Received: 13 October 2015 | Revised: 29 January 2019 | Accepted: 8 February 2019

DOI: 10.1111/isj.12239

RESEARCH ARTICLE

WILEY

# Studying the multilevel impact of cohesion versus structural holes in knowledge networks on adaptation to IT-enabled patient-care practices

Roopa Raman[1] | Varun Grover[2]

[1] Department of MIS, Operations Management, and Decision Sciences, University of Dayton, Dayton, OH 45469, USA

[2] David D Glass Endowed Chair and Distinguished Professor of Information Systems, University of Arkansas, Walton College of Business, Fayetteville, AR 72701, USA

**Correspondence**
Roopa Raman, Assistant Professor, Department of MIS, Operations Management, and Decision Sciences, University of Dayton, Dayton, OH 45469.
Email: rraman1@udayton.edu

## Abstract

We investigate the impact of cohesion versus structural holes in two different types of knowledge networks—help-seeking networks and voluntary contribution networks—on adaptation to health IT-enabled patient-care practices. In a multimethod study conducted within a large hospital system, qualitative and quantitative data were collected from 806 clinicians working with electronic medical record systems in 27 inpatient patient-care units. Multilevel analysis of the data revealed that overall network cohesiveness versus location in structural hole positions related to adaptation differently, depending on the type of network. In help-seeking networks, location in structural hole positions was negatively related to adaptation, while network cohesion had a bell-shaped curvilinear relationship with adaptation; in voluntary contribution networks, the overall cohesiveness of the network was negatively related to adaptation, but location in structural hole positions was irrelevant to adaptation. Our findings suggest a more nuanced way of monitoring and utilising different sets of informal social interactions at work to maximise employees' adaptation to IT-enabled work.

KEYWORDS

adaptation, electronic medical records, IT implementation, IT-enabled work practices, knowledge networks, social interaction

  

## 1 | INTRODUCTION

Health information technologies (ITs), such as electronic medical records (EMRs), aim to transform patient-care work to make it safer and of higher quality (Halbesleben, Savage, Wakefield, & Wakefield, 2010; Middleton et al, 2013; Wulff, Cummings, Marck, & Yurtseven, 2011). To realise this promise of health ITs, health-care professionals must adapt to new health IT-enabled patient-care practices by consistently complying with the new tasks created by technology (Barley, 1990; Davidson & Chismar, 2007; Feldman & Rafaeli, 2002; Fiol & Lyles, 1985; Ng, Kankanhalli, & Yip, 2011). However, such adaptation is challenging due to the high levels of coordination needed on interdependent work involving multiple providers (Debono et al, 2013; Hertzum, 2010; Lapointe & Rivard, 2007). To cope with this challenge, knowledge sharing is pivotal as professionals deal with IT-enabled work practices.

Social interaction is recognised as an enabler of adaptation by facilitating knowledge sharing, in the form of advice and help, as people try to adapt (Gallivan, Spitler, & Koufaris, 2005; Sykes, Venkatesh, & Gosain, 2009). This is particularly true for adaptation to health IT-enabled patient-care work, given that, by its very nature, this type of work involves interdependent coordinated engagement of multiple professionals working together (Novak, Brooks, Gadd, Anders, & Lorenzi, 2012). However, what is often disputed are the particular social interaction structures that are the most conducive to successful adaptation (for a review, see Flap, Bulder, & Voker, 1998). Extant literature presents inconsistent evidence regarding the ability of an individual to adapt when embedded in overall cohesive network structures, in the extremes of which every member of the network is directly connected to every other member, versus when located in structural hole positions that bridge across otherwise disconnected portions of the network (Burt, 1992; Coleman, 1988; Dong & Yang, 2015, 2016). On the one hand, Coleman (1988) argues that highly cohesive structures enable better communication as well as a normative culture that promotes trust and discourages opportunistic behaviour, which can facilitate adaptation (Gargiulo & Benassi, 2000). On the other hand, Burt (1992, 1997) and others argue that positions of structural holes offer greater flexibility of interaction and better coordination of actions when adapting to new ways of working, which also facilitates adaptation (Burt, 1992, 1997, 2000; Hansen, 1999).

Recent studies have sometimes shown cohesion and at other times shown structural holes as being more conducive to such outcomes as adaptation, change, innovation, social capital, etc (Battilana & Casciaro, 2012; Gargiulo & Benassi, 2000; Tortoriello, 2015). This has further fuelled questions about whether cohesion or structural holes is the dominant factor impacting various outcomes relevant to adaptation and change (Chai & Rhee, 2009). However, cohesion and structural holes are characteristics of network structure that exist at different levels of analysis and need not be mutually exclusive (Hanneman & Riddle, 2005). Cohesion is a network-level concept, while structural holes is defined at the level of individual or nodal position (Borgatti, Everett, & Johnson, 2013; Burt, 1992); someone who is not in a cohesive network is not automatically in a high structural hole position and vice versa. Given that these structures are not mirror opposites, it makes sense that they could both relate to outcomes, as current cumulative evidence suggests. Therefore, resolving this apparent inconsistency of cohesion versus structural holes in knowledge networks may not be a question of whether—but rather, of when—these two structures assume greater salience in impacting outcomes of interest (Chai & Rhee, 2009; Xiao & Tsui, 2007). In taking this approach, we join other studies that have also presented various contingency theories explaining when—rather than whether—cohesion versus structural holes are salient to outcomes of interest (Battilana & Casciaro, 2012; Chai & Rhee, 2009; Xiao & Tsui, 2007).

To investigate this question of "when," we undertake a disaggregated view of knowledge networks. Help-seeking networks are structures through which people actively seek help and advice when faced with a problem in health IT-enabled patient-care work. Voluntary contribution networks are structures through which people voluntarily share useful tips, tricks, and insights with others, without the latter facing any problems in health IT-enabled patient-care work (Gray & Meister, 2004; Hurlbert, Haines, & Beggs, 2000; Konrad, Radcliffe, & Shin, 2016; Obukhova & Lan, 2013; Renzulli & Aldrich, 2005; Sykes et al, 2009). Recent IS work has shown that disaggregating social networks, such as advice networks or knowledge networks, into more nuanced components can provide a finer understanding

of the impact of network structure on outcomes (Sykes et al, 2009; Sykes, Venkatesh, & Johnson, 2014; Zhang & Venkatesh, 2013). We investigate the roles of cohesion and structural holes in both types of knowledge networks, which coexist within the same set of nodes. We address the following broad non–context-specific research question: *What is the impact of cohesion and structural holes in help-seeking networks and voluntary contribution networks on adaptation to IT-enabled work practices?* We answer this question in the specific context of health IT-enabled patient-care practices.

Through extensive field observation (qualitative) and quantitative data, we empirically investigate the roles of cohesion and structural holes in 27 sets of help seeking and voluntary contribution networks co-occurring within the entire population of 27 inpatient patient-care units within a large urban hospital system, representing 806 health-care providers. This hospital system had implemented a clinical information system, comprising EMRs and associated decision support technologies. Each patient-care unit within the hospital provided a unique localised context within which providers working in that unit needed to adapt to the same hospital-wide EMR-enabled patient-care practice. Our goal in this study is to provide a more fine-tuned story about when each structural feature is more relevant than the other in knowledge networks—when the network is viewed from the perspective of the knowledge seeker (help-seeking network) versus the knowledge donor (voluntary contribution network) as the driver of content flow.

Below, we describe the setting that allows us to contextualise the theoretical background for the study, followed by hypotheses, method, and results. In the Discussion section, we describe the contributions that our study makes to research and practice.

## 2 | THE SETTING

To better contextualise the theoretical background, we begin with a description of setting, as observed in our qualitative fieldwork. Here, we describe the specific health IT-enabled patient-care practice that we focused on, namely, the EMR-enabled medication verification practice. We also describe our outcome of interest, namely, *adaptation* to health IT-enabled patient-care work, and illustrate the types of knowledge networks and their importance in achieving adaptation.

### 2.1 | EMR-enabled medication verification practice, adaptation, and knowledge sharing

Organisational work practices involve multiple people working jointly in repetitive recognisable patterns of interdependent actions (Feldman & Pentland, 2003; Pentland & Rueter, 1994). Therefore, adapting to IT-enablement of organisational work practices presents additional challenges of coordination and interdependencies across multiple providers acting as agents responsible for different aspects of the work.

In this paper, we focus on adaptation to IT-enablement—specifically, EMR enablement—of a specific organisational work practice that is salient in inpatient hospital settings, namely, "medication verification practice" (Beagley, 2011; Garber, 2011; Novak et al, 2012; Prakash et al, 2014). Appendix A describes the medication verification practice before and after EMR enablement, as observed in qualitative fieldwork at our field-site hospital, as well as the practical issues and challenges that typically manifest as providers adapt to the new EMR-enabled system.[1] Briefly, the medication verification practice is one of the practices relevant to administering medications to patients admitted to the inpatient division of a hospital. The purpose of this practice is to allow nurses/respiratory therapists (RTs) to systematically check/verify every new medication for each of their patients received from pharmacy against the physicians' original prescription; this is an important check-and-balance mechanism to reduce errors of translation between prescribing physicians and fulfilling pharmacy personnel. The practice itself includes a sequence of tasks that involves change of hands between physicians, pharmacy, nurses, and respiratory therapists as the primary participants and unit secretaries and patient care technicians as support participants; these tasks are detailed in Appendix

[1]We supplement this presentation with references from the medical informatics literature as evidence of the generalisability of our qualitative findings to other healthcare organisations.

A. The practice unfolds primarily within the various inpatient patient-care units throughout the hospital, with some steps being executed centrally within the pharmacy department; it unfolds multiple times throughout the day—each time a physician writes a new medication order or changes an existing medication order, a new instantiation of the medication verification practice initiates.

EMR enablement introduced several changes in this practice (see Appendix A); these changes were intended to reduce errors and improve patient safety. Many of the changes were in the form of new tasks that were created because of the technology itself, which did not exist prior to the technology; as such, the very doing of these tasks indicated adaptation to the IT-enabled changes introduced in the practice. We chose one such EMR-enabled task, which was a core task within the overall EMR-enabled medication verification practice, as an indicator of adaptation to the EMR-enabled practice.

Adaptation to the EMR-enabled practice is embodied in compliance with a new medication verification task that was specifically created because of EMR enablement and did not exist in the pre–EMR-enabled version (see Appendix A for details). This task required each new medication appearing on the EMR screen in a given shift to be verified, on the same shift, against the physician's original order.[2] Compliance with this EMR-enabled task involved more than simply accepting the technology to conduct a task. Rather, in many ways (see Measurement section for details), compliance with this task inextricably represented a rich set of necessary process modifications following EMR enablement. It was therefore appropriate as a measure of adaptation to the EMR-enabled medication verification practice as a whole, rather than simply as a measure of EMR system acceptance. The number of new medications that were verified, as described above, was indicative of the extent of adaptation to the EMR-enabled version of the practice; fewer medications verified within the same shift indicated lower adaptation to the EMR-enabled practice as compared with more medications verified.

Patient-care practices in inpatient hospital settings are interdependent on many dimensions—interdependencies extend across work roles, across tasks within a single patient-care practice, and across tasks from cross-cutting patient-care practices. For example, nurses must depend on physicians to write the prescription order before they can verify information about the processed order on the EMR screen. Nurses may also need to depend on laboratory to process ordered blood work in a timely fashion (a different patient-care practice) so that physicians can review the test results and prescribe any changes to already-ordered medications. These changed medications would then need to be refilled by pharmacy before the nurse could do his/her job of verifying the accuracy of the refilled medication. Verification of new medications is, in turn, a necessary precursor to administering medications to patients. The EMR system digitised not just the medication verification practice but the whole gamut of cross-cutting patient-care practices relevant to the entire inpatient hospital setting. As such, EMR enablement created new challenges of coordination and communication within and across patient-care practices; the requirement to streamline most coordination of work and communication between personnel in particular EMR-enabled ways was a key constraint fuelling many of these challenges, as elaborated in Appendix A.

The interdependent complex and challenging nature of the EMR-enabled medication verification practice—and of EMR-enabled patient-care work in general—created fertile ground for help seeking and voluntary contribution interactions between health-care providers within a patient-care unit as they went about these practices (Borgatti & Cross, 2003; Feldman & Pentland, 2003; Leonardi, 2011; Sykes et al, 2014). Help-seeking interactions occurred in response to any problems that arose in daily performance of EMR-enabled work (see Appendix A) (Bates, Ebell, Gotlieb, Zapp, & Mullins, 2003). For example, clinicians would seek each other's help on their unit when delays in receiving test results from laboratory stalled their medication verification work, pushing it close to shift-change time. Instead of quietly waiting for the test results to show up on the EMR screen, as they were expected to do, or calling laboratory, as they were discouraged to do, nurses would seek help from colleagues on their unit, such as other nurses or unit secretaries, about how to resolve this issue. Should they call lab, how long should they wait before

[2]In the pre-EMR version, information on the medication vial would be verified against the physician's prescription order. In the EMR-enabled version, this verification would be performed in addition to the verification of the information appearing on the EMR screen; the latter is the new task that did not exist prior to the EMR system and is the focus of our DV.

calling? If so, whom should they call—who, in lab, would be more receptive or helpful with such a phone call? At what point should the physician be notified of an excessive delay?

Opportunities for voluntary contribution of one's insights to others also abound in this context (Hurlbert et al, 2000; Konrad et al, 2016; Obukhova & Lan, 2013; Renzulli & Aldrich, 2005). As people engaged with the EMR-enabled medication verification practice on a daily basis, they would come upon useful tips, tricks, and insights that would help them adapt more readily to these practices. Patient-care work is interdependent, involving multiple people (Leonardi, 2011; Sykes et al, 2009). Caring for the well-being of all patients, not just the ones assigned to them, is a characteristic of health-care professionals. So, when people uncovered something useful in the course of working with the EMR-enabled medication verification practice, they would tend to pass it along to others so that others may also benefit from the insight. Because of interdependencies in work, voluntarily contributing insights to others even helped the contributors do their work more smoothly and reduced interruptions in their workflows.

We observed multiple instances of voluntary contribution of insights in our qualitative fieldwork. For example, medication names can sometimes be tricky, because the same medication could typically have multiple different names and different medications could have very similar sounding names (Lisby, Nielsen, & Mainz, 2005; Orrico, 2008). In the interest of patient safety, the EMR system would only allow one set of hospital-approved names for all the medications that were prescribed in the hospital. Often, physicians would break hospital-approved protocol and call-in verbal orders over the phone; when they did so, they typically used their own preferred names for the medications they were calling in, rather than the hospital-approved names (Koczmara, Jelincic, & Perri, 2006; West et al, 1994). However, when processing this order into the EMR system, pharmacy would be constrained by the EMR system to only use one set of standardised hospital-approved names. This would increase the number of medication name discrepancies between the EMR screen versus the physician's verbal order that nurses would then need to reconcile. One nurse figured out a way to keep a written log of all previously resolved discrepancies in medication names so as to not have to reinvent the wheel with each new prescription order. This nurse passed along this insight to others on her unit so that others could also contribute to this log based on their own experiences. In this way, she helped not only others, but also herself, adapt better to the EMR-enabled medication verification practice by learning from medication name discrepancies that other nurses had resolved and added to the log.

Our qualitative observations, therefore, revealed the many interdependencies in the EMR-enabled medication verification practice, intensified by EMR enablement, which caused social networks to be salient for adapting to individual-level tasks within this practice. This sets the stage for the following theoretical background on cohesion and structural holes, as discussed in prior literature on adaptation, change, and related concepts.

## 3 | THEORETICAL BACKGROUND

### 3.1 | Network cohesion and structural holes

Cohesion and structural holes are key concepts in social network studies of various organisational phenomena related to adaptation, such as organisational change, innovation, and adapting to different professional roles. For example, the role of cohesion and structural holes is invoked to explain how people can adapt to changes in task interdependencies (Gargiulo & Benassi, 2000). Cohesion and structural holes also affect how individuals acquire external knowledge and transform it into innovations (Tortoriello, 2015). These characteristics have been discussed as enabling or hindering social capital (Chai & Rhee, 2009; Gargiulo & Benassi, 2000), organisational change (Battilana & Casciaro, 2012), the change of network relations following transitions in professional roles (Jonczyk, Lee, Galunic, & Bensaou, 2016), and others. Prior literature, therefore, provides good support for investigating cohesion and structural holes as network structural antecedents to adaptation to EMR-enabled patient-care work in this study.

Cohesion is a property of the whole network in which there are close ties, involving few intermediaries, connecting everyone in the network (Gargiulo & Benassi, 2000; Hanneman & Riddle, 2005; Reagans & McEvily,

2003). It is well established in prior literature that cohesive network structures facilitate collaboration and trust among people by creating a normative culture that favours collaborative collective action and disfavours acts of defection or opportunism (Coleman, 1988; Gargiulo & Benassi, 2000). In cohesive networks, people connected to each other are more likely to have common third parties as contacts. In exchanges within cohesive structures, therefore, people are likely to act in collaborative and trustworthy ways because acts of opportunism would be visible to the common third parties and may preclude individuals exhibiting such behaviour from receiving future social benefits (Gargiulo & Benassi, 2000; Granovetter, 1985). While cohesive structures offer this safety of trust and close-knittedness, they are also described in the literature as being inflexible and difficult to change (Burt, 1997; Gargiulo & Benassi, 2000).

Structural holes define a property of social networks at the individual nodal-level (Burt, 1997; Gargiulo & Benassi, 2000). Structural holes are created when pockets of disconnection arise in the network, offering the unique positional advantage of bridging across disconnected clusters. These positions allow access to and monitoring of knowledge and opportunities across disconnected network clusters whose knowledge content would otherwise have had no way to connect and merge (Burt, 1997; Hahl, Kacperczyk, & Davis, 2016). People in structural hole positions can act as brokers negotiating the sharing of knowledge and communication across disconnected clusters (Hahl et al, 2016; Quintane & Carnabuci, 2016). Unlike cohesive networks, structural holes offer more flexibility due to greater disconnections between nodes. These positions are more likely to facilitate coordination of work, especially in response to changes in task needs and interdependencies (Gargiulo & Benassi, 2000). Although cohesion and structural holes are defined at different levels of analysis and, as such, are not mirror opposites of each other, they are nonetheless opposing structural tendencies. In other words, networks that are more cohesive would tend to have fewer structural holes in them and vice versa (Burt, 1997; Gargiulo & Benassi, 2000).

One stream of research in this domain has emphasised the contrasting roles of cohesion versus structural holes for various outcomes of interest (Burt, 2004; Gargiulo & Benassi, 2000; Reagans & McEvily, 2003). For example, Gargiulo and Benassi (2000) found that social structures rich in structural holes were better than cohesive structures in allowing flexibility and change in network structure following changes in task interdependencies. Other work has identified different sets of benefits of each structural characteristic in the generation of social capital (Chai & Rhee, 2009; Gargiulo & Benassi, 2000).

