A KNOWLEDGE-SHARING COMMUNICATION NETWORK APPROACH TO

TRANSACTIVE MEMORY SYSTEMS IN VIRTUAL WORK ARRANGEMENTS

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ABSTRACT OF THE DISSERTATION

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This study explores the relationships between expertise recognition—which is the key element of transactive memory systems (TMS)—and virtuality, while taking into account the effects of network diversity and network closure. It also examines the relationships between expertise recognition and knowledge-seeking behaviors and between expertise recognition and information-allocation. This study sheds light on the difficulties that individuals may face in establishing TMS in virtual work arrangements. Using hierarchical multiple regression and exponential random graph modeling, this study shows that the two main network properties, network diversity and network closure, not only influence expertise recognition positively but also moderate the effects of the structural aspects of virtuality on expertise recognition. Further, this study identifies alternating bivariate network relationships among the three main elements of TMS—

expertise recognition, knowledge seeking, and information allocation—indicating that individuals' perceptions of others' expertise shape patterns of knowledge-sharing.

Acknowledgements and Dedication

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Chapter 1. Introduction

To be successful, modern organizations must respond swiftly to ever-changing business needs. In recent decades, advanced information and communication technologies have radically transformed the way that organizations can navigate dynamic organizational environments. Virtual network organizations have emerged as one way to facilitate innovation and knowledge-sharing (Ahuja & Carley, 1999; DeSanctis & Monge, 1999). Despite their usefulness in mitigating the spatial and temporal limitations of work processes, virtual work environments also pose challenges to knowledge-sharing. Because virtual workers are physically distributed across space, their work often involves a fluid network structure that is characterized by electronic communication with culturally-diverse individuals. The characteristics of virtuality—which include “geographic dispersion”, “electronic dependence”, “national diversity”, and “dynamic structure” (Gibson & Gibbs, 2006)—may make it more difficult to establish mutual knowledge and form shared mental models of tasks (Cramton, 2001; Senge, 1990).

Virtual work environments present opportunities and challenges. They can mobilize diverse sets of unevenly distributed knowledge resources via various virtual organizations. Traditional forms of organizational relationships are not feasible when members work in different locations and rely primarily on electronic communication. For instance, individuals cannot readily observe how much effort others are expending. Performing tasks with previously unacquainted team members could be challenging. Unfamiliarity with each other could lead to less confidence in coworkers’ abilities. Due to the situational invisibility inherent to distributed work, virtual workers may be prone to attribute another individual’s behaviors to his or her dispositional characteristics rather than situational information about that person's behaviors, which would likely produce more false attributions (Cramton, Orvis, & Wilson, 2007). However, when face-to-face contact is too costly or simply impossible, virtual organizations use cooperative work to accomplish goals. Despite challenges such as low cohesion, disconnection, and knowledge-sharing difficulties, virtual organizations have become increasingly prevalent.

Virtual teams are quite prevalent (Okkonen, 2004); however, they are not the only type of virtual work arrangement. The word "virtual" describes multiple aspects of the workplace: virtual employees, virtual groups, virtual teams, and virtual organizations (Watson-Manheim, Chudoba, & Crowston, 2002). Virtual employees are those who are not all affiliated with the same organization or workgroup membership, or those who are physically and/or temporally distant from one another. Individuals in virtual groups and virtual teams use technology to span geographic and temporal boundaries. According to Watson-Manheim et al., the main difference between virtual groups and virtual teams is that the composition of virtual teams can be discontinuous in that virtual teams could include individuals who are affiliated with different organizations, whereas virtual groups only include individuals within the same organization. Virtual organizations contain individuals who collaborate across traditional organizational boundaries (e.g., a consortium created by multiple organizations).

In contrast to previous studies of virtual work environments, which have tended to focus exclusively on virtual teams (Gibson & Gibbs, 2006; Griffith & Neale, 2001), this study focuses more broadly on virtual work arrangements, which are characterized by virtual and/or non-virtual dynamics within organizations. The term "team" can be overly narrow because it is often used to refer to a specific organizational unit; virtual work arrangements are fluid and do not always involve virtual teams. Consider, for example, an individual virtual work pattern like telecommuting, which may or may not be used within a conventional work group, team, or organization.

Virtuality is the defining concept that underlies virtual work environments. Departing from an earlier understanding of virtuality as being completely mediated by technology, Griffith, Sawyer, and Neale (2003) portrayed virtuality as existing along a continuum from complete reliance on technological mediation to entirely face-to-face interactions. While Griffith et al. mainly focused on virtual work that uses technology to connect workers who are separated by great physical distances, virtual work does not necessarily require high levels of technical support, nor must virtual workers be physically distant from one another. Gibson and Gibbs (2006) broadened the dimensions of virtuality to include the following: “geographic dispersion”, “dynamic structure”, “electronic dependence”, and “national/cultural diversity”. Geographic dispersion refers to the extent to which coworkers operate in different geographic locations (Chudoba, Wynn, Lu, & Watson-Manheim, 2005; Gibson & Gibbs). Dynamic structure refers to the degree of turnover in workgroup membership (Gibson & Gibbs). Electronic dependence indicates the extent to which an individual relies on electronic communication tools to communicate with other people in their organizational units (Gibson & Gibbs). Cultural diversity is defined by the degree to which an individual works with people from diverse cultural backgrounds (Chudoba et al.). Given the fact that virtuality is a broader and higher-level concept than its specific instantiations in virtual employees, groups, teams, or organizations, the present study was not restricted to any specific virtual work arrangement; rather, it focused on virtuality emerging in and across various types of virtual work arrangements.

Compared with traditional organizations, individuals who work in virtual work environments may experience difficulty in becoming familiar with one another. As a result, knowing what other members know is a challenge for individuals who work in virtual work environments. One of the advantages of using virtual work arrangements (particularly, virtual teams) is that they are comprised of individuals with diverse expertise. However, individuals may not be able to take advantage of the benefits of virtual work arrangements if they are not aware of their coworkers' expertise. It is the active use of such diverse expertise that provides desirable benefits. Given that virtual work arrangements are often distributed across space, time, and culture, individuals will require an active communication network. For the benefits of diversity in virtual work arrangements to be realized, a requisite condition is the presence of transactive memory system (TMS), that is, "a set of individual memory systems in combination with the communication that takes place between individuals" (Wegner, 1987, p. 186). TMS theory suggests that knowing "who knows what" (Monge & Contractor, 2003, p. 198) influences how effectively people utilize others' expertise (Wegner). TMS forms when people become cognizant of others' knowledge, expertise, and skills, and it develops more fully as individuals learn about one another. Such "expertise recognition" (Garner, 2006) is one of the most important antecedents for effective knowledge-sharing, which ultimately leads to better group performance (Hollingshead, 2000). Regarding information processing, Hollingshead has defined TMS as "the specialized division of labor with respect to the encoding, storage, and retrieval of information" (p. 258). Each individual has his or her own knowledge and skills, and TMS development depends on how specialized that knowledge is (Moreland & Myaskovsky, 2000). Organizational members who work in virtual work arrangements cannot attempt to utilize one another's expertise and knowledge if they do not know who knows what. The presence of a well-developed TMS is considered a necessary condition for distributed teams to perform successfully.

Why do transactive memory systems matter in organizations? The answer can easily be found in situations in which organizations want their members to make the best use of other members' expertise and skills for tasks, rather than learn these on their own *de novo*. Previous studies (Moreland, 1999; Moreland & Myaskovsky, 2000) have implied that each team member does not necessarily need to learn all necessary skills and expertise, because they can exchange knowledge with one other. The existence of a well-developed TMS may indicate optimal knowledge-sharing in an organization.

This study has several goals. First, it aims to better understand the development of expertise recognition—the key element of TMS—using communication networks. Although pertinent studies tend to view TMS in terms of significantly improving organizational performance—for example, in terms of increased knowledge sharing (Argote & Ingram, 2000; Rulke, Zaheer, & Anderson, 2000)—little is known about how communication is associated with perceptions of expertise. Virtual work arrangements can make TMS development particularly difficult. It is reasonable to speculate that some of the challenges faced by organizational members who work in virtual work environments may also affect TMS development negatively. However, this study rests on the premise that communication plays a key role in moderating the effects of discontinuities on virtuality. For example, establishing a psychologically-safe communication climate—in which individuals can say what they think and identify potential problems in the organization—may help to mitigate the negative effect of virtuality on innovation (Gibson & Gibbs, 2006).

