributions

One of the most important practical contributions is the empirical evidence in favor of the positive impacts of e-healthcare system use. Although positive benefits have been touted, empirical evidence at the microlevel has been fairly limited. By linking system use to key metrics of quality of care, the current work suggests that e-healthcare systems can greatly help improve health care in many ways, especially given that quality was operationalized to include both the mean and consistency. The various specific metrics that are influenced by e-healthcare system use help us understand the rich and far-reaching impacts that e-healthcare systems can have. In this context, quality of care, e.g., reduction in errors, is frequently mentioned as a critical benefit. However, the evidence in this work suggests that there can be other benefits, such as better interactions with patients in terms of communication, interpersonal interactions, and time spent. Specifically, the evidence linking e-healthcare system use to better communication about diagnoses, tests, and follow-up care are important metrics that relate patient understanding about their health and safety and have implications for their long-term health because they will be able to better care for themselves outside the hospital setting.

[4] Our findings could be explained by a range of other theoretical possibilities rather than just negativity and resistance. First, it could be that well-connected doctors (through a measure of those seeking advice from others) are able to delegate technology-related work to other junior physicians who are not as well connected. Second, it could be that physicians who seek advice from other physicians use the system less because they rely upon collegial sources of information, as opposed to the system, to inform their decision making. Third, doctors who seek more advice from others may use the computer systems less because they need help using the system, versus those less-connected physicians who do not need the help from other physicians. Such alternative explanations should be examined in future research to examine the validity of the mechanisms proposed in this work.

The current work also brings a note of caution in that ties to the strongest members of the hierarchy represent a key hindering force in achieving successful outcomes. Although doctors have resisted such systems for a long time, as noted earlier, the current work sheds light on how far-reaching the impacts of this may be. The most critical practical implications relate to the potential interventions that can be designed to overcome the barriers observed. Much trade press has called for a variety of approaches to increase doctors' buy-in to such systems. Some of these recommended approaches, e.g., opinion leadership and greater user involvement, are those that have been suggested in prior IS implementation research and practice as well, but there are some approaches, e.g., designing systems to fit traditional practice and altering healthcare education, that are unique to the healthcare context. Both research and practice must work hand-in-hand to assess the merits of general and specific strategies to understand the relative and complementary efficacy of these approaches. It is clear that the traditional/current system design and implementation approaches, despite the potential benefits of the systems, face significant obstacles in delivering the potential benefits. Further, the countervailing effects of ties, i.e., negative effects of ties to doctors and positive effects of ties to paraprofessionals and administrative personnel, among a large section of the user community may cause job stress beyond what is already typical in times of organizational change. In sum, interventions related to our findings may enhance the possibility of achieving positive outcomes related to e-healthcare system implementations.

Conclusions

Based on a longitudinal field study of an e-healthcare system implementation in a hospital, we found support for our theory that ingroup and outgroup ties play a critical role in influencing e-healthcare system use. Further, such use had a positive effect on a variety of quality-of-care metrics that in turn influenced patient satisfaction. This work contributes to our understanding of e-healthcare system use by identifying, justifying, and finding empirical evidence for determinants and consequences of use. Overall, the nomological network presented in this work can serve as a platform for future research and practice on interventions to enhance e-healthcare system use with a view toward gaining performance benefits. This work complements prior work, especially in IS, on e-healthcare system impacts in particular and IS impacts in general, at the macrolevel by providing strong evidence of benefits at the microlevel.

Appendix. Surveys

Doctors, Paraprofessionals, and Administrative Personnel Survey

Gender: Male Female

Age: ——years

Organizational tenure: How long have you worked at this hospital?
——years

Training attendance: obtained from hospital archives

Training satisfaction (7-point agreement scale)
Overall, I was satisfied with the training.
The training provided comprehensive coverage of the system and how I would use it in my job.
The training materials were comprehensive.

Change management support (7-point agreement scale)
The change management support was available whenever I needed it.
The change management consultants understood my problems well.
The change management consultants resolved the problems I faced.

Conscientiousness (7-point agreement scale)
I keep my belongings clean and neat.
I'm pretty good about pacing myself so as to get things done on time.
I am a very methodical person.
I try to perform all tasks assigned to me conscientiously.