Another stream of research has recognised the importance of both cohesion and structural holes for outcomes of interest and has focused on identifying the contingent factors and circumstances under which each is relatively more salient than the other (Battilana & Casciaro, 2012; Xiao & Tsui, 2007). For example, with respect to organisational change, structural holes are found to be more conducive than cohesion for change initiatives that diverge significantly from the institution's status quo but not for less radical change initiatives (Battilana & Casciaro, 2012). Other work has found both cohesion and structural holes to impact the network structure transitions that occur following role transitions and promotions in organisations (Jonczyk et al, 2016). Still other studies have found cultural factors to play a contingency role in the relative importance of cohesion versus structural holes towards social capital (Chai & Rhee, 2009; Xiao & Tsui, 2007). IT-enabled capability can also have a contingent effect on the extent to which structural holes can impact the intensity of competitive action undertaken by a firm (Chi, Ravichandran, & Andrevski, 2010).

In this study, we join the latter stream of research that has emphasised a contingency perspective on elucidating the relative significance of cohesion and structural holes. The contingency factor that we consider in this study is the mode of disaggregation of the network itself, based on whether the seeker or the contributor is driving the flow of content through the network.

## 3.2 | Help seeking versus voluntary contribution networks

Help seeking versus voluntary contribution are two different modes—pull versus push—through which knowledge gets shared in organisations (Acharya, Franklin, & Zdonik, 1997; Gray & Meister, 2006; Kendall & Kendall, 1999; Unni

& Harmon, 2007). Help seeking is when people encounter problems in their work, for example, in the EMR-enabled medication verification practice, and reach out to others to help resolve these problems (Gray & Meister, 2004). Voluntary contribution is not initiated by any problem that the recipient is facing. Instead, voluntary contribution involves people coming across a useful tip or insight in their daily performance of the EMR-enabled medication verification practice and voluntarily passing it along to others so that they may also benefit from this insight. These voluntary contributions are one-on-one interactions between the contributor and the people to whom he/she chooses to pass on the insights. As such, voluntarily shared insights are not formalised into a knowledge repository that is freely available to everyone in the organisation. Social interaction is, therefore, essential for the flow of these unsolicited insights. Help-seeking and voluntary contribution differ in terms of the agent that is actively driving the flow of network content (Howard-Grenville, 2005; Schultze & Orlikowski, 2004; Unni & Harmon, 2007), thereby emphasising the "why," in addition to the "what," underlying network flows.

Figure 1 illustrates the dyadic unit of interaction underlying each network. Help-seeking interactions are characterised by the flow of "requests for advice," initiated by a focal node encountering problems and terminating on an alter node in the same unit who may be able to help. A dyad in voluntary contribution networks involves "preferred unsolicited insights" from the donor (the alter node) flowing to a potential recipient (the focal node) within the same work unit who finds this insight useful. The two networks, therefore, differ in the actual content that is flowing through them and in the drive for each of these flows: in the help-seeking network, seeker-initiated "requests for advice" in response to encountered problems, and in the voluntary contribution network, donor-initiated "unsolicited preferred insights" unrelated to any problem on the recipient's end. We demonstrate the conceptual, operational, and analytical distinctiveness of these two networks, which represent two distinct network structures between the same set of nodes, rather than different perspectives on a single network structure.

In the next section, we develop our hypotheses linking cohesion and structural holes in help-seeking networks and voluntary contribution networks to adaptation to the EMR-enabled medication verification practice. In doing so, we offer a contingency explanation of cohesion and structural holes as antecedents to adaptation by undertaking a disaggregated view of traditional knowledge networks.

## 4 | RESEARCH MODEL AND HYPOTHESES DEVELOPMENT

In this section, we will first present a set of boundary conditions within which our research model (Figure 2) and its hypotheses would be relevant. We then develop hypotheses pertaining to the help-seeking network followed by the voluntary contribution network.

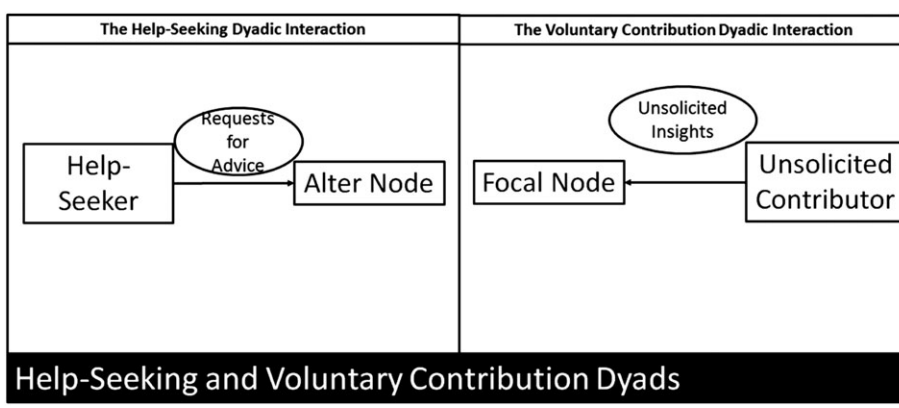


**FIGURE 1** Help seeking and voluntary contribution dyads

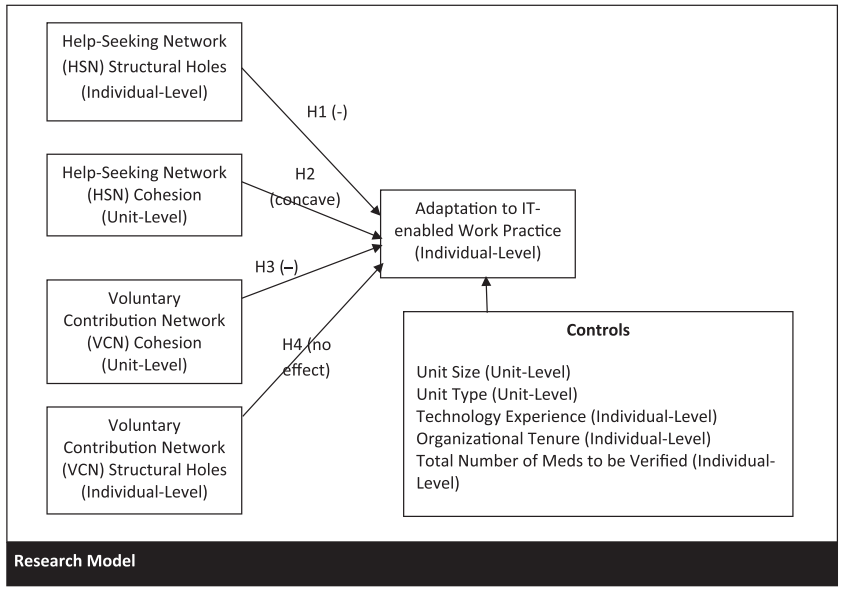


**FIGURE 2** Research model

## 4.1 | Boundary conditions

### 4.1.1 | One: Middle-of-the-continuum network structures that are partially cohesive and also have some structural holes within the same network

In prior social networks literature, structural holes and cohesion are treated as being on opposite ends of a continuum—a network is either cohesive, where the contacts of a person's contacts are mostly connected to each other, or it is rich in structural holes. Most studies have compared the behaviours of networks that are on either end of this continuum (Burt, 1997; Coleman, 1988; Gargiulo & Benassi, 2000). Our study purposefully focuses on network structures that are in the middle of this continuum, where both structural characteristics—cohesiveness and structural holes—can simultaneously exist. In these middle-of-the-continuum structures, there is variance in both cohesion and structural holes.

### 4.1.2 | Two: Multilevel comparison of cohesion versus structural holes

In social network theory, the concept of cohesion is a whole network property, while structural holes is a property of node positions within the network (Burt, 1997; Hanneman & Riddle, 2005). Extant studies that apply these concepts, particularly in a comparative mode, tend to view these two properties at the same whole-network level of analysis. For example, studies have compared cohesive networks against *networks that are rich in structural holes* (Burt, 1992, 2000; Chai & Rhee, 2009; Gargiulo & Benassi, 2000). In this study, we keep apart the levels of these two structural characteristics, in line with their theoretical definitions, and perform a multilevel investigation comparing these two characteristics.

In our hypotheses development, which follows, we evaluate the implications of such multilevel network location and network embeddedness on individuals' adaptation to IT-enabled work practices. The theorisations elaborated in the sections that follow are supported, in Appendix B, by practical illustrations from the healthcare context.

## 4.2 | Cohesion and structural holes in the help-seeking network

In help-seeking networks, people seek advice to help resolve problems that they have encountered while adapting to IT-enabled work practices; finding help to resolve a problem is, therefore, the key factor driving content flow in this network. As help is mobilised, problems are more likely to get resolved, and people are more likely to adapt to IT-enabled work practices (Giampaoli, Ciambotti, & Bontis, 2017; Tyre & von Hippel, 1997). We expect that two different characteristics of help-seeking network structures—location in structural hole positions versus embeddedness in overall cohesive network structures—would relate in qualitatively different ways to individuals' problem solving and, in turn, to their adaptation to IT-enabled work practices.

The central premise guiding our theorising is that, in help-seeking networks, closeness of connections—rather than newness of insights—is the dominant factor relating to problem resolution. Problem solving requires close collaborative interaction—ie, frequent contact via relatively few intermediaries—between the advice seeker who is facing the problem and others who are likely to offer advice (Brown & Duguid, 2001; Hansen, 1999, 2002). Helping to resolve a problem involves more than simply the give-and-take of preformed knowledge (Nickerson & Zenger, 2004; Szulanski, 2000). Rather, problem resolution is constructed within its local context by applying, integrating, and synthesising received knowledge with the specific characteristics of the local context and the nuances of the problem at hand (Howard-Grenville, 2005; Szulanski, 1996; von Hippel, 1998). This requires in-depth familiarity with the context and the ability to learn deeply about the problem, often through back-and-forth verbal reconstruction with the help seeker (Nickerson & Zenger, 2004; Szulanski, 2000). It also requires considerable investment of time and energy from the provider of help, which is likely to be more forthcoming if the helper feels like he/she can relate to or empathise with the predicament of the help seeker (Granovetter, 1985; Tyre & von Hippel, 1997; von Hippel, 1998). People are also more likely to invest time and energy into helping others in need when their actions are observable to those around them (Gargiulo & Benassi, 2000). There is greater incentive to help others when doing so earns helpers the kudos, positive regard, and hopefully future help of others in their network (Adler & Kwon, 2002; Inkpen & Tsang, 2005. All of these benefits are likely to be realised when the help seeker can connect through close interaction with others in the help-seeking network.

For the most part, the newness or novelty of knowledge is not particularly important for problem resolution (Hansen, 2002). For one, since, in the help-seeking context, relevant knowledge is tied to the problem at hand, it could not, by design, be too drastically new or different. Furthermore, relatedness—rather than novelty or distinctiveness—of knowledge received from different sources is likely to lend the knowledge more readily to integration, application, and synthesis in the local problem-specific context (Goh, 2002; Hansen, 2002; Tyre & von Hippel, 1997). Entirely new or different insights may, in fact, create difficulties in translation or understanding of how these insights connect with each other and apply to the specific problem within the local context (Roberts, Galluch, Dinger, & Grover, 2012; Tsai, 2001).

### 4.2.1 | Structural holes in help-seeking networks

Given the above characteristics of help seeking and problem solving, we expect structural hole positions in help-seeking networks to be negatively related to adaptation. People who occupy high structural hole positions in help-seeking networks (Figure 3A.1) engage with others, who are themselves disconnected from each other, for problem-specific advice (Burt, 1997; Hanneman & Riddle, 2005). They are also only sparsely connected to the people immediately spanning the structural hole, rather than having dense connections with entire clusters of people on each side of this hole (Burt, 1997; Granovetter, 1985). As such, these positions do not allow deep embeddedness within local network contexts. This, in turn, precludes the close collaborative interaction and familiarity with the help-seeker's local work context that is necessary for complex problem-solving. Relatedly, the characteristic lack of common third party contacts in these positions (Burt, 1997; Gargiulo & Benassi, 2000) is likely to result in help-giving responses that are less observable for judgement or reward by others in the network, reducing accountability and, in

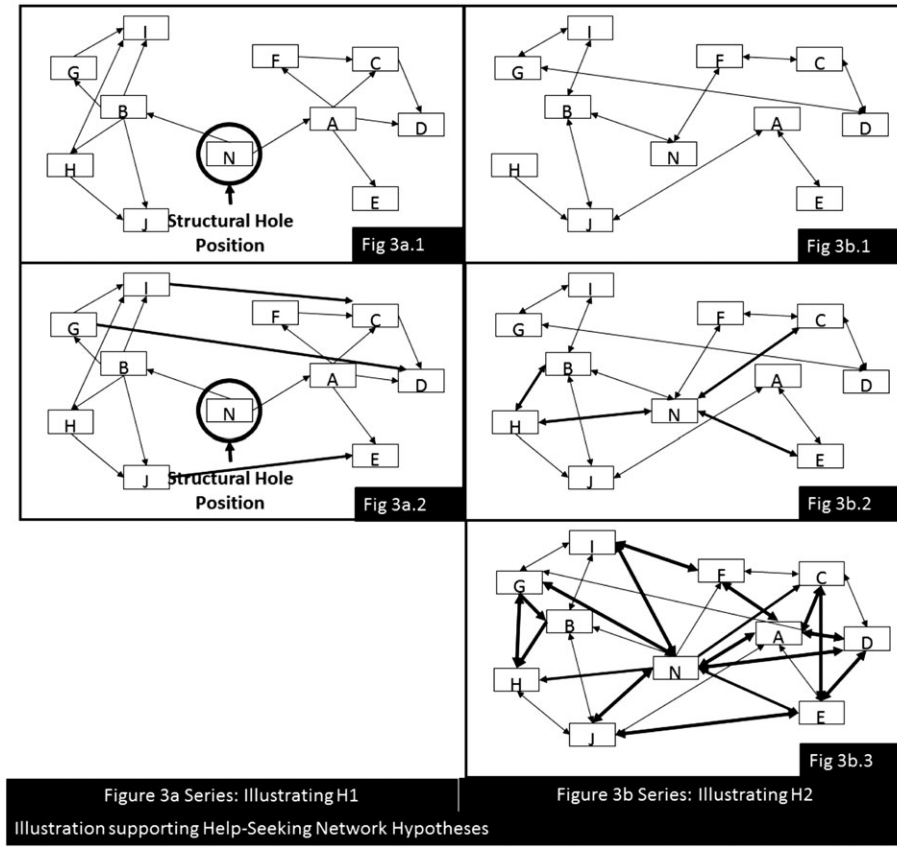


**FIGURE 3** Illustration supporting help-seeking network hypotheses. NOTE 1: Within each vertical series of figures, some arrows are represented in wider/darker form simply to more easily highlight the difference with the previous figure in the same vertical series. The width of the arrows in these network illustrations do not convey any substantive information about the strengths of the corresponding interactions. NOTE 2: No corresponding figure supporting the voluntary contribution network hypotheses (H3 and H4) is provided since the theorising and practical examples supporting these hypotheses (in the article text and in Appendix B) do not refer to a pictorial illustration

turn, incentive to help when called upon (Gargiulo & Benassi, 2000). Consequently, people in high structural hole positions likely find it more difficult to resolve problems and, in turn, to adapt to IT-enabled work practices.

As the extent of "structural hole"-ness of the position decreases (Figure 3A.2), this means that more cross-cluster links are created between people across the hole (Borgatti et al, 2013). As this happens, greater connectedness is created in the local network surrounding the person in the structural hole position, arguably at no extra cost to him/her. All of the previously mentioned benefits of closer interaction to problem solving are now more likely to be experienced as the "structural hole"-ness of the position decreases, relating in turn, to better adaptation to the IT-enabled work practice.

### 4.2.2 | Cohesion in help-seeking networks

A less cohesive help-seeking network (Figure 3B.1) is one involving open nonclustered forms where, in the smallest unit, if A asks B for help and B asks C for help, it is less likely that A would also ask C for help (Borgatti et al, 2013; Hanneman & Riddle, 2005). Thus, there are open strings of help-seeking interactions that involve larger numbers of intermediaries between help seekers and most providers. In these less cohesive (but still connected) structures, there is very little closeness of interaction (Borgatti et al, 2013; Scott, 2000). So a person seeking help while being

embedded in this type of overall network structure is less likely to mobilise the resources needed to solve the problem. The first reason for this is that his/her own connectivity in the network is more likely to be sparse, involving larger numbers of intermediaries. This would make it more difficult for him/her to engage suitable help givers in response, within his/her local problem context and, therefore, to mobilise the help that would be needed for problem resolution (Hansen, 1999;Szulanski, 2000 ; Tyre & von Hippel, 1997). Second, the sparseness in overall network connectivity would weaken broader social accountability and reward mechanisms that may have kept responding help givers more "honest" or proactive in providing help (Adler & Kwon, 2002; Inkpen & Tsang, 2005; Konrad et al, 2016). Individuals' adaptation to IT-enabled work practices is, therefore, likely to be low when they are embedded in less cohesive overall network structures.

As network cohesiveness grows (Figure 3B.2), people are more closely connected to each other through fewer intermediaries separating pairs of nodes (Borgatti et al, 2013). An individual encountering a problem when embedded in such a network is more likely to engage people who can integrate and synthesise what they know, in a context-specific manner, and apply it to the problem at hand (Szulanski, 2000; Tyre & von Hippel, 1997). People's actions are also more readily "watched" amidst such closed structures, creating greater incentive for them to respond to calls for help, and in turn, greater likelihood for people to mobilise help (Gargiulo & Benassi, 2000; Inkpen & Tsang, 2005). Thus, as the cohesiveness of the overall network increases, people embedded in these network structures find it easier and/or quicker to resolve problems and, in turn, to adapt to IT-enabled work practices.

As the level of cohesion in the help-seeking network keeps increasing (Figure 3B.3), it is likely that, beyond a certain point, further adding to the connectedness of individuals—ie, adding even more ties in an already well-connected network—is likely to yield diminishing returns for problem solving (Falci & McNeely, 2009; Molina-Morales & Martínez-Fernández, 2009; Wise, 2014). This is because, in a well-connected network, there are already many people who can readily be brought to bear on a problem (Coleman, 1988; Tyre & von Hippel, 1997). Further adding connections is likely to be redundant with respect to the help that can be mobilised in such tightly closed structures (Molina-Morales & Martínez-Fernández, 2009). This means that, for help seekers, as cohesiveness of their network increases, so does redundancy in the information being brought to bear on the problem, resulting in lower rates of problem resolution and adaptation (Wise, 2014).

As the cohesiveness of the help-seeking network grows even further, problem-solving for help-seekers embedded in such structures is likely to become increasingly negative. In addition to the redundancy problem mentioned earlier, as the overall number of help-seeking ties in the network grows even further, there is now a cost or burden that people begin to face in such structures from being overloaded with too many requests for help from too many people that are too close to them (Bawden & Robinson, 2009; Eppler & Mengis, 2004; O'Reilly, 1980). As a result, at such high levels of cohesion, potential help givers are more likely to be fatigued or even irritated due to the increasing demands on their time from having to attend to others' problems (Speier, Valacich, & Vessey, 1999). Consequently, the quality of help that is mobilised to the problem is likely to suffer; people may make hurried or distracted offers of help without listening carefully to the problem, because of being overburdened by too many requests for help, which may backfire and actually lower adaptation to greater and greater extents (Buchanan & Kock, 2001; Speier et al, 1999).