To capture the effects of communication on virtuality, this study sees communication in terms of networks. Communication networks are defined as "the regular patterns of person-to-person contacts that we discern as people exchange information in a human social system" (Monge & Contractor, 1988, p.107). A knowledge-sharing communication network can capture relationships among individuals with diverse knowledge, skills, experiences, and expertise (Monge & Contractor, 2003). Provided that communication networks represent actual communication reasonably well, I argue that the negative relationship between virtuality and TMS may be attenuated by two of the main features of emergent knowledge-sharing communication networks: network closure and network diversity. Network closure refers to the extent to which individuals create more cohesive relationships (Coleman, 1988), whereas network diversity reflects the extent to which individuals have more efficient access to information resources (Burt, 1992). In the context of knowledge-sharing communication networks, network diversity reflects the degree of nonredundant communication ties for knowledge-sharing and network closure reflects the degree of clustering/embeddedness in a communication network.

Second, this study examines TMS in virtual work arrangements. Previous studies have examined TMS in various contexts, including AM radio assembly in an experimental setting (Moreland, Argote, & Krishnan, 1996), interpersonal relationships

(Hollingshead, 1998a; 1998b), and actual organizational sites (Palazzolo, 2005; Yuan, Fulk, & Monge, 2007; Yuan, Fulk, Monge, & Contractor, 2010). However, existing TMS studies have not explicitly considered how virtuality may affect TMS formation and development. Virtual work arrangements present opportunities to examine interactions which are not limited to face-to-face interaction within certain physical places, but rather, take place in virtual environments. This study investigates the relationship between virtuality and TMS in the context of virtual work arrangements.

This study also examines the specific network configurations (e.g., transitivity) that result from patterns of interaction among organizational members who are geographically dispersed. Predicated on the notion that an entire communication network is the product of each of the specific network configurations that it contains, this study examines the emergence of specific patterns of interaction in a communication network. To that end, I investigate whether TMS produces specific patterns of interaction.

In sum, this study addresses the following questions:

- What is the relationship between virtuality and expertise recognition, the key element of TMS?
- How do the properties of an emergent knowledge-sharing communication network moderate the relationship between virtuality and expertise recognition?
- To what extent does TMS explain the specific interaction patterns that emerge in a knowledge-sharing communication network?

This dissertation proceeds as follows. I begin by reviewing the literature on TMS. After discussing the theories that inform my hypotheses and research questions, I describe the methods I used to test those hypotheses. After presenting the results, I conclude by discussing the theoretical and practical implications of this study.

Chapter 2. Literature Review

Transactive Memory Systems as a Pre-Condition of Knowledge-Sharing

When TMS is well-developed among individuals in an organization, knowledge-sharing flourishes. TMS, which is a pre-condition of knowledge-sharing in organizations (Hollingshead & Brandon, 2003), is intimately related to what virtual work arrangements aim to achieve: diverse sources of information, knowledge, and expertise. For virtual work arrangements to achieve these benefits, a relevant condition should be met: the presence of a well-developed TMS. If there is a well-functioning TMS in an organization, then this means that its members possess differentiated knowledge (i.e., expertise), trust one another's expertise, and can effectively coordinate their expertise. Once organizational members have developed TMS, the cognitive burden on each individual is reduced, providing them with access to diverse sources of information (Monge & Contractor, 2003).

In particular, TMS is relevant to understanding how knowledge is shared in an organizational setting. It is important for organizational members to recognize one another's expertise so that they can successfully complete their own tasks, but recognizing that expertise can be difficult (Garner, 2006). TMS theory has been employed widely as an instrumental theoretical framework to explain knowledge- and resource-management, including knowledge-sharing. Wegner's concept of TMS has its origins in information-processing theory (Wegner, 1987). It is beneficial to know Wegner's earlier conceptualization of TMS. Following his categorization of memory, I will discuss individual memory, external memory, and transactive memory.

Individual memory. According to Wegner (1987), individual memory is shaped and developed as individuals encode, store, and retrieve information. When individuals encounter new information, they categorize and label it ("encoding"). For example, an object *lily* could be encoded with the smell *sweet*. Even if someone has encoded an event that he or she experienced, he or she may have difficulty in retrieving information related to that event. Effective retrieval requires that information be stored in an organized manner (Kim, 2010). Thus, Wegner emphasizes the importance of metamemory, that is, an individual's ability to recall information about memories, such as the kind of memory (the senses that were used, the emotions that were at play, etc.) and the richness of the memory (its duration, the breadth of the details that were stored, etc.).

External memory. As knowledge becomes more specialized and the amount of information increases exponentially, it is impossible for individuals to learn everything. No one can memorize all of the information needed to complete certain complex tasks, and no one wants to. Accordingly, no employer wants employees to be overburdened by learning too many new skills and memorizing vast quantities of information. Rather than learn or master it themselves, individuals can store information externally. According to Wegner (1987), external storage entails identifying the *location* of the information whereas internal storage entails knowing the particular *items* that are stored. In the realm of external memory, loss of information may ensue if an item's location is not memorized. Just as things like USB sticks, notebooks, stickers, organizers, index cards, etc., function as "external storage," so too does the cognitive capacity of others.

Transactive memory. While individuals build up their own individual memories, they also contribute to collective memory, which is stored interdependently. Just as with individuals' internal memory, transactive memory is formed through the encoding, storage, and retrieval of information (Wegner, 1987). Transactive memory, however, is shaped and developed across different people (Lewis, 2003). According to Wegner, transactive encoding entails decisions about who will store what information, and transactive retrieval occurs when individuals with different kinds of internal memory seek out other people's internal memory.

The TMS concept originated in laboratory studies exploring the extent to which individuals use their capacity for social cognition to solve a given task by sharing knowledge with one another (Wegner, 1987). The earliest TMS studies centered on whether TMS could be possible in dyads: memory (Wegner, Erber, & Raymond, 1991) and memory tasks (Hollingshead, 1998a; 1998b) in the context of romantic relationships. However, because these studies were performed in laboratories, they were unable to address whether TMS could develop in natural (non-laboratory) settings. Moreland (1999) provided a basis for the transition from interpersonal relationships to larger groups, such as workgroups and organizations. Liang et al. (1995) demonstrated that subjects who were trained in groups to complete tasks tended to exhibit higher levels of performance and to recall more task-related information than those who were trained alone, mainly because of task differentiation and specialization by those in groups. Moreland argued that TMS will develop best when group members continue working as a group after training together and receive continued training as a group. However, as he admitted, this often is impractical, especially in virtual teams, which are characterized by dynamic changes in structure (Gibson & Gibbs, 2006). As an alternative to group training, Moreland suggested that managers inform their groups about each member's role and expertise. However, this may be an inadequate way to keep abreast of changes in team members' performance.

Early TMS studies also centered on the impact of TMS on group performance. The literature demonstrates that TMS does impact group performance (Liang et al., 1995; Moreland, 1999). TMS has emerged as a significant concept in organization studies. TMS has been studied empirically and is theoretically useful for explaining information-sharing (Fulk, Monge, & Hollingshead, 2005; Palazzolo, 2005; Palazzolo, Serb, She, Su, & Contractor, 2006; Yuan et al., 2010).

There are two emerging streams in recent TMS studies: the social constructivist approach (Leonardi & Treem, 2012) and stochastic network analysis (Su & Contractor, 2011; Su, Huang, & Contractor, 2010). According to Leonardi and Treem, many studies have assumed that a TMS is something that can be *identified* or *recognized*; in contrast, Leonardi and Treem stress that expertise is something that can be *performed* and *constructed*. Using an ethnographic approach, Leonardi and Treem found that people who are spatially isolated from their team members tend not to reveal their actual expertise as it is; rather, they engage in a strategic presentation of their expertise. Leonardi and Treem argued that TMS researchers should pay more attention to how people recognize others' expertise in distributed contexts and to the factors that play a role in expertise recognition.

Recent TMS studies in organizational communication have also attempted to employ stochastic network analysis to explain the formation and development of TMS (Palazzolo, 2005; Palazzolo et al., 2006). Using the p* model, Palazzolo found that a variety of forms of interaction in dyads, triads, and larger groups may be reflected in information-sharing. Extending the use of stochastic network analysis (e.g., exponential random graph modeling (ERGM)), Su et al. (2010) found that if person *i* retrieves information from person *j*, then *i* is likely to forward unsolicited information to *j*, and if person *i* retrieves information from person *j*, then *j* will tend to forward some information to *i*. Expertise recognition, a key aspect of TMS, is associated with information-seeking behaviors (Su & Contractor, 2011). These ERGM-driven studies revealed that TMS plays a key role in producing certain patterns of knowledge-sharing.