Job satisfaction (7-point agreement scale)
Overall, I am satisfied with my job.
I would prefer another, more ideal job. (reverse score)
I am satisfied with the important aspects of my job.

Job performance: On the 1–10 scale used for performance evaluations at the hospital, what was your rating last year?

Perceived usefulness (7-point agreement scale)
I believe the system would be useful in my job.
Using the system will enable me to accomplish tasks more quickly.
Using the system will increase my productivity.
If I use the system, I will increase my chances of getting a raise.

Perceived ease of use (7-point agreement scale)
My interaction with the system would be clear and understandable.
It would be easy for me to become skillful at using the system.
I would find the system to be easy to use.
Learning to operate the system would be easy for me.

Social Networks
Indicate which of the following individuals are important sources of work-related advice or whom you approach if you have a work-related problem:
<Name 1>
...
<Name *n*>

Note. Scale ranging from 1 to 7, where 1 = never; 2 = rarely (less than once a month); 3 = a few times a month; 4 = weekly; 5 = daily; 6 = A few times a day; 7 = hourly or more.

Patient Survey (7-Point Agreement Scale)

Overall satisfaction

For each doctor:
I am very satisfied with the care I received.
The medical care I received was excellent.
The care was just about perfect.

For each paraprofessional:
I am very satisfied with the care I received.
The medical care I received was excellent.
The care was just about perfect.

For each patient's administrative team:
I am satisfied with the administrative processes at the hospital.
The administrative procedures were perfect.
The administrative personnel who worked on my case handled it excellently.

Technical quality

For each doctor:
The doctor was careful to check everything.
The doctor knew the latest medical developments.
I have complete faith in the ability of the doctor.
I have full faith in the diagnosis of the doctor.

For each paraprofessional (*items for nurses are shown*)*:*
The nurse was careful to check everything.
The nurse knew the latest medical developments.
I have complete faith in the ability of the nurse.
I have full faith in the advice the nurse gives me.

For each patient's administrative team:
The administrative personnel were thorough.
The administrative personnel understood all aspects of my insurance.
I have complete faith in the billing procedures.
I have full faith in the accuracy of my bill.

Communication

For each doctor:
The doctor explained the reason for tests.
The doctor discussed everything important with me.
The doctor listened carefully to me.

For each paraprofessional (*items for nurses are shown*)*:*
The nurse explained the details of the procedures.
The nurse discussed everything important with me.
The nurse listened carefully to me.

For each patient's administrative team:
The hospital administration explained my bill clearly.
The administrative personnel discussed everything important with me.
The administrative personnel listened carefully to me.

Interpersonal interactions

For each doctor:
The doctor did his/her best to keep me from worrying.
The doctor showed genuine interest in me.
The doctor was very friendly and courteous.

For each paraprofessional (*items for nurses are shown*)*:*
The nurse did his/her best to keep me from worrying.
The nurse showed genuine interest in me.
The nurse was very friendly and courteous.

For each patient's administrative team:
The administrative personnel did their best to keep me from worrying.
The administrative personnel showed genuine interest in me.
The administrative personnel were very friendly and courteous.

Time spent

For each doctor:
The doctor spent plenty of time with me.
The doctor was never rushed when treating me.
I always felt that the doctor was spending enough time with me.

For each paraprofessional (*items for nurses are shown*)*:*
The nurse spent plenty of time with me.
The nurse was never rushed when treating me.
I always felt that the nurse was spending enough time with me.

For each patient's administrative team:
The administrative personnel spent plenty of time with me.
The administrative personnel were never rushed when talking to me.
I always felt that the administrative personnel were spending enough time with me.

Financial aspects

I received care without a major financial setback.
I felt the hospital acted in a way to protect me from financial hardship.
I am well insured and thus protected financially.
The amount I expect to pay for the care I receive is reasonable.

Access/Availability/Convenience (*answer only questions applicable to this visit, circle NA otherwise*)

I got hospital care at <hospital name> without trouble.
It was easy to get care at <hospital name> on short notice.
It was easy to get care at <hospital name> in an emergency.
<hospital name> is conveniently located.
I did not wait too long for emergency treatment at <hospital name>.
I was able reach someone at <hospital name> for help with medical questions.
It was easy to get appointment right away at <hospital name>.
The office hours at <hospital name> were convenient to me.
I was not typically kept waiting for a doctor.
It was easy to get access to specialists.

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