Therefore, we expect that, as the cohesion of the help-seeking network increases, it will initially relate positively but then reach diminishing returns with respect to problem resolution and, in turn, to adaptation to IT-enabled work practices. If the cohesion of the network continues to grow even higher beyond this point, it is likely to relate to an increasingly negative relationship with adaptation. So the overall cohesiveness of help-seeking networks is expected to have a bell-shaped or concave diminishing curvilinear relationship with individuals' adaptation to IT-enabled work practices.

This leads to the first two hypotheses of this study, pertaining to help-seeking networks:

> **H1.** *Location in structural hole positions in help-seeking networks is negatively related to adaptation to IT-enabled work practices for individuals occupying these positions.*

**H2.** *The overall level of cohesiveness of the entire help-seeking network is likely to have a bell-shaped concave relationship with adaptation to IT-enabled work practices for individuals embedded in these networks (ie, the relationship is positive with diminishing returns, turning negative at high levels of cohesion).*

## 4.3 | Cohesion and structural holes in the voluntary contribution network

In voluntary contribution networks, people voluntarily share with others helpful tips, tricks, and insights that have allowed them to work better with the IT-enabled practice, so that others may also benefit from these insights. A key distinction from the help-seeking network is that the flow of content in this network is driven by the contributor (not the seeker/recipient), based on what he/she has found useful when working with IT-enabled practices and not by any problem faced by the recipient. We hypothesise that, in the voluntary contribution network, structural hole positions are not relevant, but the overall cohesiveness of network structure is significant for individuals embedded in these networks to adapt to IT-enabled work practices.

The central premise guiding our theorising on voluntary contribution networks is that the perceived newness of shared insights in this network is the key factor relating to adaptation to IT-enabled work practices. People are likely to pay attention to received unsolicited insights if the insights are offering something new that they did not already know (Reagans & McEvily, 2003; Tortoriello, 2015; Tortoriello & Krackhardt, 2010). As people pay attention to received unsolicited insights, they are likely to apply them in their own work and to benefit from these insights, since these had already proven useful to the contributor. This way, recipients are likely to improve their adaptation to IT-enabled work practices by taking advantage of the learning experiences of others in the network (Boud & Middleton, 2003; Boyd, Richerson, & Henrich, 2011; Kim & Miner, 2007).

Furthermore, because of interdependencies of work created by IT-enabled work practices, as others apply the insights shared by the contributor, this in turn increases the value of these insights to the contributor (Howard-Grenville, 2005) and improves the latter's adaptation to the IT-enabled work practice as well. As more people accept and apply shared insights, any errors or opportunities to improve them are more readily brought to the awareness of the contributor and can be corrected or improved. The act of teaching one's insights to others, in the process of sharing these insights, also increases the contributor's own proficiency with the insight (Nestojko, Bui, Kornell, & Bjork, 2014).

Increased attention to shared insights in voluntary contribution networks, sparked by newness of these insights, is, therefore, likely related to greater adaptation to IT-enabled work practices for everyone involved.

### 4.3.1 | Cohesion in voluntary contribution networks

In less cohesive voluntary contribution networks, people share unsolicited insights with other people through larger numbers of intermediary contacts in open nonclustered structures (Borgatti et al, 2013; Hanneman & Riddle, 2005). In such network structures, individual experiences with IT-enabled work practices, as well as the insights that people gain from these experiences, are seldom common across large numbers of people and also take much longer to equilibrate across people due to the sparseness of connections between them (Chai & Rhee, 2009; Gargiulo & Benassi, 2000; Xiao & Tsui, 2007). So, when someone uncovers a useful insight in such a network structure, it is likely that there would be others in the network to whom this would be a novel insight and who would therefore pay attention to it (Burt, 1997; Gargiulo & Benassi, 2000). More of the insights that are shared in an unsolicited manner in less cohesive network structures are likely to be perceived as new by others in the network and, therefore, likely to receive their attention.

As the level of cohesiveness of voluntary contribution networks increases, more people are directly connected to each other, and their contacts are also connected to each other in closed clusters (Borgatti et al, 2013; Coleman, 1988; Scott, 2000). In such structures, people's experiences with IT-enabled work practices, and the insights that they gain from these experiences, are likely to be similar to each other (Hansen, 2002; Monge & Contractor, 2003;

Reagans & McEvily, 2003). This is because close-knit direct connections enable shared and readily shareable experiences, which lead to overlapping and related insights about IT-enabled work practices emerging from these experiences (Coleman, 1988; Gargiulo & Benassi, 2000; Granovetter, 1985). Also, more cohesive networks include more redundant paths connecting nodes in the network (Hanneman & Riddle, 2005; Scott, 2000). As a result, individuals within more cohesive networks may be receiving the same insights via multiple paths, thereby further reducing the overall newness of the set of insights they receive in such structures. It is, therefore, less likely for someone to come upon distinctively novel insights from the network when embedded in cohesive network structures (Burt, 1997; Gargiulo & Benassi, 2000). Moreover, the greater connectedness that exists in close-knit network structures implies that a much larger number of unsolicited insights, in total, is likely to actually be circulating in increasingly cohesive voluntary contribution networks (Rowley, 1997). Therefore, as the cohesiveness of voluntary contribution networks increases, people embedded in these networks are likely to suffer from increasing levels of attention fatigue, which may desensitise them into paying lesser attention to received unsolicited insights in general (Grise & Gallupe, 2000; Hunter, 2004; Kock, 2000). So, as voluntary contribution network cohesion increases, individuals' adaptation to IT-enabled work practices decreases, partly because the network is likely not yielding as many fresh new insights in general and partly because the people in the network are likely overburdened with attention fatigue from too many insights floating around.

### 4.3.2 | Structural hole positions in voluntary contribution networks

A structural hole represents a point of disconnectedness in the network (Hanneman & Riddle, 2005; Scott, 2000). So, people on either side of a structural hole are likely to have different experiences with the IT-enabled work practice and, in turn, to have largely distinct sets of insights (Aarstad, 2012; Ahuja, 2000; Burt, 1997; Min, Chung, & Kim, 2017). However, a person in a high structural hole position is only sparsely connected to these people on either side of the "hole"—typically, to only one person from each disconnected group on either side of the hole—creating a rather thin connection or bridge between these two groups (Borgatti et al, 2013; Hanneman & Riddle, 2005). This creates structural limitations in the extent to which these disconnected insights—no matter how novel—can actually flow through a high structural hole position. The sparse connectedness of this position, therefore, makes the newness of these disconnected insights less relevant to a person in this position. The insights may be new, but if the position structurally does not allow much of these insights to flow through it, then that newness is not able to garner much attention from a person located in that position. If recipients in these positions are unable to receive and attend to much of these unsolicited insights, they cannot use them to improve their adaptation to the IT-enabled work practice.

As the extent of "structural hole"-ness of the position decreases, connections are formed between people across the structural hole position, creating greater interconnectedness in the local network surrounding this position (Borgatti et al, 2013). This improvement in connectivity improves the flow of unsolicited insights through the position; ironically, however, as the extent of "structural hole"-ness of the position decreases, the insights that are now flowing relatively more freely through this position are now less likely to be perceived as new (Burt, 1997; Hansen, 2002). The very connections across disconnected clusters that help to improve the flow of insights through the structural hole position also reduce the newness of the insights that are flowing. Insights that are less novel, even if there are more of them, are likely to receive less attention and, in turn, be less valuable in adapting to IT-enabled work practices.

Thus, as the extent of structural hole-ness of a position swings across from high to low, a person in this position goes from encountering very low amounts of new insights to rather large amounts of not-so-new insights. Both of these scenarios are less conducive to garnering the attention of individuals towards the received unsolicited insights and, in turn, to helping them adapt to IT-enabled work practices. Therefore, the extent of structural holeness of a position, no matter whether it is high or low, will remain irrelevant to adaptation to IT-enabled work practices for people occupying those positions.

Therefore,

**H3.** *The level of cohesiveness of the entire voluntary contribution network would be negatively related to adaptation to IT-enabled work practices for individuals embedded in this network.*

**H4.** *Location in structural hole positions within the voluntary contribution network would be unrelated to adaptation to IT-enabled work practices for individuals occupying these positions.*

# 5 | METHODS

## 5.1 | Research context

This study was conducted in a large urban hospital system that had implemented a clinical information system (CIS), including EMRs and associated decision-support technologies, in a multiphased manner over several years. Our research association with this hospital began in the early stages of this implementation process, before the major interactive functionalities of the clinical information system were implemented. The initial years of this association were spent conducting qualitative fieldwork. This allowed us to obtain an intimate understanding of our research setting and of how the unfolding implementation of the clinical information system was changing patient-care practices throughout the hospital. This in-depth understanding of the research site through extended fieldwork subsequently guided the design and conduct of quantitative data collection; the quantitative data were used to generate the findings that we report in this study.

The quantitative data were collected after the electronic medical record system, pharmacy module, laboratory module, and inpatient electronic charting components of the CIS had already been implemented and in use for several months, although other components of this system, like computerised physician order entry, were still under development. Our study is, therefore, situated in a context where the EMR technology and its use itself was not new, but people were still adapting to the standardisation of work practices, interactions, and stipulated outcomes that were enabled by the technology.

The inpatient division of this large hospital system was organised into a set of 27 patient-care units, some of which were intensive care units while others were general care areas. Work within intensive care units was relatively less predictable and of higher intensity compared with general care areas, as reflected in the lower patient-to-nurse ratio in the former. Full-time clinical employees who worked on an everyday basis in these patient-care units included nurses, respiratory therapists, patient-care technicians, and unit secretaries, and comprised our respondent pool for the quantitative study.

In terms of physical infrastructure, each patient-care unit included a nurses' station, where clinicians typically congregated in between checking up on patients. Each nurses' station included one to three desktop computer terminals. Prior to CIS implementation, these computer terminals were hooked up to the medical technologies within patients' rooms, alerting nurses to changes in patients' vital signs, etc; at this time, patient charting was done on paper-based charts, which were hung over the doors of patients' rooms. Patients' current medication records and other files on inventory management for patient-care rooms were maintained in binders that were located on shelves and cabinets at the nurses' stations.

The EMR system was at the core of the CIS, and interfaced with other functionalities, like the order management system (which processed physicians' procedure orders, such as X-rays, CT scans, and other diagnostic tests), the electronic charting system (where nonphysician clinicians, like nurses, patient-care technicians, and respiratory therapists, kept track of detailed patient-care activities and assessments), the pharmacy and laboratory modules of the CIS, the patient admissions database, and others. Together, these systems digitised delivery of a variety of interdependent patient-care practices in the inpatient division of this hospital.

As the functionalities of the CIS were implemented in phases, they became available on the computer terminals located at the nurses' stations in patient-care units. Following the first phase of implementation, as EMR and other

functionalities were implemented, providers were expected to actively enter information into the system. The hospital additionally provided a set of "computers-on-wheels" (or COWs, as they were called) to each patient-care unit. Walking into any patient-care unit, seeing two to three COWs in a hallway was a common sight. They were unwieldy, often ran out of power, and were typically not available in sufficient numbers at a time, resulting in long wait times particularly when many people needed to document at roughly the same time. Nonetheless, hospital administration expected that they would be wheeled into patients' rooms in real time for bedside charting and documentation. A common complaint from providers at this hospital was that the hospital had not been architecturally designed for digitisation. It was typically difficult to wheel the COWs into patients' rooms; there was often not much room to move around once a nurse or multiple providers were in the room along with the COW. Overall, it was a cumbersome experience working with these clunky systems while maintaining a personal connection with patients at point of care.

Despite these physical infrastructure challenges, however, implementation of the clinical information system provided the first opportunity at this hospital system to enforce and automatically track compliance with standardised hospital-approved patient-care practices. Embedding patient-care practices into the CIS introduced new technology-enabled tasks (see Appendix A) as part of these practices, designed to improve patient safety; these tasks were tracked by the organisation through periodic reports generated by the CIS. For example, nurse verification of new medications appearing on patients' EMR screens against physicians' original prescription orders was a quality management task specifically created following EMR implementation. As a result, compliance with this new medication verification task—*specifically, the number of new medications on the EMR screen that a nurse verified against the physician's original order within the same shift*—was a direct measure of adaptation to the EMR-enabled medication verification practice, our dependent variable in this study.

Finally, data entry into the system was accomplished manually by providers, using a combination of typing and drop-down boxes available through the system. At the time of our study, the hospital had begun looking into barcoding as a potential future direction for data capture but had not yet implemented automatic data capture via barcoding (Fowler, Sohler, & Zarillo, 2009; Poon, Poon, Keohane, & Yoon, 2010; Seibert, Maddox, Flynn, & Williams, 2014). Hospital administration encouraged all data entry to be done directly and, in real-time, within the computer system. However, challenges presented by technology interface, device availability, and physical building infrastructure resulted in providers often using handwritten notes while they were on-the-go around the unit, which they would later transcribe into the computer system.

## 5.2 | Measurement

Table 1 presents construct measures.

### 5.2.1 | Dependent variable

Data on the dependent variable were obtained from organisational records. From monthly EMR reports, we obtained the number of new medications that populated the EMR screen on a given shift during each month, which the responsible clinician was able to verify[3] for accuracy against the physician's original order on the same shift. This "new medication verification" task did not exist prior to the EMR system and was introduced by the EMR system as a required part of the EMR-enabled version of the medication verification practice. *As such, successful new medication verification indicated adaptation to the EMR-enabled medication verification practice*. Failure to verify was equivalent to the pre-EMR way of doing things and reflected failure to adapt to the EMR-enabled practice.

We chose the *number* of new medications verified on time, rather than the *proportion* of new medications verified on time (number of new meds verified on time/total number of new meds to be verified), as the measure of our

[3]The EMR report actually included "number of medications not verified," from which we calculated our DV measure, "number of medications verified," as follows: number of meds verified = total number of meds to be verified − number of meds not verified.

**TABLE 1** Variable definitions and measures

| | Variable Name | Variable Type | Measurement | Data Source |
|---|---|---|---|---|
| Dependent Variable | Adaptation to IT-enabled work practice | Count | *Number of new meds verified on time*: EMR enablement of the medication verification practice required that each new medication order that showed up on the nurse's/RT's view of the EMR screen on a given shift was verified by the patient's nurse/RT, on the same shift, against the physician's original prescription order. At the end of each month, the EMR system generated a report listing the total number of new medications that each provider had verified in this manner (as indicated by electronic signature) during that 1-mo period. This count serves as our measure for the DV.<br>These objective DV measures were staggered in time by 2 mo following the collection of survey data on independent and control variables. | Monthly report automatically generated by the EMR system |
| Control Variables | Unit size | Continuous | The total number of healthcare providers, including nurses, respiratory therapists, unit secretaries, and patient-care technicians, employed within each patient care unit. Physicians were excluded from this count because they tended to work all over the hospital, following their patients as they moved from one unit to another. | Organisational records |
| | Unit type | Categorical/ dummy | Whether the patient care unit is a general care area (GCA) or an intensive care unit (ICU). GCA = 1, ICU = 0 | Organisational records |
| | Total number of new medications to be verified | Count | For each healthcare provider, the *total* number of new medications that showed up on the EMR screen and therefore needed verification during the same 1-mo period as the DV measure. | Monthly report automatically generated by the EMR system |
| | Technology experience | Continuous | The number of hours in a typical work-day that the respondent spends using the EMR system. | Self-reported survey data |
| | Organisational tenure | Continuous | The number of years that the respondent has spent working in this hospital system. | Self-reported survey data |
| Relational Variables | HSN (or VCN) cohesion | Continuous | Cohesion was measured as "transitivity," which denotes the density of transitive triples in the network. It denotes the extent to which triads of nodes in the network are fully connected (Borgatti, Everett, & Freeman, 2002).<br>"Three vertices u, v, and w taken from a directed graph are transitive if, whenever vertex u is connected to vertex v and vertex v is connected to vertex w, then vertex u is connected to vertex w. The density of transitive triples is the number of triples which are transitive divided by the number of | Self-reported survey data |

(Continues)

**TABLE 1** (Continued)

| Variable Name | Variable Type | Measurement | Data Source |
|---|---|---|---|
| | | paths of length 2, ie, the number of triples which have the potential to be transitive." (Borgatti et al, 2002) | |
| HSN (or VCN) structural holes | Continuous | This was measured as the "constraint" of the focal node in the network (Burt, 1992). "It is a summary measure showing the extent to which ego is connected to others who are also connected to each other. If ego's connections all have each other as potential connections, ego is constrained. However, if ego's connections do not have many alternatives in the network, they cannot constrain ego's behavior" (Hanneman & Riddle, 2005). Therefore, greater the constraint of ego, lower is the extent to which ego is in a structural hole position.<br>Consider the constraint of focal node i, caused by a single alter node j.<br>"Alter j constrains i to the extent that:<br>• i has invested in j<br>• i has invested in people (q) who have invested heavily in j. So, i's investment in q leads back to j.<br>• Even if i withdraws from j, everyone else in i's network is still invested in j" (Borgatti, Everett & Freeman, 2002)<br>The constraint measure for each node i is a summary of the constraint values ($c_{ij}$) caused by all its alter nodes, j. Therefore, constraint for node i is<br>$Ci = \sum_j (c_{ij})$ | Self-reported survey data |

We recognise that the number of new meds that are verified on time by a provider (our DV measure) is related to the total number of new meds that the provider is responsible for verifying. Since the latter varies from provider to provider, we need to control for this variability. This could be done in one of two ways: Either, use the count measure of the "number of new meds verified on time" as DV and include "total number of new meds to be verified" as a control variable; Or, use the proportion of "number of new meds verified on time"/"total number of new meds to be verified" as the measure of the DV. In this paper, we have undertaken the former approach.

dependent variable. Although the total number of new medications that needed verification (the denominator in the "proportion" measure) could vary across patients with different needs, these differences were, nonetheless, fairly randomly distributed across clinicians within a shift. In other words, all clinicians were roughly comparable in their overall workload of the total number of medications that they may be expected to verify during a given shift; no theoretically significant differences were expected across clinicians within a shift. Therefore, we chose the *number*, rather than the proportion, of new medications verified on time as the measure of adaptation to the EMR-enabled medication verification practice.