Mutual knowledge. To clarify the factors that affect TMS, this study distinguishes between TMS and several similar concepts to explain shared mental activities among coworkers. First, TMS is not domain-specific knowledge that may be used for a specific task (e.g., financial analysis, computer programming, etc.), but rather may be thought of as a shared mental model of individuals' tasks. According to Senge (1990), mental models are defined as "deeply ingrained assumptions, generalizations, pictures, or images that influence how we understand the world and how we take action" (p. 8). Shared mental models occur when individuals understand a given task in a similar way (Blickensderfer, Cannon-Bower, & Sales, 1997). Yet, in most situations, Senge has argued that coworkers tend to be unaware that they share a mental model and are thus unaware that it affects their behavior (Senge).

There is also a distinction between knowledge transfer and TMS. Knowledge transfer reflects actual *behaviors*—the exchange of knowledge between people—whereas TMS centers on *perceptions* of, for example, what others are doing and how well they are performing. TMS is unique because it depends on specific situations where individuals are involved in a given task. TMS does not reflect individual group members' domain-specific knowledge, but rather a team's shared mental model of what is occurring among team members as they complete a task. Mutual knowledge is created when individuals share what they know with one another and know that they share it (Krauss & Fussell, 1990). Although the presence of mutual knowledge helps virtual collaborators to develop and maintain TMS, mutual knowledge in itself does not constitute TMS.

Cognitive interdependence. Wegner, Giuliano, and Hertel (1985) have viewed TMS as a mechanism for distributing cognition across individuals. Wegner et al. did not directly consider other factors that may influence how people form TMS; however, they helped to conceptualize TMS in a way that is crucial to better understanding how individuals use one another's cognitive capacity. Distributed team members may suffer from lack of mutual knowledge among team members (Cramton, 2001). But an increase in mutual knowledge can increase cognitive interdependence.

Cognitive factors significantly influence the development of TMS (Brandon & Hollingshead, 2004). Hollingshead (2001) has incorporated two important factors into TMS theory: cognitive interdependence and convergent expectations. Cognitive interdependence occurs when individuals must pool their knowledge in order to be successful in a given task. Individuals with differentiated knowledge will only become cognitively interdependent if they have convergent expectations of one another. As Hollingshead has pointed out, "the extent to which group members share expectations about one another's knowledge affects how they tacitly coordinate who will learn what" (p. 1082). Cognitive interdependence is essential for TMS development.

It is important to know that cognitive interdependence among individuals occurs in the context of a given situation, such as whether people are working in virtual work arrangements, affects TMS development. Regarding virtual work arrangements, one should consider that cognitive interdependence may be influenced by virtuality. For example, it may be difficult for team members who are separated by various well-defined boundaries (e.g., geographic, cultural, or functional boundaries) to achieve cognitive interdependence, thus making it difficult for them to establish TMS, whereas a team with more porous boundaries may develop TMS relatively easily and achieve higher levels of cognitive interdependence. It also should be noted that cognitive interdependence in virtual work environments may be affected by in-group dynamics—stemming from, for example, a shared cultural identity.

Dimensions of TMS

There are divergent views on what specifically constitutes TMS. Wegner (1995) has argued that TMS depends on three processes: “directory updating”, “retrieval coordination”, and “information allocation”. Directory updating refers to a process by which individuals update their knowledge of other people’s skills and expertise. Retrieval coordination is a process by which people coordinate for effective retrieval of information they need to use. Information allocation occurs when individuals distribute information to those who appear to be the best stores for its future use.

Moreland (1999) has categorized different TMS in terms of the differentiation of each member’s expertise or knowledge (i.e., specialization), the reliability of members’ awareness of others’ expertise or knowledge (i.e., credibility), and the effectiveness of members’ coordination of knowledge and expertise (i.e., coordination). Pointing out that there is a tendency to equate these manifestations of TMS with one or more of its components, Lewis and Herdon (2011) have argued that when specialization, credibility, and coordination are manifest, then a TMS is assumed to exist. Conversely, if there is a well-developed TMS in a team, then this means that team members possess specialized knowledge, trust other members' expertise, and are able to integrate their knowledge, skills, and expertise.

More recent TMS studies have used different terms to describe the same concepts (Kanawattanachai & Yoo, 2007; Yoo & Kanawattanachai, 2001). In Kanawattanachai and Yoo's study, credibility and coordination were operationalized as cognition-based trust and task-knowledge coordination, respectively. Moreland himself later defined specialization in terms of the complexity of the knowledge that each group member possesses. Specialization refers to the extent to which individuals possess differentiated knowledge or expertise (Liang et al., 1995; Moreland & Myaskovsky, 2000). Lewis (2003) claimed that a well-established TMS results in more differentiated and specialized knowledge or expertise, because as members become accustomed to relying on others' knowledge, they gain confidence in developing knowledge that does not overlap.

Brandon and Hollingshead (2004) have argued that the notion of task representation/coordination—or "who does what" and "who knows who does what" (Monge & Contractor, 2003, p. 198) —is an important element of TMS. As organizational members perform their roles and tasks, the important thing that initially emerges is not their expertise, but their perceptions of who performs what and their ability to coordinate their performance. Credibility has been defined as people's perceptions of the reliability of other members' knowledge and expertise (Moreland & Myaskovsky, 2000). In order to gain reliable knowledge from one another, team members must have a sufficient level of trust in each other's expertise (Weick & Roberts, 1993). What is important for credibility is not only team members' beliefs about one another's knowledge but also their beliefs about how reliably other team members can execute a given task (Kanawattanachai & Yoo, 2007).

Lewis, Belliveau, Herndon, and Keller (2007) distinguish the existence of TMS from the existence of the components that usually constitute TMS. Although people tend to equate what Moreland identified as manifestations of TMS with what they call the components of TMS, these two things cannot be the same. According to Lewis et al., specialization, credibility, and coordination are present when a TMS is functioning and, thus, indicate that a TMS exists, but they cannot be mapped onto the process by which a TMS operates. Further, Lewis et al. have suggested that the components of TMS be understood in terms of structures and processes. They define the structure of TMS as "a representation of members' shared understanding of which member possesses, and is responsible for, what knowledge" (p. 162). It seems that TMS structure is more closely related to the three factors that Moreland identified (i.e., specialization, credibility, and coordination) than to the processes that Wegner claimed constituted TMS (i.e., "directory updating", "information allocation", and "retrieval coordination"). Lewis et al. have defined TMS processes as "the set of transactive processes that occur as a group encodes, stores, or retrieves information relevant to the group or [the] group's task" (p. 162). These processes focus more on the behavioral aspects of TMS, such as the extent to which people allocate information to others who they believe can store it, and the extent to which that information can be retrieved when it becomes necessary to use it. Thus, the TMS processes are related to Wegner's understanding of how TMS operates.

Although there are diverging views on how to conceptualize TMS (a latent variable-based approach vs. a TMS process-focused approach), both approaches have one thing in common: *expertise recognition.* Regardless of whether one focuses on processes (Austin, 2003; Wegner, 1995) or on specialization, coordination, and credibility (Kanawattanachai & Yoo, 2007; Lewis, 2003; Moreland, 1999), expertise recognition—the underlying premise of TMS—is assumed to be at play. In order for individuals to develop expertise (i.e., differentiated knowledge or specialization), be capable of integrating their knowledge and expertise with that of others (coordination), and trust the reliability of others' expertise (credibility), they must first recognize others' expertise. Borgatti and Cross (2003) reported that information-seeking behaviors are positively associated with (a) "knowing what another person knows," (b) "valuing what that other person knows in relation to one's work," and (c) " being able to gain timely access to that person's thinking" (p. 440). Additionally, from Wegner's point of view (1995), it is possible to argue that directory updating *precedes* information allocation and retrieval, and what is updated is an individual's perception of others' expertise.

In sum, expertise recognition rests on the notion that collaborators can only use others' expertise if they know who knows what (Wegner, 1987). Expertise recognition can be defined as the extent to which individuals recognize who in their team knows what (Monge & Contractor, 2003). Individuals use other collaborators as repositories for necessary information, knowledge, or any other resources outside of their own knowledge base (Wegner). Rather than becoming experts themselves, individuals can find and use others' expertise. But to do so, they must be aware of who knows what. In organizations, expertise recognition plays a key role in predicting individuals' information-seeking behaviors.