Performing the EMR-enabled new medication verification task represented modifications of process, rather than simply acceptance of technology (Cooper & Zmud, 1990), for a few key reasons. First, the EMR system imposed hard constraints on allowable medication names within the system, enabling substantive discrepancies between

medication names in handwritten physician orders versus those appearing on the EMR screens, as processed by Pharmacy.[4] Prior to the EMR system, when this constraint did not exist, pharmacy would simply mirror the same name on the medication vial label that the physician had used in writing the prescription order. As such, discrepancies between these two names would be primarily due to legibility concerns or careless errors. In the EMR-enabled practice, however, discrepancies could very logically extend to substantive medical reasons. Achieving a certain number of verified meds in the EMR-enabled practice, therefore, implied a significant change in the process of reconciling medication names, which nurses must have had to encounter en route to marking those medications as verified. Second, the EMR-enabled medication verification practice, for the first time, necessitated that verification be completed within the same shift. This is another substantive process change from pre-EMR to EMR-enabled. In the pre-EMR world, nurses could have verified medications at any time, regardless of shift-change, because of the lack of time-stamping facility on the paper-based system. Therefore, again, the number of medications verified within the EMR-enabled system automatically implies a modification of process wherein nurses would need to pay attention to when they were verifying the new medication compared with when the medication first showed up on the EMR screen. Finally, the EMR system had transformed the broader communication process associated with inpatient hospital work. As such, successfully verified meds within the EMR-enabled environment would have likely proceeded through a modified process wherein clinicians would have needed to communicate with pharmacy and other hospital constituents via the EMR system, instead of through the previously commonplace phone-based or in-person communication modes, unless only as a last resort. The new EMR-constrained communication rules also engendered process workarounds in which nurses would informally consult with each other to more quickly resolve a problem. For all of these reasons, "number of new meds verified on time" was chosen as a robust and rich measure of adaptation to the EMR-enabled practice.

A 2-month time lag in dependent variable measurement, compared with the measurement of independent and control variables, helped the data to establish some temporal precedence as a condition for causal inference of the relationship of the hypothesised and control variables with the dependent variable. We chose a time-lagged dependent variable to account for a broader "chicken and egg" argument that is yet unresolved in prior social network research about whether network structure impacts behavioural characteristics (eg, performance, adaptation, attitude, and psychological safety) or vice versa. Quite possibly, network structures would enable and constrain individual behaviour. Individual behaviour in turn would drive who these individuals would interact with, thereby further impacting network structure in a recursive longitudinal relationship. Contributing to this discussion is beyond the scope of our cross-sectional study, which is, in any case, focused on a different question; however, to safeguard the rigour of our findings, with respect to this issue, we chose to use a lagged dependent variable. Robustness checks, in which different lag durations were tested, supported 2 months as being the lag that, although in large part qualitatively similar to other time lags (1 month through 5 months), yielded statistically the most significant results.

### 5.2.2 | Independent (network) variables

In the course of adapting to health IT-enabled patient-care practices, help seeking and voluntary contribution interactions occurred primarily within the patient-care units where work was done, which, therefore, served as natural boundaries for each of these networks.

Help seeking and voluntary contribution network data were collected using separate socio-metric survey questions. These questions were constructed based on theoretical conceptualisation as well as practical qualitative fieldwork. The questions were developed in a way that highlighted the conceptual distinctiveness of the two networks.

[4]Notably, the follow-up implementation of technologies, like computerized physician order entry (CPOE), which would enable physicians to directly enter prescription orders into the EMR system, would not eliminate this discrepancy. Instead, CPOE and related technologies would simply shift the burden of resolving the discrepancy from the pharmacy and nurse to the physician, as the latter would now need to find the "correct" hospital-approved synonym for their preferred medication name before placing the order into the system. Moreover, in typical multiphase implementation plans, a hospital could remain in this post-EMR but pre-CPOE implementation state for 2 to 3 years, causing this discrepancy—even exactly as currently described in our field-site context—to significantly endanger patient safety and increase financial burden.

The following question was used to measure help-seeking interactions: Who do you go to for help when you encounter a problem with [name of the EMR] in your work? We asked respondents about problems faced, not just with the EMR, but with "the EMR in [their] work." This wording allowed focus on problems arising in the EMR-enabled patient-care practice, and not just on technical problems with the EMR. The question also focused on only those interactions where the help-seeker initiated the tie ("Who do you go to…" ). The advice sought by the help seeker also needed to be specific to a problem that he/she was facing and not a general insight about the system or about the EMR-enabled practice ("… when you encounter a problem …").

The following question measured "voluntary contribution" interactions: Even without your asking, who voluntarily shares useful tips, tricks, and insights with you regarding [the EMR] in your work? The focus of this question is on unsolicited voluntary contributions of knowledge ("Even without your asking, who voluntarily shares…" ). The wording emphasises general insights regarding the EMR-enabled patient-care practice that the contributor chooses and initiates ("… voluntarily shares … tips, tricks, and insights … regarding [the EMR] in your work"). Qualitative fieldwork indicated that it was best to capture voluntary contribution interactions from the point of view of the recipient, rather than of the contributor, of unsolicited insights. Doing so increased the likelihood of complete recall and excluded from consideration voluntary contributions that were considered as useless by recipients ("… who voluntarily shares *useful* tips, tricks, and insights with you …") and, therefore, unlikely to affect adaptation to IT-enabled work.

We did not restrict our network questions specifically to the EMR-enabled medication verification practice, phrasing them more generally about "the EMR in [their] work," instead. A central aspect of patient-care professionals' work in hospitals involves EMR-enabled medication administration, of which EMR-enabled medication verification is an essential component (Brady, Malone, & Fleming, 2009), so discussions of "the EMR in [their] work" invariably include this practice. Furthermore, other intersecting EMR-enabled patient-care practices, such as processing laboratory orders or waiting to receive diagnostic test results, would often get in the way of medication verification work and were relevant to adaptation to EMR-enabled medication verification. Interaction frequencies were measured on a scale from 1 (Rarely) to 7 (Often), with 0 indicating absence of connection (Marsden, 1990).

Individual responses within each unit were compiled to construct help seeking and voluntary contribution networks for that unit. Normalised measures for independent variables, as indicated in Table 1, were calculated for each network via UCINET (Borgatti et al, 2002). As an illustration, let us say, we had four respondents—Sally, Sam, Jess, and Roman—each of whom were asked the two questions in our survey for their help seeking and voluntary contribution interactions. Let us say, Sally responds that she engages in help-seeking interactions with Sam and Roman and that Jess offers her unsolicited insights (voluntary contribution interaction). Similarly, Sam may have named Roman for help-seeking interactions and Jess for voluntary contribution interactions and so on for each of the other respondents. This information from all four respondents would be compiled in UCINET to create two separate matrices—one for the help-seeking network and the other for the voluntary contribution network. The rows and columns of each matrix would list each of the same four respondents; the respondents named in the rows are where the links start (the "From" node) and the respondents named in the columns are where the links end (the "To" node). For example, Sally's help-seeking interactions would be represented in the help-seeking network, with numbers indicating reported interaction frequency (1-7), in the cells that form at the intersection of the "Sally" row and the "Sam" column and of the "Sally" row and the "Roman" column. The rest of Sally's row would be marked with zeroes, indicating no additional help-seeking interactions initiated by Sally. Sally's reported voluntary contribution interaction would be captured as a number denoting the reported interaction frequency appearing in the row for "Jess" and the column for "Sally." Notice that the voluntary contribution interactions are coded differently from the help-seeking interactions to take into account differences in the phrasing of the corresponding survey questions through which these data were collected. All other cells within the "Sally" column in the voluntary contribution network matrix would be marked as zero, indicating that Sally only receives voluntary contribution interactions from Jess. These matrices would be directed and asymmetric, indicating that the ties between respondents are not mutually reciprocated.

UCINET applied its prebuilt algorithms to each of these two matrices to calculate cohesion and structural hole values for each of the two networks. Table 1 provides the concise theoretical logic underlying the calculations made

by UCINET; while a detailed mathematical exposition of these calculations is beyond the scope of this paper, we refer the interested scholar to a few widely accepted publications (Borgatti et al, 2013; Wasserman & Faust, 1994). Note that, since cohesion is a network-level concept, it will have the same value for all individual nodes within the same network, but structural holes, which represents an individual positional characteristic, would have different values for each individual respondent/node in our dataset.

### 5.2.3 | Control variables

We controlled for characteristics of individual providers (level 1 controls) and of the patient-care units in which they worked (level 2 controls).

Our level 1 controls included the following: total number of new medications that needed verification by each respondent as well as the technology experience and organisational tenure of each respondent. The *total number of new medications that needed verification* signifies the total workload that the respondent faces. Larger workloads could make it more challenging for people to adapt. Alternatively, knowing that one has a larger workload to get through could also motivate people to work faster to get as much of this work done as possible, unless it demoralises people, which can happen if the workload is unrealistically large. *Technology experience* captures the number of hours in a typical workday that the respondent spends using the EMR system. Respondents that spend more hours on the EMR system are getting more practice with using this system, which is likely to positively impact their ability to get more new medications verified on the system. Alternatively, more time spent using the EMR system may be indicative of greater struggle in coping with new medication verification and other patient-care work using the system. Finally, *organisational tenure* refers to the number of years that the respondent has spent working within this hospital system. Those with longer organisational tenure are likely to be more resourceful when they are stuck or need help and more familiar with organisational practices and norms. However, when it comes to adapting to new ways of working, enabled by a relatively new EMR system, people who have worked longer in the organisation may find it harder to "unlearn" old ways of working and adapt to the new technology-enabled tasks. This could negatively impact the number of new medications that the respondent is able to verify on the EMR system.

We considered the following level 2 controls in this study: *unit size* and *unit type*. Unit size refers to the number of employees working within the patient-care unit in which the respondent works. This represents the total resource pool that the respondent has at his/her disposal to ask questions, seek help, and volunteer advice. In the context of interdependent complex work practices, such as the EMR-enabled medication verification practice, however, having more employees within one's work unit may also indicate higher costs of coordination and more interruptions in one's daily work. This could get in the way of the amount of work that one is able to do, ie, the number of new medications that a respondent is able to verify. Unit type refers to whether a respondent works within an intensive care unit or a general care area. Unit type reflects the design, criticality, and intensity of work that characterises the unit as a whole. It is likely that people working within high-intensity work units, with more critical high-risk patients (eg, ICUs), would find it more difficult to complete tasks, like verifying new medications. However, given the inherent importance of the medication verification task to patient safety, people in high-intensity work units—where patients are in critical condition and failures in medication verification can have drastic consequences—may also likely be more diligent towards this medication verification task.

## 5.3 | Data collection

This is a multilevel study, consisting of data on individual clinicians (level 1) nested within patient-care units (level 2). Our dependent variable measured individual clinicians' adaptation to EMR-enabled medication verification practice (level 1, in a two-level hierarchical linear model). The help seeking and voluntary contribution networks were constructed at the level of the patient-care units (level 2), by compiling the interaction responses of all clinicians within each unit. Then, within each network, we analysed the impact of the structural hole positions held by these individual

clinicians (level 1 measure) and the overall cohesiveness of the network within which the clinicians were embedded (level 2 measure) on clinicians' adaptation (ie, number of new medications verified on time). All network measures were normalised to account for differences in network size across patient-care units.

We collected data on the entire inpatient organisation of the hospital system. Data on "number of new meds verified on time," our measure for the dependent variable, were obtained from objective monthly reports generated by the EMR system. Data on social networks and the control variables were collected, using survey questionnaires, from the nonphysician clinician workforce, including nurses, respiratory therapists, unit secretaries, and patient-care technicians, who were adapting to EMR-enabled work at the time of this study. Our social network data included 27 help-seeking networks and 27 voluntary contribution networks corresponding to the 27 different patient-care units in our dataset. The response rate from each unit was over 80%, enabling the inclusion of whole-network variables, like cohesion, in our analysis (Kane & Alavi, 2007; Kane & Borgatti, 2011; Marsden, 1990; Oh, Chung, & Labianca, 2004; Sparrowe, Liden, Wayne, & Kraimer, 2001; Sykes et al, 2014). Our final dataset, after discarding missing data, consisted of 806 responses spanning 27 patient-care units.

To ensure complete and valid responses to the social network questions in our survey, we provided respondents with a "reference list" containing the names of all full-time clinical employees working in the inpatient patient-care units in this hospital system. Respondents were encouraged to consult this list when responding to the social network survey questions but also encouraged to include additional names, beyond the list, as they saw fit. Given the large network sizes in our data, this approach helped with recall and reduced cognitive load on respondents, thereby helping us to achieve high response rates (Marsden, 1990; Scott, 2000). Reference lists did not constrain responses to network questions but were only meant to serve as a reference; this minimised the possibility of measurement bias in defining network boundaries.

Empirically, help-seeking and voluntary contribution networks were distinct structures, as evident from qualitative fieldwork and quantitative network data. It was typically infeasible for people facing problems (help seeking) to specifically seek help from people who had previously shared with them their unsolicited insights (voluntary contribution) on the patient-care unit. Because of the shift-based nature of hospital work, the voluntary contributor may not even be working on the same shift when the seeker encounters a problem. Moreover, a prior voluntary contributor may be busy with his/her own work at the time of a problem, as is typical with unpredictable patient-care work. Most patient-care problems tend to be time bound and urgent, making it infeasible for the help-seeker to wait around for the voluntary contributor when other credentialed colleagues were near at hand, even if they had not previously shared their unsolicited insights. Credibility in a health-care setting derives in large part from education and experience, because of the high professional affiliation of patient-care providers, rather than simply from their informal knowledge-sharing behaviour, as one might expect on an online knowledge exchange forum, for example. These characteristics of the health-care workplace ensured the systematic conceptual and empirical distinctiveness of help seeking and voluntary contribution interactions.

A strength of our dataset is that dependent variable data were collected from a different source, namely, objective organisational records, compared with social network and control variable data. More details on further steps taken to alleviate survey bias are presented in Appendix C.

## 6 | ANALYSIS AND RESULTS

### 6.1 | Testing for distinctive help seeking and voluntary contribution interactions

We ran multiple tests to ensure the independence of help seeking and voluntary contribution interactions in our dataset (Hanneman & Riddle, 2005). Correlations between help-seeking and voluntary contribution ties were insignificant ($P < 0.05$) for more than 80% of the patient-care units in our dataset. Other regression-type tests were run to investigate the extent to which the presence of one type of tie affected the likelihood of the other type of tie

coexisting between a pair of nodes. Adjusted $R^2$ values from these regression tests were between 0% and 0.5%. Together, these tests indicated that there was no systematic correlation, or tendency towards coexistence, for the help seeking and voluntary contribution ties in our dataset.

## 6.2 | Model specification

To confirm that our nested dataset (patient-care providers nested within inpatient units) warrants multilevel analysis, we calculated the intraclass correlation coefficient (ICC)[5] using the "Analyze > General Linear Model > Variance Components" command submenu within SPSS (SPSS version 24). On the basis of this analysis, the ICC value for our model was 0.259995. This means that nearly 26% of the total variance in our dependent variable, "number of new medications verified on time," is between units, ie, arises because of unit-specific factors, rather than individual-specific factors. On the basis of this high ICC value, we proceeded to fit our data to a multilevel model.

Our dependent variable is measured with count data following a Poisson distribution instead of a normal distribution. We have, therefore, used "generalised linear modelling," which does not assume normally distributed error terms, as the broad analytical approach in this study (Fox, 2008; Hoffman, 2003; Nelder & Wedderburn, 1972). To further account for the multilevel nature of our dataset (individual patient-care providers nested within patient-care units), we have selected "generalised estimating equations" (SPSS version 24)—a class of generalised linear models—as our specific analytical approach (Ballinger, 2004; Hardin & Hilbe, 2007; Johnson & Kim, 2004).

We used the following analytical equation:

$Y_{ij}$ $\alpha + \beta X_{ij} + \gamma Z_i + \varepsilon_{ij}$, where

$Y_{ij}$ "number of new meds verified on time" by respondent j within patient-care unit i,

$X_{ij}$ individual (respondent)-level variables (such as, "technology experience" and "structural holes") of respondent j within patient-care unit i, and

$Z_i$ unit-level variables of patient-care unit i ("unit type," "unit size," "cohesion," "cohesion*cohesion"—to reflect the bell-shaped concave relationship theorised in Hypothesis 2)

We expected high multicollinearity between the square term (HSN Cohesion*HSN Cohesion) and the corresponding singular variable (HSN Cohesion) in our model. To correct for this problem, we used the residual-centring approach (Lance, 1988; Xue, Ray, & Gu, 2011). In this approach, the square term is regressed on the corresponding singular term, and the residuals from this regression are used as the values of the square term in our generalised estimating equations model used for hypotheses testing.

## 6.3 | Results

Tables 2A and 2B present summary statistics and correlations for levels 1 and 2 variables, respectively (Brady, Voorhees, & Brusco, 2012; Shin, Kim, Lee, & Bian, 2012; Suh, Shin, Ahuja, & Kim, 2011). Table 3 presents the results of hypothesis testing.

Our results support Hypotheses 1 through 4. The results show that help seeking versus voluntary contribution networks involve very different network structures, operating at different levels of analysis, to impact adaptation to "new medication verification" on the EMR system. In voluntary contribution networks, the overall cohesiveness of the entire network, rather than individual network positions, is significantly related to more medications being verified; less cohesive networks relate to more medication verification. In contrast, in help-seeking networks, individuals' locations in positions of structural holes as well as the cohesiveness of the overall network both matter to medication verification in qualitatively different ways. While structural hole positions are linearly and negatively

[5] $ICC = \sigma^2_{unit}/(\sigma^2_{unit} + \sigma^2_{error})$ (de Vet, Terwee, Mokkink, & Knol, 2011).

**TABLE 2A** Level 1 variables—Descriptive statistics and correlations

| | | Mean | SD | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|---|---|---|
| 1 | Number of new meds verified on time (DV) | 117.82 | 86.12 | 1 | | | | |
| 2 | HSN structural holes | 0.312 | 0.20 | 0.059 | 1 | | | |
| 3 | VCN structural holes | 0.464 | 0.31 | 0.037 | 0.279** | 1 | | |
| 4 | Total number of new meds to be verified | 134.23 | 91.65 | 0.991** | 0.049 | 0.036 | 1 | |
| 5 | Technology experience | 5.80 | 3.05 | 0.050 | 0.014 | 0.020 | .050 | 1 |
| 6 | Organisational tenure | 6.89 | 7.26 | −0.123** | −0.064 | −0.062 | −0.136** | −0.123** |

**Correlation is significant at the 0.01 level (two tailed).

**TABLE 2B** Level 2 variables—Descriptive statistics and correlations

| | | Mean | SD | 1 | 2 | 3 |
|---|---|---|---|---|---|---|
| 1 | HSN cohesion | 0.474 | 0.16 | 1 | | |
| 2 | VCN cohesion | 0.322 | 0.17 | 0.659** | 1 | |
| 3 | Unit size | 87.08 | 39.16 | −0.217** | −0.372** | 1 |
| 4 | Unit type | 0.44 | 0.49 | 0.115** | 0.338** | −0.390** |

**Correlation is significant at the 0.01 level (two tailed).

**TABLE 3** Results (Analytical approach: Generalized estimating equations with Poisson log linear model; SPSS Version 24). DV: No. of new meds verified on time; n = 806 patient-care providers, j = 27 patient care units

| | Unstandardised Coefficient | Standard Error | Wald $\chi^2$ | *P* Value |
|---|---|---|---|---|
| Technology experience | −0.011 | 0.004 | 8.177 | 0.004 |
| Organisational tenure | −0.009 | 0.003 | 7.599 | 0.006 |
| Total no. of new meds to be verified | 0.005 | 0.0005 | 99.436 | 0.000 |
| Unit size | −0.001 | 0.0004 | 12.847 | 0.000 |
| Unit type | 0.027 | 0.047 | 0.332 | 0.564 |
| Help-Seeking Network (HSN) Structural Holes (H1) | 0.168[a] | 0.027 | 37.755 | 0.000 |
| Help-Seeking Network (HSN) Cohesion (H2) | −0.024 | 0.123 | 0.037 | 0.847 |
| Help-Seeking Network (HSN) Cohesion* Help-Seeking Network (HSN) Cohesion (H2)[b] | −1.647 | 0.392 | 17.684 | 0.000 |
| Voluntary Contribution Network (VCN) Cohesion (H3) | −0.389 | 0.132 | 8.676 | 0.003 |
| Voluntary Contribution Network (VCN) Structural Holes (H4) | −0.036 | 0.033 | 1.214 | 0.271 |

[a]Because of the way in which structural holes is measured (see Table 1), the theoretical direction of the relationship between structural holes and the DV is the opposite of that in the empirical analysis (listed in Table 3).

[b]We have used the centering-residual value for the square term in order to correct for inherent high multicollinearity between the singular and square terms (Xue et al, 2011).

related to adaptation, network cohesion is positively and quadratically related to adaptation, with diminishing returns from increases in cohesion beyond a certain point, and increasingly negative relationship with adaptation at even greater values of cohesion, ie, an overall bell-shaped or concave relationship between HSN Cohesion and adaptation (UCLA Statistical Consulting Group, January 1, 2019). It may be noteworthy to mention here that

even negatively hypothesised relationships between specific network structural characteristics (eg, structural holes in H1 or cohesion in H3) and adaptation signal the presence of a meaningful relationship between social interaction, in general, and adaptation. This is because social interaction structures are assortments of what one may think of as two-sided concepts, where low levels of one type of structure imply high levels of the mirror-opposite type of structure, and both structural types are conceptually meaningful. For example, the negative relationship between structural holes in the help-seeking network and adaptation to IT-enabled work practice (H1) is the equivalent of a positive relationship between local connectedness (rather than local disconnectedness) and adaptation to IT-enabled work practice.

Among level 1 control variables, "technology experience" had a strongly significant negative relationship with "number of new medications verified on time," indicating that people who spent more time in a day on the EMR system possibly did so because they were taking longer to figure out how to complete work on the system. The number of years that a provider had spent working in this hospital system ("organisational tenure") also had a strongly significant negative relationship with "number of new medications verified on time," indicating that these individuals were likely more entrenched in older ways of doing things, making it more difficult for them to adapt. Also, as expected, the total number of new medications that the provider needed to verify had a strongly significant positive relationship with the number of medications that he/she was actually able to verify on time. Among level 2 control variables, unit size had a strongly significant negative relationship with "number of new medications verified on time." This suggests that the higher costs of coordinating between more number of employees and the greater likelihood of being interrupted in one's work in units with more number of employees has an adverse connection with the amount of work that individuals were able to get done in units of larger sizes.

### 6.3.1 | Goodness of fit

In ordinary least squares analysis, $R^2$ values evaluate goodness of fit of the model to the actual data. $R^2$ values show the proportion of variability in the dependent variable that is explained by the model or the improvement of the fitted model compared with the null model in explaining the variation in the outcome variable. The OLS $R^2$ value is based on minimising sum of squared errors. In this study, we used maximum likelihood as our analytical approach for fitting generalised linear models. As such, the regular OLS $R^2$ metric is not meaningful in our case.

To evaluate goodness of fit, therefore, we used a combination of different measures suited to generalised linear models (Freese & Long, 2006; Long, 1997). First, we considered the value of the deviance of the model. Deviance is a measure of badness of fit of a generalised linear model, with higher numbers indicating poorer fit. The absolute value of the deviance for a given model is not meaningful. Rather, deviance can only be interpreted by comparing two models predicting the same outcome variable, where one model is a subset of the other. In our case, going from the control-only model to the full model including the hypothesised variables reduces the deviance from 8436.29 for 698 degrees of freedom to 7728.446 for 681 degrees of freedom. This means that adding the hypothesised variables to our model reduces the deviance by an additional 707.844 for a reduction of 17 degrees of freedom. The full model, including our hypothesised variables, is therefore a much better fit to the data in comparison with the control-only model.

Next, we considered another measure of goodness of fit appropriate for generalised linear models, namely Akaike's Information Criteria (AIC). AIC is a measure that is based on deviance and, like deviance, can only be interpreted in comparison between two models; the absolute values of AIC are not meaningful. The advantage of AIC over deviance is that AIC penalises for making the model more complicated. It is, therefore, similar in principle to adjusted $R^2$ in penalising for including irrelevant predictors. In comparing between two models, the one with the lower AIC has the better fit. In our case, going from the control-only model to the full model including the hypothesised variables reduced AIC from 12 895.147 to 12 121.849, ie, a reduction of 773.298. This means that adding the hypothesised variables results in a model that has a much better fit to the data than the control-only model. These two measures taken together established confidence that our hypothesised variables were explaining a considerable proportion of the variation in our dependent variable; including these hypothesised variables resulted in a model that fit the data considerably better than the control-only model.

### 6.4 | Robustness checks

We conducted robustness checks of our theorised research model.

#### 6.4.1 | Check #1: Combining help seeking and voluntary contribution networks

A distinctive contribution of this study was to disaggregate knowledge sharing networks into help-seeking and voluntary contribution networks. While we present, in detail, the conceptual, operational, and analytical distinctiveness of these two networks, we also ran a robustness check where we combined help seeking and voluntary contribution networks into one aggregated knowledge network. The combined network model was a poorer fit to the data compared with our theorised model in which help seeking and voluntary contribution networks are considered separately.

#### 6.4.2 | Check #2: Possible quadratic effects for other hypotheses (H1, H3, and H4)

We included linear terms and square terms for all four network variables—help-seeking network structural holes (H1), help-seeking network cohesion (H2), voluntary contribution network cohesion (H3), and voluntary contribution network structural holes (H4)—in a single combined research model with the same DV. Results indicated that the quadratic effect was only statistically significant for H2, as hypothesised. For H1, H3, and H4, only the linear terms were statistically significant—not the square terms. This lends further empirical support for the theorised linear effects of H1, H3, and H4.

## 7 | DISCUSSION

Current literature has presented complex findings on the roles of cohesion versus structural holes on outcomes such as adaptation, organisational change, and innovation (Chai & Rhee, 2009; Dong & Yang, 2015, 2016; Gargiulo & Benassi, 2000; Xiao & Tsui, 2007). Viewing cohesion and structural holes as network structural properties on opposite ends of the same continuum, some studies have found cohesion to be more effective for outcomes while others have found structural holes to be better (Burt, 1997; Coleman, 1988; Tortoriello, 2015; Yu, Brett, & Oviatt, 2011). This study finds that cohesion and structural holes both impact individuals' adaptation to the EMR-enabled medication verification practice, but in different ways, depending on the particular agent (help seeker versus voluntary contributor) driving the flow of content through the network. In help-seeking networks, which are driven by the help-seeker, occupying positions of structural holes is less conducive to adaptation; embeddedness in overall cohesive network structures, initially, pays off well with respect to adaptation but at progressively higher levels of cohesion, yields diminishing returns and, eventually, increasingly negative impacts on adaptation. In voluntary contribution networks, which are driven by the unsolicited knowledge contributor, being embedded in structures that are, overall, less cohesive is more suited for adaptation, but location in structural hole positions does not matter either way.

Our study makes the following key contributions. Most studies comparing cohesion versus structural holes have primarily considered network structures that are on either end of the continuum, where these two structural characteristics tend to be mutually exclusive (Burt, 1997; Coleman, 1988; Gargiulo & Benassi, 2000). We complement this literature by focusing on network structures that are more in the middle of the continuum, in which cohesion and structural holes are likely to be copresent, and investigate the impact of each structural characteristic on adaptation in the presence of the other characteristic. This approach reveals the interesting insight that, for networks that are not at structural extremes, being cohesive on the whole is not the mirror-opposite of being located in structural hole positions. This insight also derives from our second key contribution, which is to undertake a multilevel comparison of cohesion versus structural holes. Most extant studies tend to compare these at the same level of analysis by comparing cohesive networks with networks rich in structural holes, even though the concepts of cohesion versus structural

holes are theoretically defined at the whole network level versus the individual node level respectively (Gargiulo & Benassi, 2000). Holding the levels of analysis separate reveals that it is possible to be located in structural hole positions within overall network structures that are either more or less cohesive, unless, of course, one is considering extreme network structures at one or the other end of the continuum.

Finally, our study contributes by adding to other contingency theories that have been offered in existing literature to explain the relative impact of cohesion versus structural holes on outcomes of interest (Chai & Rhee, 2009; Xiao & Tsui, 2007). We show that the type of network itself matters as a contingency factor determining whether cohesion versus structural holes would be significant with respect to our outcome of interest, adaptation to IT-enabled work. In this study, we have disaggregated knowledge networks into two conceptually, operationally, and analytically distinct networks, namely, help seeking and voluntary contribution networks, which differ in terms of the agent driving the flow of content and the nature of the content that is flowing through the network.

## 7.1 | Implications for Research

The contributions from our study bear implications for three primary streams of research: adaptation to IT-enabled work, knowledge management, and social networks.

### 7.1.1 | Adaptation to IT-enabled work

Organisational work practices are complex interdependent sequences of tasks that require the joint action of multiple people working together (Feldman & Pentland, 2003). IT enablement intensifies these task interdependencies and introduces new interdependent tasks due to the additional constraints of technology embeddedness (Howard-Grenville, 2005). For example, as we saw in the case of the EMR-enabled medication verification practice, the "new medication verification" step was a key task introduced by EMR embeddedness, where every new medication order on the EMR screen would need to be verified against the physician's original order. Even though this is an individual-level task, our study shows that when such tasks are embedded within IT-enabled organisational work practices, they actually depend on multilevel factors beyond the control of the individual responsible for the task. Yet, many times, employees are evaluated or blamed for failure to comply with individual-level tasks, such as medication verification, even when these are beyond their control, creating discontentment and possible job turnover (Lapointe & Rivard, 2007). The findings from our study reveal relevant social interaction structures that can help people adapt better to individual-level tasks embedded within IT-enabled practices, even when these tasks are not entirely within their control.

### 7.1.2 | Knowledge management

Studies that draw on knowledge management to explain various outcomes of interest typically focus on the sharing or the transfer of the knowledge itself as the key antecedent driving these outcomes (Argote, Ingram, Levine, & Moreland, 2000; Szulanski, 1996, 2000). Our study shows that even before knowledge is shared, the motive/agent that drives this knowledge sharing can have differential impact on outcomes. Our findings suggest that there may be theoretical value in disaggregating knowledge sharing networks in other ways in order to undertake further nuanced views of how these networks can impact various outcomes of interest.

### 7.1.3 | Social networks

Our findings contribute back to the social networks literature by maintaining a multilevel perspective of cohesion and structural holes (Hanneman & Riddle, 2005; Monge & Contractor, 2003). We also show that additional insights can be gained by considering network structures that are in the middle range of the continuum between cohesion and structural holes. Our findings show that, in these regions of the continuum, both cohesion and structural holes can

simultaneously exist at different levels of the network and impact adaptation to IT-enabled work, our outcome of interest, in different ways. Our findings support calls for multilevel network analysis made by other researchers (Monge & Contractor, 2003). For example, future studies could consider the comparative effects of other multilevel network characteristics, like closeness centrality (a nodal property) and indirect ties (a dyadic property), to evaluate their joint and differential impacts on various outcomes of interest.

## 7.2 | Implications for practice

Our findings offer several practical implications for managers. First, we show that individuals' adaptation to IT-enabled work is impacted by multilevel factors beyond the control of the individual responsible for this work (Howard-Grenville, 2005; Tucker, Nembhard, & Edmondson, 2007). Managers need to bring this awareness to performance evaluations and provide the support resources needed for successful adaptation to IT-enabled work. Too often, failures to adapt are attributed to employee resistance, when the underlying factors may be beyond the control of the responsible individual, leading to employee discontentment (Joia & Magalhães, 2009; Lapointe & Rivard, 2007; Ng et al, 2011).

Our findings offer insights on specific multilevel factors, beyond individual control, which are likely to impact individual-level adaptation. Many of these relate to the informal social interaction structures within which people must perform IT-enabled work. One practical implication that emerges from our network findings is that too much cohesion is likely not of value for adaptation. While managers should certainly encourage informal interactions at work, they should be watchful to ensure that these interactions are not too tightly knit, wherein everyone is interacting with everyone else on the work unit. The time and resources invested in such closed patterns of informal interactions are not likely to yield value in terms of successful adaptation of individuals to their work, based on our findings.

Another practical insight that our work reiterates is that, at any given time, people interact with each other for multiple reasons. Each of these interactions represents a different social network, and multiple social networks typically coexist between the same set of people within the same work unit. This theoretically well-known insight is often neglected in practical settings, where people tend to pool all informal interactions as one. Our findings reveal the fallacy in this approach, since different interaction types have different structural implications for the same outcome of interest. On the basis of our findings, we recommend that managers should encourage the seeking of help from positions other than brokerage or structural hole positions and within overall network structures that are not excessively cohesive. However, when it comes to sharing one's unsolicited insights with others on the unit, structural hole positions do not matter. Managers should encourage all employees, regardless of their network location, to share what they know with others, without getting too tightly knit within the unit as a whole. Our findings, therefore, suggest a more nuanced way of monitoring and utilising different sets of informal social interactions at work to maximise employees' adaptation to IT-enabled work.

Our findings carry obvious implications directed specifically to the healthcare industry. Nonetheless, this study can benefit any type of organisation where people are adapting to complex IT-enabled work, such that individual-level tasks are embedded within interdependent higher-order task structures involving multiple people and technologies.

Moreover, even within the health-care context, our study focuses on a rather vulnerable time in any hospital system's IT implementation lifecycle when the technology has already been implemented, the major financial and resource commitments have already been made, and now the uphill task of getting individuals and groups to successfully adapt their daily workflows to the technology-enabled context must begin. An understanding of social interaction structures that can facilitate or hinder this adaptation, such as that provided in this paper, would have much practical value to health-care organisations and could also generalise to other non–health-care contexts.

### 7.3 | Limitations and future directions

Our findings, although robust, are only applicable within a set of well-defined boundary conditions. This limits the range of applicability of our research model, which in some ways could be viewed as a limitation. In other ways, however, this limitation may also be turned around as a strength by providing greater nuance and focus in our understanding of relationships between network structure and outcomes. In the previous Research and Practical Implications sections, we have identified some such opportunities in which our well-defined boundary conditions could actually inform social networks research and managerial applications of this research in a more nuanced manner. In addition, future work can strive to further sharpen these boundary conditions. In this study, we submit that our findings apply to network structures that are somewhere in the middle-of-the-continuum between fully cohesive networks versus networks rich in structural holes. Future research could investigate whether and how our findings change as we slide up and down the middle range of this continuum.

## 8 | CONCLUSION

Cohesion and structural holes can have differential impacts on adaptation to the EMR-enabled medication verification practice depending on the type of network in which these structural characteristics are studied. We offer a multilevel contingency perspective on the roles of these two network structural properties in two types of social networks: help-seeking networks and voluntary contribution networks. In doing so, our study contributes to research on adaptation to IT-enabled work, knowledge management, and social networks as well as to health-care practice.

### ACKNOWLEDGEMENT

We would like to thank the entire review team for their keen eye and constructive criticism in guiding the development of our manuscript to publishable form.

### ORCID

*Roopa Raman* https://orcid.org/0000-0003-1740-6229
*Varun Grover* https://orcid.org/0000-0001-5367-2423

### REFERENCES

Aarstad, J. (2012). Do structural holes and network connectivity really affect entrepreneurial performance? *Journal of Entrepreneurship*, 21(2), 253–268. https://doi.org/10.1177/0971355712449788

Acharya, S., Franklin, M., & Zdonik, S. (1997). Balancing push and pull for data broadcast. *ACM SIGMOD Record*, 26(2), 183–194. https://doi.org/10.1145/253262.253293

Acheampong, F., Anto, B. P., & Koffuor, G. A. (2014). Medication safety strategies in hospitals—a systematic review. *International Journal of Risk & Safety in Medicine*, 26(3), 117–131. https://doi.org/10.3233/JRS-140623

Adler, P., & Kwon, S.-W. (2002). Social capital: prospects for a new concept. *The Academy of Management Review*, 27(1), 17–40. https://doi.org/10.5465/amr.2002.5922314

Ahuja, G. (2000). Collaboration networks, structural holes, and innovation: a longitudinal study. *Administrative Science Quarterly*, 45(3), 425–455. https://doi.org/10.2307/2667105

Appari, A., Carian, E. K., & Johnson, M. E. (2012). Medication administration quality and health information technology: a national study of US hospitals. *Journal of the American Medical Informatics Association*, 19(3), 360–367. https://doi.org/10.1136/amiajnl-2011-000289

Argote, L., Ingram, P., Levine, J. M., & Moreland, R. L. (2000). Knowledge transfer in organizations: learning from the experience of others. *Organizational Behavior and Human Decision Processes*, 82(1), 1–8. https://doi.org/10.1006/obhd.2000.2883

Armstrong, J. S., & Overton, T. S. (1977). Estimating nonresponse bias in mail surveys. *Journal of Marketing Research*, 14(3), 396–402. https://doi.org/10.1177/002224377701400320

Athwal, P., Fields, W., & Wagnell, E. (2009). Standardization of change-of-shift report. *Journal of Nursing Care Quality*, 24(2), 143–147. https://doi.org/10.1097/01.NCQ.0000347451.28794.38

Ballinger, G. A. (2004). Using generalized estimating equations for longitudinal data analysis. *Organizational Research Methods*, 7(2), 127–150. https://doi.org/10.1177/1094428104263672

Barley, S. R. (1990). The alignment of technology and structure through roles and networks. *Administrative Science Quarterly*, 35(1), 61–103. https://doi.org/10.2307/2393551

Bates, D. W., Ebell, M., Gotlieb, E., Zapp, J., & Mullins, H. C. (2003). A proposal for electronic medical records in US primary care. *Journal of the American Medical Informatics Association*, 10(1), 1–10. https://doi.org/10.1197/jamia.M1097

Battilana, J., & Casciaro, T. (2012). Change agents, networks, and institutions: a contingency theory of organizational change. *Academy of Management Journal*, 55(2), 381–398. https://doi.org/10.5465/amj.2009.0891

Bawden, D., & Robinson, L. (2009). The dark side of information: overload, anxiety and other paradoxes and pathologies. *Journal of Information Science*, 35(2), 180–191. https://doi.org/10.1177/0165551508095781

Beagley, L. (2011). Bedside medication verification in the PACU. *Breathline*, 31(5), 5–5.