Chapter 3. Transactive Memory Systems and Virtuality

Virtuality, Discontinuities, and TMS

According to Chudoba et al. (2005), virtuality is characterized by discontinuities that are widely seen as posing difficulties, such as with communication, conflict management, and the maintenance of social interactions across time, space, and/or organizational entities. Discontinuities are defined as “gaps or a lack of coherence in aspects of work” (Watson-Manheim, Chudoba, & Crowston, 2002, p. 194). Examples of discontinuities include temporal and spatial separation between virtual work processes (Chudoba et al.). Discontinuities can also occur when coworkers come from different cultural backgrounds (Chudoba et al.).

As Gibbs, Nekrassova, Grushina, & Abdul Wahab (2008) have pointed out, early laboratory-based studies tended to portray virtuality as a dichotomous variable: either 100% technology-mediated or 100% face-to-face (FtF). However, more recent studies view virtuality along a continuum from purely virtual to completely FtF (Griffith, Sawyer, & Neale, 2003); that is, what matters is the degree of levels of virtuality in a specific work arrangement (e.g., virtual workers or virtual teams) rather than being purely technologically mediated or completely collocated. Griffith et al. proposed three dimensions of virtuality: the percentage of time spent working across spatial and temporal discontinuities, the amount of physical separation between workers, and the degree of technological mediation.

Chudoba et al. (2005) has extended the definition of virtuality to include three dimensions: team distribution, workplace mobility, and variety of work practices. Team distribution refers to the degree to which coworkers operate across different time zone and locations. Workplace mobility refers to the degree to which they operate in multiple workplaces. Finally, variety of practices refers to the degree to which coworkers are culturally diverse and engage in a variety of work processes.

Kirkman and Mathieu (2005) have proposed a somewhat different three-dimensional model of virtuality that includes (a) the degree to which individuals use virtual technologies for their communication and tasks, (b) the informational value achieved by using virtual tools, and (c) the degree to which interactions are synchronous. Because collocated teams might actually exhibit higher levels of virtuality than distributed teams, Kirkman and Mathieu chose to deemphasize the importance of geographical dispersion in their definition of virtuality.

Virtuality enables virtual workers to span the boundaries of space, time, and organizations. Griffith and Neale (2001) have stated that the basic reason why organizations implement virtual work arrangements is to benefit from diverse sources of expertise and resources, connecting people across teams, organizations, and countries (cf. Chudoba et al., 2005). Moreover, virtuality is also thought to reduce redundancies in expertise. One of the advantages of virtual work arrangements, spanning boundaries, reflects the importance of weak ties. Granovetter (1973) has argued that weak ties are sometimes beneficial because weak ties may increase access to more nonredundant sources of information. On the other hand, the boundaries of space, time, and organizations may weaken cohesion. Scott and Timmerman (1999) have pointed out that advanced communication technologies are a double-edged sword: they eliminate spatial barriers to collaboration, providing workers with freedom and flexibility, but they distance them from their organizations.

Work within virtual organizations is often disconnected or lacking coherence (Chudoba et al., 2005). Virtual organizations in which members show cohesion in their work arrangements are "continuous," whereas those whose members lack cohesion are "discontinuous." For example, discontinuities may occur during trust development. Compared with those who communicate FtF, those who belong to a virtual organization may have more difficulty trusting their coworkers. Discontinuities in virtual organizations may delay or even hamper the development of trust. In this vein, virtuality may make it difficult to develop TMS.

There are two reasons why expertise recognition and, further, overall TMS formation is likely to be negatively affected by virtuality. First, geographic dispersion makes it difficult to attain mutual knowledge, which in turn makes it difficult to form TMS (Cramton, 2001; Thompson & Coovert, 2003). Technological mediation offers diminished social and contextual cues. To perform effectively, it is crucial that organizations develop mutual knowledge (Cramton). However, compared to collocated workers, geographically distributed team members may experience some difficulty in obtaining direct knowledge from one another (Driskell, Radtke, & Salas, 2003).

Second, virtuality may hamper the development of TMS if distributed collaborators lack a shared understanding of their tasks and the way that other collaborators work. For example, person *i* may feel that there is an issue with the way person *j* shares what he or she knows. Simultaneously, *j* may think that the way he or she shares knowledge with *i* works well. Such disparity in understanding one another's way of operating may be more likely to occur in virtual work arrangements.

In sum, this study is predicated on the notion that TMS can thrive only under certain conditions, including effective communication, warm social relationships, and acceptance of cultural differences. Virtuality decreases individuals' shared understanding of a given task (Watson-Manheim et al., 2002). Shared understanding of tasks and others' expertise are crucial features of TMS. The following subsections discuss how each element of virtuality affects TMS by fostering (or inhibiting) discontinuities.

Geographic dispersion. In contrast with physically collocated work arrangements, individuals in virtual work arrangements are dispersed across various locations and time zones (Gibbs et al., 2008). Geographic dispersion needs to be discussed in terms of its impact on performance and relationship-building. The distance between people affects how they interact with each other. Collocated interactions offer individuals rapid, often nonverbal, feedback about what is on one another's mind, which can help resolve misunderstandings or disagreements, or possibly prevent them from occurring (Olson & Olson, 2000). Geographically dispersed collaborators lack the advantages that collocated workers can enjoy. Increased physical distance has been linked to reduced attention and effort among workers (Kiesler & Cummings, 2002). Further, geographically dispersed members may experience more difficulty in forming shared mental models, which are essential for a well-functioning team.

Because geographically dispersed collaborators tend to have less frequent communication than collocated workers, virtuality is likely to impede the three main processes of TMS (directory updating, information allocation, and retrieval coordination). Specifically, geographic dispersion often requires that coworkers spend more time and effort to be aware of one another's expertise and tasks. Likewise, they may be unable to retrieve relevant information from others when necessary. If locating, storing, and retrieving information cannot occur seamlessly, virtual workers may feel less confident in relying on one another's expertise, becoming *less* interdependent. As a result, they may not have a mutually shared understanding of one another's expertise. In addition, they may not be able to keep track of the specific tasks that each team member is working on. The above discussion suggests the following hypothesis:

Hypothesis 1: Geographic dispersion is negatively related to expertise recognition in virtual work arrangements.

Dynamic structure. According to Gibson and Gibbs (2006), dynamic structure of virtual collaboration is a main aspect of virtuality. This dynamism seems to contradict what Moreland (1999) regarded as the ideal situation for TMS, in which team members train together and continue to work together as one team. However, virtual work arrangements are often structurally dynamic due to frequent changes in the composition of organization members and their task-related roles (Brown & Eisenhardt, 1995). As such, Moreland's recommendation may not be applicable to virtual work arrangements.

Gibson and Gibbs (2006) have pointed out that dynamically structured collaborations would bring about more uncertainty to virtual collaborators, weaken their relationships, and negatively impact team innovation. A compositional change in a team would inevitably spur instability in an already-established shared mental model and/or mutual knowledge, making it difficult to learn other people's expertise and their tasks (Moreland, 1999). Frequent turnover is harmful to TMS, because it renders obsolete team members' awareness of other members' knowledge and skills (Moreland). Given that certain levels of cumulative interaction are vital for establishing shared mental models, any compositional changes, especially frequent ones, would likely hinder virtual collaborators' ability to establish and sustain shared mental models of their tasks and relevant contexts surrounding their tasks, making it difficult to learn other works' expertise and knowledge. In addition, it usually takes time for newcomers to learn the shared mental models of the incumbent members. Dynamic structure might make it even more difficult for coworkers to attain a shared mental model. Instability in virtual work arrangements may reduce organizational members' motivation to actively collaborate with one another. As discussed previously, geographic dispersion makes it difficult to form and sustain individuals' perceptions of one another's expertise, but I speculate that the dynamic nature of structure disrupts perceptions of expertise, making it difficult to establish or maintain TMS. The above discussion leads to the following hypothesis:

Hypothesis 2: Dynamic structure is negatively related to expertise recognition in virtual work arrangements.

Electronic dependence. Due to geographic dispersion, individuals who work in virtual work arrangements often rely more on communication technologies and less on FtF communication (Shin, 2005). Electronic communication has been framed in two different ways: either as deficient (the "Cues-Filtered-Out" perspective, Culnan & Markus, 1987) or not deficient (Social Information Processing Theory and the Hyperpersonal Communication Perspective, Walther, 1992). Early computer-mediated communication (CMC) research argued that the lack of nonverbal cues may hamper effective communication and that using electronic media may limit the amount of social and nonverbal cues that characterize effective communication (Kiesler, Siegel, & McGuire, 1984; Sproull & Kiesler, 1986). Electronic dependence makes it more difficult for workers to form cohesive interactions that would help them to establish mutual knowledge of their task and necessary expertise. Gibson and Gibbs (2006) argued that the more virtual team members rely on electronic communication, the more difficulties they will have in exercising subtle control over their interactions with others and interpreting the knowledge which they process for innovation. Likewise, despite the availability of synchronous electronic media, CMC may delay feedback among workers, constraining their ability to learn who knows what and who does what.

However, social information processing (SIP) theory provides a different perspective on electronic dependence. This theory argues that it is possible to form and develop productive interpersonal relationships via CMC (Walther, 1992). According to SIP theory, the only difference between CMC and FtF lies in the initial difference in the degree of information transfer, not the extent of possible information exchange. Such differences will be resolved with repeated interactions over time (Walther). There have been studies that compare the capabilities of CMC and FtF in terms of information exchange. When team members who use CMC interact with one another for a sufficient amount of time, they turn out to be just as effective as FtF teams (Chidambaram, 1996; Wilson, Straus, & McEvily, 2006). Wilson et al. have demonstrated that over time there is no significant difference between levels of trust in teams that have only FtF contact and those that are mediated by communication technologies. Virtual groups with CMC develop similar levels of trust as FtF groups, due to the fact that CMC groups exchange more messages (Krebs, Hobman, & Bordia, 2006). In sum, according to SIP theory, CMC does not necessarily inhibit the development of TMS, because virtual group members may use CMC technologies to learn the expertise and know-how of other members who work in different geographic locations.

There is disagreement as to how electronic communication impacts TMS. Moreland (1999) has suggested the use of what he called electronic Yellow Pages in promoting one's perception of who knows what. He claimed that people can easily access the information and knowledge necessary to complete their tasks when it is organized based on well-defined keywords. Hollingshead, Fulk, and Monge (2002) have suggested that using an intranet makes information more accessible. Digital information repositories have been highlighted as an effective tool for sharing information and knowledge that cannot be shared via FtF communication (Hollingshead, 2000; Hollingshead et al., 2002; Moreland, 1999). The emphasis on such information repositories reflects the fact that organizations are becoming increasingly more reliant on electronic communication.

However, although online knowledge repositories are widely believed to provide some advantages, such as speedy and cost-effective access to vast amounts of information, their presumed benefits to TMS development have yet to be established empirically. A recent study has revealed that the use of online knowledge repositories does not boost the accuracy of expertise recognition. Su (2012) found that digital knowledge repositories (e.g., an intranet) do not have an impact on how accurately team members recognize one another's expertise, suggesting that, due to the overwhelming amount of information that is available in online knowledge repositories, people use digital knowledge repositories for time- and cost-effectiveness. Su explained that they use digital knowledge repositories to avoid the social costs inherent in FtF meetings. As a result, they tend not to pay attention to who authors what on digital repositories, which prevents them from being able to accurately recognize the identity of experts. For online information repositories to promote TMS, it is crucial to keep relevant information up to date (Su). Outdated information accumulated in digital knowledge repositories may not help individuals learn who knows what, and can even discourage them from taking advantage of such repositories. The aforementioned conflicting theories and results led me to propose the following research question:

Research question 1: For virtual workers, what is the relationship between electronic dependence and expertise recognition?

Cultural diversity. Cultural diversity may have differing effects in organizations. On one hand, culturally diverse teams are often expected to exhibit a variety of innovative perspectives. On the other hand, "thinking differently" may not always yield positive results. In some cases, the ostensible merits of virtual work arrangements, such as diversity, might also produce unintended consequences (e.g., disharmony among members, or conflicting solutions). Cultural diversity—i.e., the extent to which individuals have different cultural backgrounds (Shin, 2005)—can make it difficult for workers to communicate with one another. Culturally diverse teams have been found to yield weak performance in terms of communication, decision making, and conflict resolution (Thompson, 1999).

Cultural diversity can fragment the flow of communication in a team by facilitating the formation of subgroups (Cramton, 2001). The existing literature has shown that the presence of cultural subgroups can fragment communication (Cramton) and foster conflicts (Mortensen & Hinds, 2001). The logic behind this is that there are more negative than positive impacts on group performance when cultural homophily generates in-group–out-group dynamics within a geographically distributed team. Due to the presence of strong subgroups, the emergent communication network may be limited to the boundaries of a relatively homogenous faction/clan. This may lead to a complete breakdown in communication, which in turn may result in an underdeveloped TMS.

However, the subgroups created by cultural diversity can be productive (Gibson & Vermeulen, 2003). In particular, subgroups with moderate strength are conducive to learning behavior while weak and strong subgroups are negatively related to learning behavior (Gibson & Vermeulen). Throughout the learning process, a cohesive cultural subgroup may play the role of a "cohort" (Gibson & Vermeulen). This cohort effect can be supported by the fact that members within cohesive subgroups interact proactively. In addition to the positive cohort effect, subgroups may help to preserve diverse ideas within a dense cluster, which results in larger quantities of information in the overall network (Fang, Lee, & Schilling, 2010). A medium level of subgroup strength is related to low levels of conflict in the work process and high levels of performance and morale while either low or high levels of subgroup strength have a negative impact on these outcomes (Thatcher, Jehn, & Zanutto, 2003).

With respect to the positive effect of moderate subgroup strength, cultural diversity may not always make it difficult for team members to obtain and maintain such a collective understanding of their work. A recent study has shown that pockets of shared cultural backgrounds can be helpful in fostering awareness of other individuals' expertise. Because cultural cues may play a role as heuristics, individuals with similar cultural backgrounds may be better able to discern one another's expertise (Yuan, Bazarova, Fulk, & Zhang, 2013)

Interestingly, a meta-analysis has shown that cultural diversity has a nuanced effect on communication effectiveness (Stahl, Maznevski, Voigt, & Jonsen, 2010): the effect appears to be negative when assessing cultural diversity with manifest measures (i.e., race, ethnicity, and nationality), and positive when using latent variables (i.e., personality, values, and attitudes). Cultural diversity has been found to hinder the development of common goals and commitments (in what is termed “convergence”), while fostering heterogeneous inputs such as different ideas and perspectives (in what is called “divergence”) (Stahl et al.). These conflicting conclusions about whether cultural diversity helps or hinders the collective understanding of tasks led me to propose the following research question:

Research question 2: For virtual workers, what is the relationship between cultural diversity and expertise recognition?

An Emergent Communication Network Perspective

Though virtual work is characterized by discontinuities, it is also characterized by continuities. Continuities are “a collective understanding of some aspects of the work environment” (Watson-Manheim et al., 2002, p. 200), such as “shared motivation, understanding of the task, [and] mutual expectations” (p. 201). It is legitimate to ask how such continuities can be achieved and maintained in virtual work arrangements.

Some of the discontinuities that virtual collaborators encounter stem from not operating in the same physical location, not sharing the same/similar nationality, and not obtaining a stable organizational structure of membership. Watson-Manheim et al. (2002) point out that discontinuities are inherent to virtuality. However, virtual workers are typically required and/or expected to forge communication ties with other members who have different cultural or national backgrounds at a physical distance. That is, the emergence of communication networks in and/or across virtual work units is inevitable. Even if this process is not prescribed by the plans of management, it often emerges from organizational members' necessities. To better understand the continuities produced by virtual work arrangements, it is important to understand the role of emergent communication networks within and/or across teams.

An emergent communication network perspective helps explain why some continuities can be achieved and sustained. For example, Watson-Manheim et al. (2002) showed that a shared understanding of tasks is an important indicator of continuities in virtual networks. It is difficult to think that those in virtual work arrangements would exhibit such continuities at the start of their relationship. Although management may seek to impose continuities from above, continuities are mainly achieved and maintained by ad hoc communication.