Berg, M. (1999). Accumulating and coordinating: occasions for information technologies in medical work. *Computer Supported Cooperative Work (CSCW)*, 8(4), 373–401. https://doi.org/10.1023/A:1008757115404

Bhosale, M. S., Jadhav, N. B., & Adhav, C. V. (2013). Analysis of completeness and legibility of prescription orders at a tertiary care hospital. *International Journal of Medicine & Public Health*, 3(3), 180–183. https://doi.org/10.4103/2230-8598.118975

Bodenheimer, T. (2008). Coordinating care—a perilous journey through the health care system. *The New England Journal of Medicine*, 358(10), 1064–1071. https://doi.org/10.1056/NEJMhpr0706165

Borgatti, S., & Cross, R. (2003). A relational view of information seeking and learning in social networks. *Management Science*, 49(4), 432–445. https://doi.org/10.1287/mnsc.49.4.432.14428

Borgatti, S. P., Everett, M. G., & Freeman, L. C. (2002). *Ucinet for windows: software for social network analysis*. Harvard, MA: Analytic Technologies.

Borgatti, S. P., Everett, M. G., & Johnson, J. C. (2013). *Analyzing social networks*Sage Publications.

Boud, D., & Middleton, H. (2003). Learning from others at work: communities of practice and informal learning. *Journal of Workplace Learning*, 15(5), 194–202. https://doi.org/10.1108/13665620310483895

Bower, R., Jackson, C., & Manning, J. C. (2015). Interruptions and medication administration in critical care. *Nursing in Critical Care*, 20(4), 183–195. https://doi.org/10.1111/nicc.12185

Boyd, R., Richerson, P. J., & Henrich, J. (2011). The cultural niche: why social learning is essential for human adaptation. *Proceedings of the National Academy of Sciences*, 108(Supplement 2), 10918–10925.

Brady, A. M., Malone, A. M., & Fleming, S. A. (2009). A literature review of the individual and system factors that contribute to medication errors in nursing practice. *Journal of Nursing Management*, 17(6), 679–697. https://doi.org/10.1111/j.1365-2834.2009.00995.x

Brady, M. K., Voorhees, C. M., & Brusco, M. J. (2012). Service sweethearting: its antecedents and customer consequences. *Journal of Marketing*, 76, 81–98. https://doi.org/10.1509/jm.09.0420

Brown, J. S., & Duguid, P. (2001). Knowledge and organization: a social-practice perspective. *Organization Science*, 12(2), 198–213. https://doi.org/10.1287/orsc.12.2.198.10116

Buchanan, J., & Kock, N. (2001). Information overload: a decision making perspective. In *Multiple criteria decision making in the new millennium* (pp. 49–58). Berlin, Heidelberg: Springer.

Burt, R. S. (1992). *Structural holes: the social structure of competition*. Cambridge, MA: Harvard University Press.

Burt, R. S. (1997). The contingent value of social capital. *Administrative Science Quarterly*, 42(2), 339–365.

Burt, R. S. (2000). The network structure of social capital. In R. I. Sutton, & B. M. Staw (Eds.), *Research in organizational behavior* ( ed., Vol. 22). *JAI Press*. (pp. 345–423). CT: Westport.

Burt, R. S. (2004). Structural holes and good ideas 1. *American Journal of Sociology*, 110(2), 349–399. https://doi.org/10.1086/421787

Carayon, P., Alyousef, B., Hoonakker, P., Hundt, A. S., Cartmill, R., Tomcavage, J., … Walker, J. (2012). Challenges to care coordination posed by the use of multiple health IT applications. *Work*, 41, 4468–4473.

Chai, S.-K., & Rhee, M. (2009). Confucian capitalism and the paradox of closure and structural holes in East Asian firms. *Management and Organization Review*, 6(1), 5–29.

Chi, L., Ravichandran, T., & Andrevski, G. (2010). Information technol**ogy**, network structure, and competitive action. *Information Systems Research*, 21(3), 543–570. https://doi.org/10.1287/isre.1100.0296

Cina, J. L., Gandhi, T. K., Churchill, W., Fanikos, J., McCrea, M., Mitton, P., … Poon, E. G. (2006). How many hospital pharmacy medication dispensing errors go undetected? *The Joint Commission Journal on Quality and Patient Safety*, 32(2), 73–80. https://doi.org/10.1016/S1553-7250(06)32010-7

Cohen, M. R. (2012). Medication errors. *Nursing*, 42(8), 12–12. https://doi.org/10.1097/01.NURSE.0000421381.05618.a6

Coleman, J. (1988). *Social capital in the creation of human capital*. *American Journal of Sociology* ( ed., Vol. 94) (pp. S95–S120). https://doi.org/10.1086/228943

Coletti, D. J., Stephanou, H., Mazzola, N., Conigliaro, J., Gottridge, J., & Kane, J. M. (2015). Patterns and predictors of medication discrepancies in primary care. *Journal of Evaluation in Clinical Practice*, 21(5), 831–839. https://doi.org/10.1111/jep.12387

Cooper, R. B., & Zmud, R. W. (1990). Information technology implementation research: a technological diffusion approach. *Management Science*, 36(2), 123–139.

Crooks, J., Clark, C. G., Caie, H., & Mawson, W. B. (1965). Prescribing and administration of drugs in hospital. *The Lancet*, 285(7381), 373–378. https://doi.org/10.1016/S0140-6736(65)91800-3

Dahl, F. C., & Davis, N. M. (1990). A survey of hospital policies on verbal orders. *Hospital Pharmacy*, 25(5), 443–447.

Davidson, E. J., & Chismar, W. G. (2007). The interaction of institutionally-triggered and technology-triggered social structure change: an investigation of computerized physician order entry. *MIS Quarterly*, 31(4), 739–758. https://doi.org/10.2307/25148818

de Vet, H. C. W., Terwee, C. B., Mokkink, L. B., & Knol, D. L. (2011). Measurement in medicine: a practical guide. http://www.clinimetrics.nl/images/upload/files/Chapter%205/chapter%205_5_Calculation%20of%20ICC%20in%20SPSS.pdf

Debono, D. S., Greenfield, D., Travaglia, J. F., Long, J. C., Black, D., Johnson, J., & Braithwaite, J. (2013). Nurses' workarounds in acute healthcare settings: a scoping review. *BMC Health Services Research*, 13(1), 1.

Devine, E. B., Hollingworth, W., Hansen, R. N., Lawless, N. M., Wilson-Norton, J. L., Martin, D. P., … Sullivan, S. D. (2010). Electronic prescribing at the point of care: a time–motion study in the primary care setting. *Health Services Research*, 45(1), 152–171. https://doi.org/10.1111/j.1475-6773.2009.01063.x

Dong, J. Q., & Yang, C. H. (2016). Being central is a double-edged sword: knowledge network centrality and new product development in U.S. pharmaceutical industry. *Technological Forecasting and Social Change*, 113(1), 379–385.

Dong, J. Q., & Yang, C.-H. (2015). Information technology and organizational learning in knowledge alliances and networks: evidence from U.S. pharmaceutical industry. *Information and Management*, 52(1), 111–122.

Eppler, M. J., & Mengis, J. (2004). The concept of information overload: a review of literature from organization science, accounting, marketing, MIS, and related disciplines. *The Information Society*, 20(5), 325–344. https://doi.org/10.1080/01972240490507974

Falci, C., & McNeely, C. (2009). Too many friends: social integration, network cohesion and adolescent depressive symptoms. *Social Forces*, 87(4), 2031–2061. https://doi.org/10.1353/sof.0.0189

Feldman, M. S., & Pentland, B. T. (2003). Reconceptualizing organizational routines as a source of flexibility and change. *Administrative Science Quarterly*, 48(1), 94–118. https://doi.org/10.2307/3556620

Feldman, M. S., & Rafaeli, A. (2002). Organizational routines as sources of connections and understandings. *Journal of Management Studies*, 39(3), 309–331. https://doi.org/10.1111/1467-6486.00294

Fiol, C. M., & Lyles, M. A. (1985). Organizational learning. *Academy of Management Review*, 10(4), 803–813. https://doi.org/10.5465/amr.1985.4279103

Flap, H., Bulder, B., & Voker, B. (1998). Intra-organizational networks and performance: a review. *Computational & Mathematical Organization Theory*, 4(2), 109–147. https://doi.org/10.1023/A:1009675906926

Flynn, F. (2016). Progressive care nurses improving patient safety by limiting interruptions during medication administration. *Critical Care Nurse*, 36(4), 19–35. https://doi.org/10.4037/ccn2016498

Fowler, S. B., Sohler, P., & Zarillo, D. F. (2009). Bar-code technology for medication administration: medication errors and nurse satisfaction. *Medsurg Nursing*, 18(2), 103–109.

Fox, J. (2008). *Applied regression analysis and generalized linear models* (2nd ed.). Thousand Oaks, CA: Sage Publications.

Freese, J., & Long, J. S. (2006). *Regression models for categorical dependent variables using Stata*. College Station: Stata Press.

Gallivan, M. J., Spitler, V. K., & Koufaris, M. (2005). Does information technology training really matter? A social information processing analysis of coworkers' influence on it usage in the workplace. *Journal of Management Information Systems*, 22(1), 153–192.

Garber, M. (2011). Combating medication verification workarounds in an electronic world. *American Nurse Today*, 6(2), 1–1.

Gargiulo, M., & Benassi, M. (2000). Trapped in your own net? Network cohesion, structural holes, and the adaptation of social capital. *Organization Science*, 11(2), 183–196. https://doi.org/10.1287/orsc.11.2.183.12514

Giampaoli, D., Ciambotti, M., & Bontis, N. (2017). Knowledge management, problem solving, and performance in top Italian firms. *Journal of Knowledge Management*, 21(2), 355–375. https://doi.org/10.1108/JKM-03-2016-0113

Gibson, T. (2001). Nurses and medication error: a discursive reading of the literature. *Nursing Inquiry*, 8(2), 108–117. https://doi.org/10.1046/j.1440-1800.2001.00098.x

Goh, S. C. (2002). Managing effective knowledge transfer: an integrative framework and some practice implications. *Journal of Knowledge Management*, 6(1), 23–30. https://doi.org/10.1108/13673270210417664

Gorbach, C., Blanton, L., Lukawski, B. A., Varkey, A. C., Pitman, E. P., & Garey, K. W. (2015). Frequency of and risk factors for medication errors by pharmacists during order verification in a tertiary care medical center. *American Journal of Health-System Pharmacy*, 72(17), 1471–1474. https://doi.org/10.2146/ajhp140673

Granovetter, M. (1985). Economic action and social structure: a theory of embeddedness. *American Journal of Sociology*, 91, 481–510. https://doi.org/10.1086/228311

Gray, P. H., & Meister, D. B. (2004). Knowledge sourcing effectiveness. *Management Science*, 50(6), 821–834. https://doi.org/10.1287/mnsc.1030.0192

Gray, P. H., & Meister, D. B. (2006). Knowledge sourcing methods. *Information & Management*, 43(2), 142–156. https://doi.org/10.1016/j.im.2005.03.002

Grise, M.-L., & Gallupe, R. B. (2000). Information overload: addressing the productivity paradox in face-to-face electronic meetings. *Journal of Management Information Systems*, 16(3), 157–185.

Grossman, J. M., Gerland, A., Reed, M. C., & Fahlman, C. (2007). Physicians' experiences using commercial e-prescribing systems. *Health Affairs*, 26(3), w393–w404. https://doi.org/10.1377/hlthaff.26.3.w393

Hahl, O., Kacperczyk, A. O., & Davis, J. P. (2016). Knowledge asymmetry and brokerage: linking network perception to position in structural holes. *Strategic Organization*, 14(2), 118–143. https://doi.org/10.1177/1476127015624274

Halbesleben, J. R., Savage, G. T., Wakefield, D. S., & Wakefield, B. J. (2010). Rework and workarounds in nurse medication administration process: implications for work processes and patient safety. *Health Care Management Review*, 35(2), 124–133. https://doi.org/10.1097/HMR.0b013e3181d116c2

Hammon, E., Hawkeye Production Llc. (2009). System and portable apparatus for securely dispensing and maintaining accurate inventory of controlled substances in a hospital setting. U.S. Patent Application 12/354,367.

Hannan, T. J. (1996). Electronic medical records. Health Informatics: An Overview, 133.

Hanneman, R. A. & Riddle, M. (2005). *Introduction to social network methods*. *Riverside*, *CA: University of California*, *Riverside* (published in digital form at http://faculty.ucr.edu/~hanneman/)

Hansen, M. T. (1999). The search-transfer problem: the role of weak ties in sharing knowledge across organization subunits. *Administrative Science Quarterly*, 44(1), 82–111. https://doi.org/10.2307/2667032

Hansen, M. T. (2002). Knowledge networks: explaining effective knowledge sharing in multiunit companies. *Organization Science*, 13(3), 232–248. https://doi.org/10.1287/orsc.13.3.232.2771

Hardin, J. W., & Hilbe, J. M. (2007). *Generalized linear models and extensions* (2nd ed.). College Station, TX: StataCorp LP.

Hertzum, M. (2010). Breakdowns in collaborative information seeking: a study of the medication process. *Information Processing & Management*, 46(6), 646–655. https://doi.org/10.1016/j.ipm.2009.10.005

Hewitt, P. (2010). Nurses' perceptions of the causes of medication errors: an integrative literature review. *Medsurg Nursing*, 19(3), 159–167.

Hoffman, J. P. (2003). *Generalized linear models: an applied approach*. Boston: Pearson, Allyn, & Bacon.

Howard-Grenville, J. A. (2005). The persistence of flexible organizational routines: the role of agency and organizational context. *Organization Science*, 16(6), 618–636. https://doi.org/10.1287/orsc.1050.0150

Hughes, R., & Stone, P. (2004). The perils of shift work: evening shift, night shift, and rotating shifts: Are they for you? *American Journal of Nursing*, 104(9), 60–64. https://doi.org/10.1097/00000446-200409000-00026

Hunter, G. L. (2004). Information overload: guidance for identifying when information becomes detrimental to sales force performance. *Journal of Personal Selling & Sales Management*, 24(2), 91–100.

Hurlbert, J. S., Haines, V. A., & Beggs, J. J. (2000). Core networks and tie activation: what kinds of routine networks allocate resources in nonroutine situations? *American Sociological Review*, 65(4), 598–618. https://doi.org/10.2307/2657385

Inkpen, A., & Tsang, E. (2005). Social capital, networks, and knowledge transfer. *The*. *Academy of Management Review*, 30(1), 146–165. https://doi.org/10.5465/amr.2005.15281445

Introduction to SAS. UCLA: Statistical Consulting Group (n.d.). from https://stats.idre.ucla.edu/other/mult-pkg/faq/general/faqhow-do-i-interpret-the-sign-of-the-quadratic-term-in-a-polynomial-regression/ (accessed January 1, 2019)

Johnson, T. R., & Kim, J.-S. (2004). A generalized estimating equations approach to mixed-effects ordinal probit models. *British Journal of Mathematical and Statistical Psychology*, 57(2), 295–310. https://doi.org/10.1348/0007110042307177

Joia, L. A., & Magalhães, C. (2009). Implementation of an electronic prescription system in a Brazilian general hospital: understanding sources of resistance. *Electronic Journal on Information Systems in Developing Countries*, 39, 2.

Jonczyk, C. D., Lee, Y. G., Galunic, C. D., & Bensaou, B. M. (2016). Relational changes during role transitions: the interplay of efficiency and cohesion. *Academy of Management Journal*, 59(3), 956–982. https://doi.org/10.5465/amj.2013.0972

Kane, G. C., & Alavi, M. (2007). Information technology and organizational learning: An investigation of exploration and exploitation processes. *Organization Science*, 18(5), 796–812.

Kane, G. C., & Borgatti, S. P. (2011). Centrality-IS proficiency alignment and workgroup performance. *MIS quarterly*, 1063–1078.

Kaushal, R., Kern, L. M., Barrón, Y., Quaresimo, J., & Abramson, E. L. (2010). Electronic prescribing improves medication safety in community-based office practices. *Journal of General Internal Medicine*, 25(6), 530–536. https://doi.org/10.1007/s11606-009-1238-8

Kendall, J. E., & Kendall, K. E. (1999). Information delivery systems: an exploration of web pull and push technologies. *Communications of the Association for Information Systems*, 1(4), 1.

Kim, J. Y. J., & Miner, A. S. (2007). Vicarious learning from the failures and near-failures of others: evidence from the US commercial banking industry. *Academy of Management Journal*, 50(3), 687–714. https://doi.org/10.5465/amj.2007.25529755

Kock, N. (2000). Information overload and worker performance: a process-centered view. *Knowledge & Process Management*, 7(4), 256–264. https://doi.org/10.1002/1099-1441(200010/12)7:4<256::AID-KPM79>3.0.CO;2-U

Koczmara, C., Jelincic, V., & Perri, D. (2006). Communication of medication orders by telephone-" Writing it right". *Dynamics (Pembroke, Ont.)*, 17(1), 20–24.

Konrad, A. M., Radcliffe, V., & Shin, D. (2016). Participation in helping networks as social capital mobilization: impact on influence for domestic men, domestic women, and international MBA students. *Academy of Management Learning & Education*, 15(1), 60–78. https://doi.org/10.5465/amle.2014.0050

Kwan, J. L., Lo, L., Sampson, M., & Shojania, K. G. (2013). Medication reconciliation during transitions of care as a patient safety strategy: a systematic review. *Annals of Internal Medicine*, 158(5 Pt 2), 397–403. https://doi.org/10.7326/0003-4819-158-5-201303051-00006

Lance, C. E. (1988). Residual centering, exploratory and confirmatory moderator analysis, and decomposition of effects in path models containing interactions. *Applied Psychological Measurement*, 12(2), 163–175. https://doi.org/10.1177/014662168801200205

Lapointe, L., & Rivard, S. (2007). A triple take on information systems implementation. *Organization Science*, 18(1), 89–107. https://doi.org/10.1287/orsc.1060.0225

Leonardi, P. M. (2011). When flexible routines meet flexible technologies: affordance, constraint, and the imbrication of human and material agencies. *MIS Quarterly*, 35(1), 147–167. https://doi.org/10.2307/23043493

Lisby, M., Nielsen, L. P., & Mainz, J. (2005). Errors in the medication process: frequency, type, and potential clinical consequences. *International Journal for Quality in Health Care*, 17(1), 15–22. https://doi.org/10.1093/intqhc/mzi015

Long, J. S. (1997). *Regression models for categorical and limited dependent variables*. Thousand Oaks: Sage Publications.

Mahoney, C. D., Berard-Collins, C. M., Coleman, R., Amaral, J. F., & Cotter, C. M. (2007). Effects of an integrated clinical information system on medication safety in a multi-hospital setting. *American Journal of Health-System Pharmacy*, 64(18), 1969–1977. https://doi.org/10.2146/ajhp060617

Marsden, P. V. (1990). Network data and measurement. *Annual Review of Sociology*, 16(1), 435–463. https://doi.org/10.1146/annurev.so.16.080190.002251

Massaro, T. A. (1993). Introducing physician order entry at a major academic medical center: I. Impact on organizational culture and behavior. *Academic Medicine*, 68(1), 20–25. https://doi.org/10.1097/00001888-199301000-00003

Mekonnen, A. B., Abebe, T. B., McLachlan, A. J., & Brien, J. E. (2016). Impact of electronic medication reconciliation interventions on medication discrepancies at hospital transitions: a systematic review and meta-analysis. *BMC Medical Informatics & Decision Making*, 16, 1–14.

Metules, T. J., & Bauer, J. (2007). JCAHO's patient safety goals: preventing med errors. *Rn*, 70(1), 39–44.

Middleton, B., Bloomrosen, M., Dente, M. A., Hashmat, B., Koppel, R., Overhage, J. M., & Zhang, J. (2013). Enhancing patient safety and quality of care by improving the usability of electronic health record systems: recommendations from AMIA. *Journal of the American Medical Informatics Association*, 20(e1), e2–e8. https://doi.org/10.1136/amiajnl-2012-001458

Miller, R. H., & Sim, I. (2004). Physicians' use of electronic medical records: barriers and solutions. *Health Affairs*, 23(2), 116–126.

Min, J., Chung, S., & Kim, M. (2017). Relationship between buyer-supplier integration and new product development: the moderating effect of structural holes. *Journal of Marketing Thought*, 4(1), 59–64.

Molina-Morales, F., & Martínez-Fernández, M. (2009). Too much love in the neighborhood can hurt: how an excess of intensity and trust in relationships may produce negative effects on firms. *Strategic Management Journal*, 30(9), 1013–1023. https://doi.org/10.1002/smj.766

Monge, P. R., & Contractor, N. S. (2003). *Theories of communication networks*. New York, NY: Oxford University Press.

Nelder, J. A., & Wedderburn, R. W. M. (1972). Generalized linear models. *Journal of the Royal Statistical Society*, 135(3), 370–384. https://doi.org/10.2307/2344614

Nestojko, J. F., Bui, D. C., Kornell, N., & Bjork, E. (2014). Expecting to teach enhances learning and organization of knowledge in free recall of text passages. *Memory & Cognition*, 42(7), 1038–1048. https://doi.org/10.3758/s13421-014-0416-z

Ng, B. Y., Kankanhalli, A., & Yip, J. (2011). Use of healthcare IS by multiple user groups: an empirical study of a medication management system. *Proceedings of 2011 ICIS Conference*, http://aisel.aisnet.org/icis2011/proceedings/IThealthcare/4/

Nickerson, J. A., & Zenger, T. R. (2004). A knowledge-based theory of the firm: the problem-solving perspective. *Organization Science*, 15(6), 617–632. https://doi.org/10.1287/orsc.1040.0093

Novak, L., Brooks, J., Gadd, C., Anders, S., & Lorenzi, N. (2012). Mediating the intersections of organizational routines during the introduction of a health IT system. *European Journal of Information Systems*, 21(5), 552–569. https://doi.org/10.1057/ejis.2012.2

Obukhova, E., & Lan, G. (2013). Do job seekers benefit from contacts? A direct test with contemporaneous searches. *Management Science*, 59(10), 2204–2216. https://doi.org/10.1287/mnsc.1120.1701

Oh, H. S., Chung, M. H., & Labianca, G. (2004). Group social capital and group effectiveness: the role of informal socializing ties. *Academy of Management Journal*, 47(6), 860–875. https://doi.org/10.5465/20159627

O'malley, A. S., Grossman, J. M., Cohen, G. R., Kemper, N. M., & Pham, H. H. (2010). Are electronic medical records helpful for care coordination? Experiences of physician practices. *Journal of General Internal Medicine*, 25(3), 177–185. https://doi.org/10.1007/s11606-009-1195-2

O'Reilly, C. A. III (1980). Individuals and information overload in organizations: Is more necessarily better? *Academy of Management Journal*, 23(4), 684–696. https://doi.org/10.5465/255556

Orrico, K. B. (2008). Sources and types of discrepancies between electronic medical records and actual outpatient medication use. *Journal of Managed Care Pharmacy*, 14(7), 626–631. https://doi.org/10.18553/jmcp.2008.14.7.626

Paparella, S. (2004). Avoid verbal orders. *Journal of Emergency Nursing*, 30(2), 157–159. https://doi.org/10.1016/j.jen.2004.01.014

Pentland, B. T., & Rueter, H. H. (1994). Organizational routines as grammars of action. *Administrative Science Quarterly*, 39(3), 484–510. https://doi.org/10.2307/2393300

Podsakoff, P. M., MacKenzie, S. B., Lee, J. Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: a critical review of the literature and recommended remedies. *Journal of Applied Psychology*, 879–903.

Podsakoff, P. M., & Organ, D. W. (1986). Self-reports in organizational research: problems and prospects. *Journal of Management*, 12(4), 531–545. https://doi.org/10.1177/014920638601200408

Poon, E. G., Poon, E. G., Keohane, C. A., & Yoon, C. S. (2010). Effect of bar-code technology on the safety of medication administration. *New England Journal of Medicine*, 362(18), 1698–1707. https://doi.org/10.1056/NEJMsa0907115

Prakash, V., Koczmara, C., Savage, P., Trip, K., Stewart, J., McCurdie, T., … Trbovich, P. (2014). Mitigating errors caused by interruptions during medication verification and administration: interventions in a simulated ambulatory chemotherapy setting. *BMJ Quality and Safety*, 23(11), 884–892. https://doi.org/10.1136/bmjqs-2013-002484

Quintane, E., & Carnabuci, G. (2016). How do brokers broker? Tertius gaudens, tertius lungens, and the temporality of structural holes. *Organization Science*, 27(6), 1343–1360. https://doi.org/10.1287/orsc.2016.1091

Ray, S. M., Clark, S., Jeter, J. W., & Treadway, S. A. (2013). Assessing the impact of mobile technology on order verification during pharmacist participation in patient rounds. *American Journal of Health-System Pharmacy*, 70(7), 633–636. https://doi.org/10.2146/ajhp120219

Reagans, R., & McEvily, B. (2003). Network structure and knowledge transfer: the effects of cohesion and range. *Administrative Science Quarterly*, 48(2), 240–267. https://doi.org/10.2307/3556658

Renzulli, L. A., & Aldrich, H. (2005). Who can you turn to? Tie activation within core business discussion networks. *Social Forces*, 84(1), 323–341. https://doi.org/10.1353/sof.2005.0122

Roberts, N., Galluch, P. S., Dinger, M., & Grover, V. (2012). Absorptive capacity and information systems research: review, synthesis, and directions for future research. *MIS Quarterly*, 36(2), 625–648. https://doi.org/10.2307/41703470

Rowley, T. J. (1997). Moving beyond dyadic ties: a network theory of stakeholder influences. *Academy of Management Review*, 22(4), 887–910. https://doi.org/10.5465/amr.1997.9711022107

Schultze, U., & Orlikowski, W. J. (2004). A practice perspective on technology-mediated network relations: the use of Internet-based self-serve technologies. *Information Systems Research*, 15(1), 87–106. https://doi.org/10.1287/isre.1030.0016

Scott, J. (2000). *Social network analysis: a handbook* (2nd ed.). London; Newbury Park: Sage Publications.

Seibert, H. H., Maddox, R. R., Flynn, E. A., & Williams, C. K. (2014). Effect of barcode technology with electronic medication administration record on medication accuracy rates. *American Journal of Health-System Pharmacy*, 71(3), 209–218. https://doi.org/10.2146/ajhp130332

Shin, S. J., Kim, T.-Y., Lee, J.-Y., & Bian, L. (2012). Cognitive team diversity and individual team member creativity: a cross-level interaction. *Academy of Management Journal*, 55(1), 197–212. https://doi.org/10.5465/amj.2010.0270

Shojania, K. G., Duncan, B. W., McDonald, K. M., & Wachter, R. M. (2002). Safe but sound: patient safety meets evidence-based medicine. *Jama*, 288(4), 508–513. https://doi.org/10.1001/jama.288.4.508

Sparrowe, R. T., Liden, R. C., Wayne, S. J., & Kraimer, M. L. (2001). Social networks and the performance of individuals and groups. *Academy of Management Journal*, 44(2), 316–325.

Speier, C., Valacich, J. S., & Vessey, I. (1999). The influence of task interruption on individual decision making: an information overload perspective. *Decision Sciences*, 30(2), 337–360. https://doi.org/10.1111/j.1540-5915.1999.tb01613.x

Strauss, L. J. (2015). Electronic medical records—benefits and liabilities. *Journal of Health Care Compliance*, 17(2), 57–58.

Suh, A., Shin, K.-S., Ahuja, M., & Kim, M. S. (2011). The influence of virtuality on social networs within and across work groups: a multilevel approach. *Journal of Management Information Systems*, 28(1), 351–386. https://doi.org/10.2753/MIS0742-1222280111

Sykes, T. A., Venkatesh, V., & Gosain, S. (2009). Model of acceptance with peer support: a social network perspective to understand employees' system use. *MIS Quarterly*, 33(2), 371–393. https://doi.org/10.2307/20650296

Sykes, T. A., Venkatesh, V., & Johnson, J. L. (2014). Enterprise system implementation and employee job performance: understanding the role of advice networks. *MIS Quarterly*, 38(1), 51–A4. https://doi.org/10.25300/MISQ/2014/38.1.03

Szulanski, G. (1996). Exploring internal stickiness: impediments to the transfer of best practices within the firm. *Strategic Management Journal*, 17, 27–43. https://doi.org/10.1002/smj.4250171105

Szulanski, G. (2000). The process of knowledge transfer: a diachronic analysis of stickiness. *Organizational Behavior and Human Decision Processes*, 82(1), 9–27. https://doi.org/10.1006/obhd.2000.2884

Tang, C. and Carpendale, S. (2007), April. An observational study on information flow during nurses' shift change. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems* (pp. 219-228). ACM.

Tortoriello, M. (2015). The social underpinnings of absorptive capacity: the moderating effects of structural holes on innovation generation based on external knowledge. *Strategic Management Journal*, 36, 586–597. https://doi.org/10.1002/smj.2228

Tortoriello, M., & Krackhardt, D. (2010). Activating cross-boundary knowledge: the role of Simmelian ties in the generation of innovations. *Academy of Management Journal*, 53(1), 167–181. https://doi.org/10.5465/amj.2010.48037420

Tsai, W. (2001). Knowledge transfer in intraorganizational networks: effects of network position and absorptive capacity on business unit innovation and performance. *Academy of Management Journal*, 44(5), 996–1004.

Tucker, A. L., Nembhard, I. M., & Edmondson, A. C. (2007). Implementing new practices: an empirical study of organizational learning in hospital intensive care units. *Management Science*, 53(6), 894–907. https://doi.org/10.1287/mnsc.1060.0692

Tyre, M. J., & von Hippel, E. (1997). The situated nature of adaptive learning in organizations. *Organization Science*, 8(1), 71–83. https://doi.org/10.1287/orsc.8.1.71

Unni, R., & Harmon, R. (2007). Perceived effectiveness of push vs. pull mobile location-based advertising. *Journal of Interactive Advertising*, 7(2), 28–40.

von Hippel, E. (1998). Economics of product development by users: the impact of 'sticky' local information. *Management Science*, 44(5), 629–644. https://doi.org/10.1287/mnsc.44.5.629

Wasserman, S., & Faust, K. (1994). *Social Network Analysis: Methods and Applications*. Cambridge, UK: Cambridge University Press.

West, D. W., Levine, S., Magram, G., MacCorkle, A. H., Thomas, P., & Upp, K. (1994). Pediatric medication order error rates related to the mode of order transmission. *Archives of Pediatrics & Adolescent Medicine*, 148(12), 1322–1326. https://doi.org/10.1001/archpedi.1994.02170120084016

Wise, S. (2014). Can a team have too much cohesion? The dark side to network density. *European Management Journal*, 32(5), 703–711. https://doi.org/10.1016/j.emj.2013.12.005

Wulff, K., Cummings, G. G., Marck, P., & Yurtseven, O. (2011). Medication administration technologies and patient safety: a mixed-method systematic review. *Journal of Advanced Nursing*, 67, 2080–2095. https://doi.org/10.1111/j.1365-2648.2011.05676.x

Xiao, Z., & Tsui, A. S. (2007). When brokers may not work: the cultural contingency of social capital in Chinese high-tech firms. *Administrative Science Quarterly*, 52, 1–31. https://doi.org/10.2189/asqu.52.1.1

Xue, L., Ray, G., & Gu, B. (2011). Environmental uncertainty and IT infrastructure governance: a curvilinear relationship. *Information Systems Research*, 22(2), 389–399. https://doi.org/10.1287/isre.1090.0269

Yu, J., Brett, A. G., & Oviatt, B. M. (2011). Effects of alliances, time, and network cohesion on the initiation of foreign sales by new ventures. *Strategic Management Journal*, 32, 424–446. https://doi.org/10.1002/smj.884

Zhang, X., & Venkatesh, V. (2013). Explaining employee job performance: the role of online and offline workplace communication networks. *MIS Quarterly*, 37(3), 695–A3. https://doi.org/10.25300/MISQ/2013/37.3.02

**AUTHOR BIOGRAPHIES**

**Roopa Raman** is Assistant Professor at the Department of MIS, Operations Management, and Decision Sciences in the School of Business Administration at University of Dayton. Prior to this, Dr Raman worked at Clemson University. She received her PhD degree from the Goizueta Business School at Emory University. Her research interests include technology-enabled change in health care, social network analysis, and knowledge management, with a particular emphasis on how social structure and individual as well as organisational behaviour impact healthcare work practices in an IT-enabled world. Roopa's research has been published in journals such as Organization Science, Communications of the AIS, and International Journal of Person-Centered Medicine.

**Varun Grover** is the David D. Glass Endowed Chair and Distinguished Professor of Information Systems at University of Arkansas. Prior to this, Dr Grover worked at Clemson University. He has published extensively, with over 200 publications in major refereed journals. Nine recent articles have ranked him among the top four researchers based on publications in the top Information Systems journals, as well as citation impact (h index). Dr Grover is Senior Editor for MISQ Executive, and Senior Editor (Emeritus) for MIS Quarterly, the Journal of the AIS and Database. He is currently working in the areas of IT and organisational value, system politics, and process transformation and recently released his third book (with M. Lynne Markus) on business process change. He is recipient of numerous awards from USC, Clemson, AIS, DSI, Anbar, PriceWaterhouse, etc. for his research and teaching and is a Fellow of the Association for Information Systems.

**How to cite this article:** Raman R, Grover V. Studying the multilevel impact of cohesion versus structural holes in knowledge networks on adaptation to IT-enabled patient-care practices. *Info Systems J*. 2020;30:6–47. https://doi.org/10.1111/isj.12239

# APPENDIX A
# DESCRIPTION OF THE MEDICATION VERIFICATION PRACTICE

## Pre-EMR version

In its pre-EMR paper-based version, the medication verification practice began with the physician prescribing a medication order (Beagley, 2011; Garber, 2011; Prakash et al, 2014). Pharmacy would then process this order and send over the actual medication to the patient-care unit. At the time of medication administration, the nurse/respiratory therapist (RT)

would need to verify the medication information on the vial/container/packaging sent over by pharmacy against the physician's original prescription order and then administer the medication. In the case of controlled substance medications, such as morphine for pain relief, a witness nurse would need to coverify this medication information (Crooks, Clark, Caie, & Mawson, 1965; Gibson, 2001). The primary nurse would walk over to the witness nurse, with the medication vial and the patient's paper-based chart containing the prescription order in hand, to obtain the witness' signature.

If any discrepancies in medication information were identified during verification, the nurse/RT would pick up the phone and call pharmacy, and the issue would be resolved in real-time over the phone. This approach had created unpredictable and interruption-prone workflows for pharmacists (Coletti et al, 2015; Prakash et al, 2014).

In some cases, physicians would call in new or changed medication orders from their offices. These were known as verbal orders (Dahl & Davis, 1990; Massaro, 1993; Paparella, 2004). Nurses/RTs would take down verbal orders over the phone, repeat these orders back to physicians over the phone, and then the orders would be processed as usual by pharmacy. Hospital administration strongly discouraged the use of verbal orders due to safety concerns (Shojania, Duncan, McDonald, & Wachter, 2002).

Medication reconciliation would be conducted at every change of shift in the hospital (Acheampong, Anto, & Koffuor, 2014; Hughes & Stone, 2004; Kwan, Lo, Sampson, & Shojania, 2013). In this task, the outgoing nurse/RT from the previous shift would sit down with the incoming nurse/RT from the next shift, with all of their patients' charts, in order to transfer care over to the next shift. As part of this process, the outgoing nurse/RT would go over every single medication that the patient had been prescribed during his/her shift and the current status of that medication. Other issues relating to medication ordering, processing, and administering, encountered on the previous shift, were also discussed. In the pre-EMR version, this would involve thumbing through paper charts in a free-flowing conversation with no particular standardised structure. As such, medication information would, at times, be communicated repetitively and, at other times, be missed. Any slip-ups in medication-related tasks during the previous shift were also difficult to catch during medication reconciliation, in this pre-EMR version, because of the reliance on paper-based charts.

## Post-EMR version

Following EMR implementation, the EMR-enabled medication verification practice was instituted, hospital wide, to replace its pre-EMR version (Appari, Carian, & Johnson, 2012; Mahoney, Berard-Collins, Coleman, Amaral, & Cotter, 2007; Prakash et al, 2014; Ray, Clark, Jeter, & Treadway, 2013). The EMR system captured real-time tracking information and generated periodic reports on providers' compliance with key tasks in this changed EMR-enabled practice (Bates et al, 2003; Hannan, 1996).

The EMR-enabled medication verification practice began with the physician prescribing a handwritten paper-based medication order (Devine et al, 2010; Grossman, Gerland, Reed, & Fahlman, 2007; Kaushal, Kern, Barrón, Quaresimo, & Abramson, 2010). After processing the order by entering order details in the EMR system, pharmacy would send over the actual medication vial to the patient-care unit. Simultaneously, information about this order displayed on the nurse's/RT's view of the patient's EMR screen. Every new medication order that showed up on the EMR screen during a work-shift would then need to be verified, on the same shift, against the physician's original order. The nurse/RT would need to check the medication information—for example, name, strength, timing, and dosage—appearing on the EMR system to ensure that it exactly matched the physician's original prescription. The nurse/RT would then place an electronic signature in the EMR system denoting successful verification. This was an entirely new task created within the EMR-enabled medication verification practice, which did not exist in the pre–EMR-enabled version of the practice. As such, compliance with this task denoted adaptation to the EMR-enabled practice. Failure to comply, ie, failure to document verification of new medications by placing the digital signature stamp in the EMR system, denoted inability to adapt to the EMR-enabled practice. The EMR system generated a monthly report that captured, for each nurse/RT, the number of medications that he/she had not verified within the same shift during that month and the total number of medications that he/she was responsible for verifying in the same time period.