As discussed previously, one TMS premise is that individuals can serve as external information repositories for one another. TMS requires individuals to encode, store, and retrieve one another's knowledge and information (Wegner). Whereas individual memory is basically a cognitive process occurring within individual brains, transactive memory operates *across* individuals, with each person acting as external memory for the others. Thus, without communication, individuals cannot share their knowledge with others (i.e., transactive encoding), cannot acquire new information from them (i.e., transactive retrieval) and, subsequently, cannot sustain a transactive memory system (Hollingshead & Brandon, 2003). Communication enables people to identify experts and share knowledge and information with one another (Hollingshead &

Brandon). Yuan et al. (2010) have analyzed expertise exchange in organizations by examining the strength of communication ties among individuals. Analyzing data from individuals belonging to different organizations, Yuan et al. found that as the strength of individual communication ties increases, individuals will likely exchange expertise, one of the outcomes of TMS.

Incorporating social network analysis perspectives into communication theory was made possible by Rogers and Kincaid's convergence model of communication (1981). By critiquing the conventional model of communication, which emphasized the mechanical, unidirectional flow of content, Rogers and Kincaid proposed a convergence model of human communication that is characterized by "mutual causation" and by an "interdependent relationship" among communicators. This model shifts the focus of communication from what is transferred among communicators to what they create and share. Rogers and Kincaid defined communication as a "process in which the participants create and share information with one another in order to reach a mutual understanding" (p. 63). Because communication is a "joint occurrence" and a "mutual process of information-sharing between two or more persons," a communication network is comprised of "interconnected individuals who are linked by patterned flows of information" (p. 63).

Social network approaches provide a new understanding of emergent communication networks (Monge & Contractor, 2001; Monge & Eisenberg, 1987). Stated differently, communication networks reflect "who speaks to whom in a group or organization" (Feeley & Barnett, 1997, p. 371). Ties between nodes/actors in a given communication network represent actual communicative behaviors (e.g., individual members have contact with one another, and share the information, skills, and knowledge necessary for task completion). Because the way in which individuals communicate directly influences their behavior, studying communication networks adds explanatory value to their actions in an organizational context—e.g., group connectivity and attitude–belief uniformity (Danowski, 1980) and organizational commitment (Eisenberg, Monge, & Miller, 1983).

The literature has shown that the social network approach is one of the relevant tools for examining how TMS form and evolve in organizational settings (Palazzolo, 2005; Palazzolo et al., 2006). A social network approach can explain how individuals' communication ties affect information retrieval (Palazzolo). The structural and relational attributes of teams may account for perceptions of expertise, because communication ties can be used to depict patterns of interaction among team members.

Network Diversity and Network Closure

In this section, I propose that the two major network perspectives—network closure (Coleman, 1990) and network diversity (Burt, 1992)—are two mechanisms that affect expertise recognition and moderate the negative effects of virtuality on expertise recognition. In particular, I base this argument on Reagans and McEvily's (2003) findings that network cohesion and diversity can work together to promote knowledge transfer. In this section, I review their work and related studies.

Social cohesion and structural holes can benefit social networks (Burt, 1992; Coleman, 1990). A network closure perspective (Coleman) suggests that network closure, which is defined by the presence of cohesive strong ties, benefits social networks. Arguably, cohesion is an indicator of continuity. Similarly, the lack of cohesion indicates the existence of organizational discontinuities. Group cohesion is associated with strong ties (Wasserman & Faust, 1994). However, a structural holes perspective (Burt) holds that network benefits can be realized through access to nonredundant information ties.

Network closure is defined as the degree to which people in relationships are connected by “mutual third parties” (Coleman, 1988; 1990). The network closure perspective highlights people’s relationships in terms of multiple third-party relationships rather than purely dyadic relationships. According to Coleman, the more closely tied people are in a network, the more they will be required to honor obligations and social norms, which ultimately increases mutual trust. Coleman has emphasized the emergence of normative environments where people are, voluntarily or involuntarily, expected to show some level of commitment to one another. Contrastingly, diversity reflects the extent to which individuals have access to diverse information resources (Burt, 1992). The benefits of diversity are facilitated not only by weak ties (Granovetter, 1973) but also by structural holes (Burt). Diverse and nonredundant communication ties promote a sense of which other members have specialized knowledge and expertise. According to Burt, the benefits of social networks may result from increased access to diverse sources of information via brokers, who span otherwise disconnected network clusters and thus have more information and resources at their disposal.

A cohesive network provides trust and cooperation among closely-tied people, while a network that includes more structural holes provides access to more diverse sources of information (Podolny & Baron, 1997). Reagans & McEvily (2003) showed that social cohesion, measured by network density, and network diversity, measured by network range, can both facilitate knowledge transfer. Based on the above discussion, this study argues that the development of expertise recognition should be understood in terms of two seemingly conflicting, yet not mutually exclusive, factors: network closure and network diversity. This is because these network effects have a different advantage in fostering expertise recognition. Such a synergistic effect has been examined in the context of knowledge-sharing (Reagans & McEvily). Network diversity and network closure are likely to attenuate the possible negative effects of virtuality on expertise recognition. This study argues that both network diversity and network closure increase the level of continuity in virtual work arrangements, albeit in different ways: network closure can promote cohesion by increasing connections, and network diversity can reduce discontinuities by spanning the boundaries between distinct networks. As discussed previously, virtuality is characterized by multiple discontinuities that are thought to hamper TMS. The existence of boundaries presents virtual team members with challenges such as gaps in their work (Watson-Manheim et al., 2002). However, if individuals do not feel that such boundaries hinder their ability to determine who knows what, then these boundaries may not in themselves be an obstacle for the development of TMS (Chudoba & Watson-Manheim, 2008).

Whereas transactive memory can be an individual cognitive capability, TMS exists and operates *among* individuals (Lewis, 2003). Reflecting this, TMS can be best understood in light of a network. I would argue that TMS can be a perceived network formed and shaped in team members' minds reflecting their perceptions of who knows what and "who knows who knows what" (Monge & Contractor, 2003, p. 198). For example, TMS is very similar to a network that includes possibly many nonredundant contacts/information sources (i.e., structural holes) and more cohesive clusters.

(Individuals who are embedded are more likely to perceive "who knows what" and "who does what" in Figure 2 than in Figure 1.) Although it may sound too prescriptive, expertise recognition can be better developed in a network that includes possibly many structural holes (i.e., more diverse communication ties) and, simultaneously, more cohesive clusters.

INSERT FIGURE 1 AND FIGURE 2 ABOUT HERE

Network diversity. From the emergent communication network perspective, information does not always flow along formal organizational channels (Krackhardt & Hanson, 1993). Communication networks emerge as individuals share information with one another, regardless of whether they are connected according to a formal organizational structure (Monge & Eisenberg, 1987). If, despite being dispersed geographically and connected electronically, virtual collaborators are able to develop and maintain communication ties within and/or across their work unit, they may be able to use informal networks to bridge the discontinuities in virtual work arrangements.

Network diversity, defined as the degree of nonredundant ties among individuals, can bridge the gaps created by various boundaries inherent in virtual work arrangements. Such gaps created by boundaries may be bridged through the emergence of communication networks among virtual team members. Larger numbers of nonredundant communication ties, conceptualized as increased network diversity, increase access to information about what other people are working on and, furthermore, to information about which of these people might possess relevant expertise.

Structural holes theory (Burt, 1992) provides a relevant theoretical framework regarding the benefits of diverse and nonredundant ties: individuals whose network spans structural holes benefit from an increased flow of information. By linking individuals to others' work without being directly connected to their activities, structural holes grant virtual coworkers access to diverse sources of information. Structural holes present opportunities for brokering the flow of information among individuals. Those who broker information between different units have enhanced access to other people's knowledge and expertise. They tend to be promoted sooner than workers with less-diverse ties (Burt). The more an individual's workgroup spans structural holes, the more likely he or she can broker the flow of information within the organization (Burt, 2000). Spanning structural holes has been shown to impact team performance within the context of organizations. For example, it can help teams to more efficiently coordinate information, which can lead to more effective solutions to organizational problems (Powell, Koput, & Smith-Doerr, 1996). Organizational units differ in their "absorptive capacity"—that is, the extent to which they are capable of assimilating and replicating knowledge obtained from external sources (Cohen & Levinthal, 1990; Tsai, 2001). Spanning structural holes can increase absorptive capacity and, by extension, team performance (Burt, 2005). It can also enhance the diversity of views and ideas within an organization (Balkundi, Kilduff, Barsness, & Michael, 2007).