For controlled substance medications, this verification task would need to be performed in the copresence of a witness nurse/RT, who would need to electronically sign on the EMR screen in real-time with the patient's primary nurse/RT (Cina et al, 2006; Hammon, 2009).

At the time of medication administration, a second verification step would need to be performed, this time, comparing the information on the medication vial and that on the patient's EMR screen. This task was similar in intent to the verification task in the pre-EMR-enabled practice mentioned earlier, but was different in actual form/content, since it involved verifying the medication vial against the EMR screen, rather than against the original physician order. The monthly EMR report mentioned earlier, counting the number of verified medications within the same shift and serving as a measure of adaptation to the EMR-enabled practice, did not include this verification task.

Finally, during medication reconciliation, the incoming and outgoing nurses/RTs would now sit together with the EMR screen, rather than with paper charts, open in front of them (Kwan et al, 2013). They would go through every single medication on this screen, discussing anything special or out of the ordinary that had occurred with that medication during the previous shift, such as, discontinued medications, waiting to receive a patient's laboratory test results for the physician to determine medication changes. At this time, any missed new medication verification tasks would readily be noticed because of a flag that appeared on the screen next to that medication. When such slip-ups were identified, the outgoing nurse/RT would need to pause transfer of care to complete this medication verification task, in turn, potentially delaying medication verification, administration, and other tasks for the nurse/RT taking over the next shift.

## Challenges experienced

A variety of challenges typically occurred that got in the way of successful adaptation to the above-mentioned EMR-enabled medication verification practice. For example, discrepancies were often encountered between the new medication information on the EMR screen, as processed by pharmacy, versus the physician's original order (Mekonnen, Abebe, McLachlan, & Brien, 2016; Metules & Bauer, 2007). Accidental discrepancies, such as because of careless errors or illegible handwriting, were just as likely to occur in the EMR-enabled as well as the pre-EMR versions of the practice (Bhosale, Jadhav, & Adhav, 2013; Cohen, 2012; Gorbach et al, 2015; Hewitt, 2010). However, in the EMR-enabled practice, these accidental discrepancies were joined by additional systematic substantive discrepancies as physicians used their preferred medication names to write their handwritten orders, which did not always match with the hospital's approved names for the same medications that were embedded in the EMR system. Any given medication typically has multiple different names, which are all synonymous to each other, and different medications can sometimes end up having similar sounding names as well. In the EMR-enabled practice, to process the physician's order, pharmacy would need to translate the medication name written by the physician to the corresponding hospital-approved synonym available through the EMR system. For a nurse/RT participating in the EMR-enabled medication verification practice, this created substantive discrepancies between the name on the EMR screen and that in the original prescription order.

In the pre-EMR practice, discrepancies could be resolved in real-time through a quick phone call to pharmacy. In the EMR-enabled practice, resolving such problems required considerable discretion and often needed to be accomplished by sending an electronic message through a “Feedback” button available within the EMR system, rather than through a phone call. The pharmacist would then prioritise the order in which he/she would respond to these messages received from all across the hospital. This constraint of electronic communication through the EMR presented another challenge unique to EMR enablement of the medication verification practice. A nurse/RT waiting to hear back from pharmacy on such an electronic question would often get busy with other work and forget to verify this medication before his/her shift ended, or the pharmacist may not have a chance to respond to the nurse's/RT's message until much later (Bower, Jackson, & Manning, 2015; Flynn, 2016).

For controlled substance medications, the need for real-time coordination between primary and witness nurses/RTs, in the presence of the computer system, created additional challenges. Nurses/RTs may be unavailable to serve as witnesses right when they were needed because of their own patient-care demands, delaying new

medication verification tasks and potentially causing them to be forgotten as a result (Prakash et al, 2014). In the pre-EMR system, witnessing in real-time was made easier by the primary nurse being able to walk over the paper chart to where the witness nurse was working. This was much harder to do with the clunky computers-on-wheels displaying the EMR screens, often necessitating witness nurses to have to leave what they were doing and walk over to the computer system, instead.

Yet other challenges in verifying new medications, which were entirely beyond the control of the verifying nurse/RT, would arise when, for various reasons, new medications needing verification would appear on the EMR screen relatively close to shift-change time (Carayon et al, 2012). For example, a physician may call in a verbal order close to a change of shift. Or clinicians may be waiting for results from patients' laboratory tests and other procedures to populate on the EMR system before physicians could decide on necessary medication changes (Miller & Sim, 2004). In the pre-EMR system, nurses/RTs would typically just call laboratory to inquire about delayed or missing test results. However, with EMR implementation, they were expected to wait for the results to auto-populate on the EMR system, since hospital administration was keen on using the system to streamline and document hospital-wide communication (Strauss, 2015). Therefore, even such things as technical difficulties in the laboratory module of the information system or difficulties in synchronising between the lab module and nursing module would delay receipt of test results, and in turn, prescription orders (Berg, 1999; Bodenheimer, 2008; O'malley, Grossman, Cohen, Kemper, & Pham, 2010). Sometimes, laboratory may have even uploaded test results in the clinical information system, but the results would just not be showing up on the nurses'/RT's view, because of these technology synchronisation issues. Technology issues would, therefore, actually create these major communication gaps that would delay medication prescriptions (O'malley et al, 2010). In the EMR-enabled practice, nurses/RTs would need to wait patiently for the test results to appear on their screen, particularly because they would not know, until a significant amount of time had passed, whether the delays were due to a technical glitch or because laboratory just needed more processing time. Because of such interdependencies in the work of multiple providers and technicians throughout the hospital, new medications would often end up appearing on nurses'/RTs' view of the EMR screen close to shift-change time, for reasons beyond the nurse's/RT's control. When this happened, the nurse/RT would either not be able to verify the medication on the same shift, which would look bad on his/her record. Or he/she would stay overtime to finish verifying the medication, which would then delay transfer of care to the next shift, not to mention loss of employee morale.

Challenges that affected the EMR-enabled medication verification practice also occurred in the medication reconciliation task of this practice due to the standardised transfer of care format enabled by the EMR system (Athwal, Fields, & Wagnell, 2009; Tang & Carpendale, 2007). The EMR system clearly flagged down every new medication order that was pending verification. This made it very easy for slip-ups in medication verification to be detected during medication reconciliation. This was a good thing for patient safety, of course, but it also meant delays in transferring care over to the next nurse/RT, creating delays in the latter's work that were beyond his/her control.

# APPENDIX B

## PRACTICAL ILLUSTRATIONS, FROM HEALTHCARE CONTEXT, OF THEORISATIONS LEADING TO HYPOTHESES

### Help-seeking network hypotheses—Illustrations supporting H1 (structural holes) and H2 (cohesion)

Consider Figure 3 as representing a help-seeking network among clinicians working within a hospital patient-care unit; Figure 3A series illustrates H1 and Figure 3B series illustrates H2.

In Figure 3A.1, nurse N occupies a structural hole position; she is flanked on either end by nurses A and B, who are disconnected from each other and are connected to their own sets of contacts in the help-seeking network.

Let us say that Nurse N is waiting for her patient's laboratory results to auto-populate on the EMR screen; before this information appears on the EMR screen and has been reviewed by the physician, nurse N is unable to verify the accuracy of future medication dosages and timings for her patient. The delay that she is experiencing, though, may be excessive and likely to stall her medication verification task until it was too close to shift-change. This is the problem that nurse N needs to resolve.

As Nurse N seeks help from others on her unit to resolve this problem, she is unable to directly tap into the rich insights of the two clusters on either end of her position due to her relatively loose connection to each cluster via simply a single node, A or B. Even nodes A and B are less likely to be committed to helping node N since the corresponding network repercussions or rewards relating to nurse N would not be that high. Since the majority of node A's or B's connections are within their respective clusters, that is where their allegiance primarily lies. This is because node A's or B's actions are most visible and, therefore, subject to positive or negative judgement, within the clusters that contain the majority of their connections in the network. Node A or B would, therefore, be more likely to invest in helping nodes within their respective clusters rather than in helping node N, who is outside of this cluster with no common third party contacts beyond the cluster. Consequently, nurse N is likely to take longer to resolve her problem of delays in the patient's laboratory test results populating on the EMR screen. As she waits longer for these results to show up on the EMR screen, she is more likely to not be able to complete medication verification before her work-shift ends. Her resulting ability to verify fewer of her patients' medications on the same shift would reflect poorer adaptation to the EMR-enabled medication verification practice. Thus, being in a high structural hole position within the help-seeking network makes it less likely for nurse N to adapt to EMR-enabled medication verification work.

Now let us consider a scenario, in Figure 3A.2, where nurses on either side of nurse N's position—for example, I and C, G and D, and J and E—start to connect with each other through help-seeking interactions. As nurses I, G, and J engage with their counterparts on the other side of nurse N, namely, nurses C, D, and E, seeking help for their problems, explaining their problem contexts, being asked for help with the others' (eg, C, D, or E's) problems, and having to engage with their problem contexts, the closeness in the immediate local environment of nurse N increases. As a result, the direct contacts of nurse N on either side of nurse N's position—namely, nurses A and B—now have better appreciation for the general local context within which nurse N works. In other words, nurse B's understanding of local context and problems is not just limited to the circumstances of nurses I, G, and J in B's immediate local cluster but also to the circumstances of their contacts, C, D, and E on the other side of the structural hole position. Nurses A and B are now more likely to understand and empathise with the problem of delayed laboratory test results facing nurse N. Perhaps this sort of delay in laboratory test results is more likely with certain kinds of tests that nurse N happens to encounter more often; nurses B or A may never have known about this until their contacts started interacting with each other for help across the structural hole. Understanding nurse N's work context can help nurses A and B suggest more helpful workarounds for nurse N to be able to continue with her medication verification work despite the delay in laboratory test results. Moreover, nurses A's and B's responses towards nurse N's requests for help are now readily visible to more people in the network. If B chooses to ignore nurse N's call for help, he/she risks not just those within his/her cluster knowing about this (namely, nurses I, G, H, and J) but also everyone on the other side of the structural hole (namely, A, F, C, D, and E) due to the indirect connections between them. This gives nurse N's contacts greater incentive to help nurse N and less opportunity to ignore nurse N's pleas for help. Thus, as the extent of "structural hole"-ness of her position decreases, nurse N is able to mobilise more related insights that she can integrate and apply to her specific problem and in turn overcome her problem more quickly. As the problem gets resolved more efficiently, nurse N is more likely to successfully perform her medication verification task before shift change, allowing it to count towards her performance productivity relating to this important EMR-enabled medication verification practice.

Figure 3B represents a different version of a help-seeking network between the same set of nodes as Figure 3A, but one that focuses on the overall cohesiveness of the network, rather than focusing on the "structural hole"-ness of the position of one of the nodes (node N) as in Figure 3A. When there are very few connections in this network (see Figure 3B.1), nurse N may find it more difficult to mobilise the help that she needs in order to figure out suitable

workarounds for timely medication verification work despite the delay in laboratory test results. For example, in Figure 3B.1, nurse N is directly connected to only nurses B and F, which are, therefore, the only nodes that can directly engage with nurse N to develop a suitable solution to nurse N's problem that would work for her. Nurse N also has several indirect connections to other nodes in the network, but getting them to engage with nurse N's local context for problem resolution is time consuming and error prone. As a brief example, an indirect contact of nurse N, such as nurse G or nurse A, in this sparsely connected overall structure may suggest that nurse N reach out to Lab Manager Susan in order to try expediting the lab results. However, her lack of immersion in nurse N's specific context, because of the large social distance between them, may have precluded her from knowing that nurse N and Lab manager Susan have a previously strained relationship, rendering this theoretically good advice inapplicable in nurse N's specific context.

As more help-seeking interactions arise between nodes in an increasingly cohesive structure (see Figure 3B.2), nurse N develops more direct contacts of her own; in Figure 3B.2, nurse N is now directly connected to nurses H, B, F, C, and E. In addition, her indirect contacts are connected to her through fewer intermediaries (eg, nurses I, J, and A connect to nurse N through only one intermediary) and/or multiple alternate paths (eg, nurse N's connections to nurses B, C, J, or H). All of this affords nurse N's contacts greater familiarity with her local work context—enough, for example, to know about nurse N's socio-professional relationship with members in the laboratory department and incorporate this information in the solutions they offer. As the cohesiveness of nurse N's broader help-seeking network increases, therefore, nurse N is able to mobilise more context-specific help from the network. This allows nurse N to more readily figure out workarounds to the problem of delayed lab results, which in turn, may increase her chances of completing medication verification work on the EMR system in a timely manner (ie, in the same shift).

Even more number of links in the network (Figure 3B.3) would result in redundant ties and likely entirely redundant information coming to nurse N. Although this information may still be useful, its incremental value to nurse N may not be as high as it was in the reasonably-high-but-not-near-closed-clustered structure in Figure 3B.2. Even further increases in the number of help-seeking links in the network would also create a general burden on people in the network from having to field too many questions from people that were connected to them either directly or through only a few intermediaries and, as such, were not easy to dismiss/decline/ignore. In such networks, nurse N's request for help may now start to be met with not only just redundant information but also erroneous or half-baked suggestions, which could end up backfiring and creating more work for nurse N. Overall, therefore, increasing cohesiveness in the help-seeking network would result in a bell-shaped concave relationship—starting off as positive, then reaching diminishing returns, and eventually turning to negative—between help-seeking network cohesion and nurse N's adaptation to the EMR-enabled medication verification practice, as hypothesised in H2.

## Voluntary contribution network hypotheses—Illustrations supporting H3 (cohesion) and H4 (structural holes)

To illustrate, consider that nurses are often learning about valid synonyms for medication names as they resolve discrepancies between physician-prescribed versus hospital/EMR-approved medication names in the course of patient care. Sharing these insights with others helps save a lot of time and aggravation for other nurses who do not need to look up this information anymore but can simply use it for their own medication verification work. Note that these insights are not shared in response to an active problem on the recipients' end, but at the time of sharing is mostly “good to know” information that can then be applied at a later time when the opportunity presented itself.

When the cohesiveness of the voluntary contribution network is low, more of the valid synonyms for medication names that are being offered up as insights by individuals in the network would appear new to others in the network. Because of the sparseness of connections in such structures, individual nurses are less likely to be aware of all the

medication name synonyms that were being discovered as part of patient-care work on the unit, except for the ones that their direct contacts and they themselves were discovering. So individuals within units with less cohesive voluntary contribution networks are likely to perform more efficiently on their EMR-enabled medication verification work due to these network contributions of new insights. This would increase the likelihood that individuals in these network structures would complete their EMR-enabled medication verification work on the same shift, ie, they would adapt better to the EMR-enabled medication verification practice.

As the cohesiveness of the network increases, however, and more direct connections are formed between individuals, newly discovered synonyms for medication names spread almost instantly to others in the network due to direct connections between many more nurses in the network and multiple alternate paths connecting the same set of nurses. So, any individual nurse may be hearing the same insight three or four times from different people in the network, depending on how many alternate paths exist in the network, which increases with the cohesiveness of the network. This creates a tendency to not pay attention to received insights, especially since any individual nurse embedded in this network is likely to be encountering many more of these shared insights simply due to the sheer number of links that now exist in more cohesive structures. The network itself, then, provides fewer new insights relating to the vast variety of synonyms for each medication name, making it likely that individuals would need to spend more time trying to figure out discrepancies in medication names on their own, when these arise during EMR-enabled medication verification tasks. More of these tasks would, then, likely have the chance of spilling over to the next shift, rather than being completed on the same shift, which would signify reduced adaptation to the EMR-enabled medication verification practice.

Finally, the extent of "structural hole"-ness of individuals' positions in the voluntary contribution network—regardless of whether it is high or low—would remain unrelated to individuals' adaptation to EMR-enabled medication verification work. A person in a high structural hole position would likely be connected to only two or three people spanning disconnected clusters in the network as a bridge between them. While these individuals would certainly have different subsets of medication name synonyms to share with the high structural hole position, the number of these unsolicited insights is likely to be much lower compared with what could have been gained from being connected to more such people in the network. As the extent of "structural hole"-ness of the position decreases, because of people across previously disconnected clusters now linking to each other, more redundant paths to the structural hole position are created. While redundant paths are good for the flow of insights they are not so good for the newness of the insights that flow through them. A structural hole position therefore, represents a classic "catch-22" in which one is doomed to either receive too few new medication name synonyms or to receive many redundant medication name synonyms. Both of these do not help as much with the efficiency of EMR-enabled medication verification work, rendering the extent of "structural hole"-ness of a position in the voluntary contribution network irrelevant to adaptation to the EMR-enabled medication verification practice.

## APPENDIX C

## ASSESSMENT OF SURVEY BIAS[6]

To assess nonresponse bias, we first interviewed a few randomly selected nonrespondents to ask them why they chose not to participate. The most common responses were lack of time or losing track of the end-date of the survey period. Second, no systematic difference between the respondent versus nonrespondent pool could be detected on

[6]Randomly chosen respondents were interviewed as part of postsurvey validity testing, where they were asked the following: (a) could they have entered additional names in response to the network questions? (b) Looking back, are the names they entered what they wanted to enter? (c) What did they think the questions were asking (this applied to network as well as non-network questions in our survey)? (d) Did they encounter difficulty understanding any of the questions in the survey. The feedback received indicated that, in general, people were comfortable answering all the questions in the survey. They also confirmed the completeness and accuracy of their network responses during these post-survey interviews.

multiple relevant characteristics, such as age, work roles, and organisational tenure (Armstrong & Overton, 1977). Finally, the potential for nonresponse bias in our dataset is significantly low due to the greater than 80% response rate (Armstrong & Overton, 1977; Sykes et al, 2014).

Several safeguards against common method bias were maintained (Podsakoff, MacKenzie, Lee, & Podsakoff, 2003). A particular strength of our research design, which also helps against common method bias, is that our dependent variable data were collected from objective organisational records while many control variables and the social networks from which independent variables were computed were collected through survey questionnaires. Differences in construct measures also helped reduce common method bias. Specifically, the dependent variable was measured as count data. Among control variables, "unit type" was measured as a categorical variable using organisational records, while "unit size," "technology experience," and "organisational tenure" were single-item continuous measures and "total number of medications that needed verification" was a count measure. Network variables were not directly measured using the same survey instrument that was used to measure the control variables. Instead, social network variables were computed, after data collection, from network matrices that were generated as a composite of individuals' responses to each socio-metric survey question. The socio-metric questions that each respondent saw in the survey, therefore, had little obvious logical connection with the network measures that were computed later. Even the social network itself was not "visible" to a single respondent, since each respondent was only privy to information about his/her own interaction partners, in responding to socio-metric questions. The network was then constructed, post–data collection, from the composite of these individual responses. Also, different scales were used for different measures in our model. Finally, we applied the Harmon single-factor test (Podsakoff & Organ, 1986) to the survey data. No single factor accounted for the majority of covariance, confirming that common method bias was not an issue.