Nonredundant ties allow for increased access to many otherwise-unconnected people and, consequently, to more information (Burt, 1992). In explaining expertise recognition in virtual work arrangements, nonredundancy of communication ties plays a significant role. This is because nonredundant knowledge-sharing communication ties positively influence perceptions of who knows what and who knows who does what. Virtual workers who develop more nonredundant communication ties make the most of diverse resources and expertise within and across workgroups. It can be speculated that individuals who have developed and maintained an expansive communication network are less constrained by the discontinuities inherent to virtuality, compared to those who have more redundant communication ties.

The extent to which an individual can shape and expand his or her communication ties directly increases his or her ability to benefit from distributed expertise across multiple virtual work arrangements. An individual who expands his or her communication ties across multiple units of his or her organizations such as a team tends to develop higher levels of recognition of other workers' expertise and tasks. This is important for organizations because virtual workers are often unaware of one another's working processes (Leinonen, Jarvela, & Hakkinen, 2005). The extent to which a group is aware of its relationships with other groups is a type of TMS that is distinct from task-oriented transactive memory. Increasing nonredundant communication ties is linked to greater awareness of external relationships and, as a result, more accurate understanding of how to take advantage of other people's knowledge (Austin, 2003). A well-developed perception of expertise is associated with higher network diversity. The number of nonredundant ties provides those who operate in virtual work arrangements more chances to forge boundary-spanning ties. Furthermore, when one forges communication ties with those who operate in other units of their organization, he or she may benefit their immediate team as well as their overall organization (Cross & Cummings, 2004). Team members who are connected to the boundary-spanner gain access to other organizational units—not necessarily within their own organization—and thus become aware of others' expertise and experiences without having to toil to span the boundary on their own. By bridging the gaps caused by boundaries, network diversity facilitates virtual team members' perceptions of who knows what and who does what. The above discussion leads to the following hypothesis:

Hypothesis 3: Network diversity is positively related to expertise recognition in virtual work arrangements.

Network diversity may affect the degree to which individuals experience discontinuities in their virtual work arrangements. If virtual workers are able to develop more diverse communication ties, the constraints that are inherent to virtuality can be overcome; individuals can develop a shared understanding of their goals and complete their tasks more efficiently. Once virtual collaborators use expanded communication ties to bridge gaps and span boundaries, they may not perceive objectively existing discontinuities as obstacles.

As discussed previously, virtual work arrangements inhibit close interactions and rapid feedback, making it more difficult to get to know coworkers' expertise. Virtual work arrangements with high levels of compositional change inevitably produce instability, making it hard for individuals to form mutual knowledge and a shared mental model of their work. However, individuals with diverse ties have access to diverse sources of knowledge, which can compensate for the aforementioned difficulties posed by virtual work arrangements. Therefore, for those who are able to develop diverse communication ties with other workers, the discontinuities stemming from geographic dispersion, dynamic structure, and, possibly, electronic dependence and cultural diversity may not be as disadvantageous as they might otherwise have been.

Considering that there have been conflicting theoretical perspectives and research findings regarding the relationships between electronic dependence and expertise recognition and between cultural diversity and expertise recognition, I did not hypothesize any specific moderating effects between network diversity and electronic dependence or between network diversity and cultural diversity. However, the same logic that applies to the moderating effect of network diversity on the associations between expertise recognition and geographic dispersion and between expertise recognition and dynamic structure can be applied to these relationships; it is thus speculated that network diversity would moderate the relationships between expertise recognition and electronic dependence and between expertise recognition and cultural diversity. The above discussion leads to the following hypothesis and research question:

Hypothesis 4: Network diversity moderates the negative effects of (a) geographic dispersion and (b) dynamic structure on expertise recognition.

Research question 3: In virtual work arrangements, does network diversity moderate the relationship between expertise recognition and (a) electronic dependence and (b) cultural diversity?

Network closure. A widely accepted indicator for network closure, social cohesion has been defined not only by the degree to which coworkers develop intense relationships with one another, but also by the degree to which they maintain overlapping ties (Coleman, 1990). Unless individuals share adequate levels of cohesion, they may not share information during their tasks, and thus have difficulty in trusting and relying on one another's expertise.

Cohesion may facilitate interpersonal interactions. The social network literature has argued that densely intertwined clusters promote trust and reciprocity among people and are, thus, conducive to a normative environment that in turn allows for higher levels of trust in network relationships (Coleman, 1988). Reciprocal relationships among members represent the degree to which teamwork is solid and stable (Ahuja & Carley, 1999). In networks with higher reciprocity, actors are more likely to get involved in more communication and are more likely to transfer more information throughout the network. Thus, the more reciprocally individuals communicate with each other, the more likely it will be for them to trust one another's expertise. For a virtual work arrangement to be successful, members directly or indirectly embedded in a unit must reach out to each other reciprocally, because they work with interdependent roles and tasks and are mutually responsible for completing a given task.

Network density reflects the extent to which "individuals are connected to one another" (Bélanger & Allport, 2008, p. 108). Network density increases coworkers' awareness of their responsibilities, i.e., role clarity (Meyerson, Weick, & Kramer, 1996). Wellman (1988) has also suggested that network density enhances social support and solidarity. An increase in density, which means an increase in interconnection among team members, may also lead to an increase in the credibility of other members' team performance.

The social network literature has illuminated the role of cohesive subgroups in the formation of networks (Coleman, 1990). Members of a virtual organization may not act as undifferentiated equals but rather as members of the subgroup to which they belong. The formation of cohesive subgroups may mainly be driven by homophily. That is, subgroups often are shaped by group members' demographic attributes (e.g., age, gender, ethnicity, etc.) as well as by other characteristics (e.g., education, tenure, and position in their organization) (Cramton & Hinds, 2005). Regarding social cohesion, subgroups have two conflicting impacts: they weaken cohesion in the overall organization, while strengthening cohesion within a given subgroup. The presence of strong subgroups reduces overall cohesion in the organization because subgroups are essentially fragmentations that develop and exist in the organization. However, while such fragmentation may constrain access to diverse sources of information, subgroup members tend to show higher cohesion via more interconnected ties (Uzzi, 1997). Social cohesion is widely seen as being related to trust (Coleman).

Individuals who are densely clustered are more willing to exchange information because they tend to have a shared identity and high levels of mutual trust (Ahuja, 2000; Coleman, 1988). Although members of cohesive subgroups tend to develop cognitive-based trust, there are different impacts of subgroup strength on information flow. The members of highly cohesive subgroups share a high level of communality, which tends to isolate them from people and information that are external to their subgroup (Lau & Murnighan, 1998). However, moderately cohesive subgroups may facilitate positive learning behaviors (Gibson & Vermeulen, 2003). A medium level of subgroup strength is related to low levels of conflict in the work process and high levels of performance and morale, while low and high levels of subgroup strength have a negative impact on these outcomes (Thatcher et al., 2003). That is, one can see a curvilinear relationship between subgroup strength and performance-related factors. Subgroup strength may indicate a positive impact that social cohesion may have on group performance.

This study also argues that cohesion increases interaction among team members, promoting perceived proximity (Wilson, O'Leary, Metiu, & Jett, 2008), which in turn reduces barriers to becoming aware of who knows what and who knows who does what. To better explain how network closure plays a role in virtual work arrangements, in this section I review the implications of perceived proximity. Proximity is one of the fundamental factors that directly influences the formation and development of ties. Proximity facilitates interpersonal interactions and, thus, knowledge sharing (Inkpen & Tsang, 2005), and it positively influences an individual's perception of being affiliated with organizations and communities (Allen, 1977). The closer people are to one another within a network, the easier it is for them to forge ties. For example, Maskell & Malmberg (1999) have examined the relationship between tacit knowledge and spatial proximity: the more tacit knowledge individuals want to share, the closer they must be to one another.

But proximity is a multifaceted concept. It is not enough to ask whether team members are physically proximate. In certain contexts, *perceived* proximity plays a more significant role than *physical* proximity; thus, each type of proximity may be more or less salient in a given situation. In virtual work arrangements, individuals are by definition geographically dispersed. Perceived proximity has emerged as a concept useful in understanding the relationship between discontinuities and continuities. It is becoming more important to know how group members perceive their closeness to other team members (Wilson et al., 2008). A virtual organization's members may perceive one another as being close, regardless of physical distance. What is important is not the actual physical distance that separates them but their perception of relational or social distance.

People's perception of proximity may be influenced by the degree to which they interact with each other.

As reviewed in the previous section, individuals in virtual work arrangements are physically dispersed across different worksites. Physical distance may weaken individuals' identification with their team and result in greater levels of conflict (O'Leary & Mortensen, 2010). Individuals who communicate with one another less frequently tend to feel more physically distant from one another (Allen, 1977). Contrastingly, however, it is possible to say that more frequent communication between individuals increases their sense of closeness (Cross & Borgatti, 2000). Perceived proximity often results not from physical co-presence but from a high frequency interactions; as a result, team members' perceptions of distance are not perfectly correlated with actual distance (Wilson et al., 2008). For example, two members may be on opposite sides of the world, but they may be able to develop a higher level of perceived proximity if they establish and maintain frequent, consistent, and intense communicative ties. This speculation is consistent with literature suggesting that when people perceive their partners as being proximate, they tend to have more contact with one another and communicate more frequently (Festinger, Schachter, & Back, 1950). The literature on organizational commitment explores the implications of "cognitive distance", which has been defined as "the degree of cognitive immediacy and salience that the employee associates with an organizational unit" (Mueller & Lawler, 1999, p. 327). An increase in communicative interactions will increase "the cognitive salience of the other" and the degree of "envisioning the other's context," while decreasing "uncertainty regarding the other" (Wilson et al., 2008, p. 985).

It is speculated that higher levels of network closure may increase perceived proximity, which in turn promotes expertise recognition. This leads to the following hypothesis:

Hypothesis 5: Network closure is positively related to expertise recognition in virtual work arrangements.

Network closure that brings about an increased level of cohesion may affect the degree to which individuals experience the geographic, cultural, and structural discontinuities posed by virtuality. As discussed previously, virtuality is associated with gaps and a lack of coherence in individuals' tasks. Although these discontinuities can make it difficult to know others' expertise, network closure may moderate such difficulties by promoting perceived proximity and a sense of cohesion among individuals. For example, it is important to see that physical distance itself may not always be detrimental to virtual work arrangements because increased communicative interactions may cause team members to perceive one another as being close, thus offsetting many of the negative outcomes associated with virtuality. This logic is consistent with a previous study (Wilson et al., 2008), in which coworkers' perceived proximity was affected by the degree to which they interacted with one another via CMC or FtF. As such, those who work in virtual work arrangements may feel little, if any, difficulty interacting with other members if they maintain adequate levels of communication, regardless of their physical distance from one another.

Cohesive communicative and knowledge-sharing ties can amplify perceived proximity within a virtual work arrangement, which may in turn moderate the negative effects of geographic dispersion and compositional instability on expertise recognition. By the same logic that applies to the moderating effect of network closure on the relationships between expertise recognition and geographic dispersion and between expertise recognition and dynamic structure, it is speculated that network closure also may moderate the relationships between expertise recognition and electronic dependence and between expertise recognition and cultural diversity. The above discussion leads to the following hypothesis and research question:

Hypothesis 6: Network closure moderates the negative effects of (a) geographic dispersion and (b) dynamic structure on expertise recognition.

Research question 4: In virtual work arrangements, does network closure moderate the relationship between expertise recognition and (a) electronic dependence and (b) cultural diversity?

INSERT FIGURE 3 ABOUT HERE

Expertise Recognition and Multiple Ties

The previous sections investigated how the major elements of virtuality affect expertise recognition, and how those relationships can change when taking into account the network features of a communication network. That was an effort to understand TMS in relation to virtuality. At the same time, I discussed the importance of communication ties in developing TMS. In this section, the focus now is on the relationships that the main component of TMS, expertise recognition, has with the other two components of TMS (information retrieval/knowledge seeking in this study and information allocation). This effort is expected to broaden our understanding of how a communication network emerges and of how expertise recognition causes multiple knowledge-sharing communication ties to form. Communication-network ties, which are captured in network configurations (e.g., reciprocity, in-stars, or out-stars), reflect interactions among team members. This section, which examines the ways in which specific patterns of interaction emerge across individuals connected by multiple ties, is based on the notion that specific network configurations result from patterns of interaction that occur among geographically-dispersed individuals.

Although there are many reasons why it might be important to understand emergent communication networks in organizational settings, little research has examined exactly how communication networks are *emergent*. The meaning or implication of being emergent has largely been discussed in terms of a discrepancy between a formal organizational structure prescribed by management and an informal network structure (Aldrich, 1976; Aldrich, 1982; Heald, Contractor, Koehly, & Wasserman, 1998); that is, the formal structure visualized as a chart may be inconsistent with the actual way that people communicate with one another. However, this conventional perspective on the emergence of communication networks may not fully explain the fact that an entire communication network is a function of each specific network configuration that reflects the patterns of communicative interaction. Further, this perspective cannot explain the mechanism by which these network configurations form. Contractor, Wasserman, and Faust (2006) have argued that it is necessary to understand "the emergence of organizational networks" through "modeling the dynamics through which flexible organizational forms emerge" (p. 682). By investigating the mechanism of network configurations, this study examines the relationships among the main elements of TMS.

Within virtual work arrangements, individuals' perceptions of where expertise is located shape their knowledge-sharing communication networks. People's specific patterns of interaction, such as who they interact with, produce specific network configurations (e.g., choice, reciprocity, cyclicity, transitivity, and/or in-degree popularity) (Palazzolo, 2005). In organizational settings, such patterns of interaction are guided by one's perception of who knows what and who does what. Several studies have investigated the effects of network configurations on TMS (Palazzolo; Palazzolo et al., 2006). The present study focuses on how individuals' perceptions of others' expertise—which will be examined *across* different types of relationships—guides their patterns of interaction. Perceptions of one another's expertise are intertwined with other ties that may be forged during a task (e.g., advice-seeking and knowledge-sharing ties). These ultimately contribute to the creation of an overall network.

Though it has been some time since Wegner (1995) described three processes that characterize TMS (directory updating, information allocation, and retrieval coordination), we have learned relatively little about how these processes are interrelated. Wegner (1987) stated that a TMS begins to develop as people have knowledge of one another's expertise. Expertise recognition is thought of as a guide that directs group members to others who have the information and expertise that they need. Further, it helps them to evaluate the usefulness of that information by knowing its source (Moreland, 1999). Su and Contractor (2011) showed that in an organizational contexts individuals tended to seek information from a digital repository (their company's intranet) that they believed to be relevant and accessible. Further, they found that the consulting company's workers were more likely to seek information from their company's intranet if others with whom they communicated via telephone, email, or in person also sought information from that digital knowledge source.

Although the TMS literature implicitly assumes that directory updating, information allocation, and information retrieval are all related to one another through the mediation of communication, it is not clear what those specific relationships are. An explanation for the relationships among the three processes of TMS can be found in a study claiming that communication acts as an opportunity for information allocation and retrieval (Hollingshead & Brandon, 2003). Communication helps individuals to get a sense of the context in which information allocation and retrieval takes place. As discussed previously, directory updating is the process by which one keeps his/her knowledge of who knows what up to date. Retrieval coordination refers to the process by which individuals use their directory of others' expertise to contact those people who possess relevant knowledge (Wegner, 1987; 1995). The terms, transactional retrieval (Hollingshead & Brandon) and information retrieval (Monge & Contractor, 2003) have been derived from retrieval coordination. Since retrieval coordination subsequently leads to effective retrieval of the information or knowledge that people need to use, this study focuses on knowledge seeking that occurs as a result of retrieval coordination. Lastly, information allocation refers to the process by which people transfer information or knowledge to others who would likely find that information or knowledge to be relevant (Wegner). Information allocation can occur when a person comes across information or knowledge that others would be better able to use or store. Palazzolo's (2005) study demonstrated that people tend to seek information from people whom they recognize as having relevant expertise. Such perceptions play a key role in information retrieval.

In relation to the role of expertise recognition, this study emphasizes that an individual's perception of other people's expertise may play a role that is equivalent to that of latent ties. As defined by Haythornthwaite (2002), a latent tie is “a tie for which a connection is available technically but that has not yet been activated by social interaction” (p. 389). Haythornthwaite argued that latent ties are not necessarily established by individuals, but might be established by organizations. For example, an organization might send an email to several people who do not know one another, or it might maintain a digital directory of people who are not currently involved in any activities in their organization, but who are on the organization’s radar. Although Haythornthwaite viewed the formation of latent ties as the result of organizational structure (e.g., individuals are enrolled in an organization’s email system), it is also possible that individuals might themselves form latent ties. This is what Wegner called directory updating. That is, individuals can develop an awareness of who knows what and who does what and update these perceptions as they learn new information about these people and as members enter and leave the organization (Wegner, 1995). Their awareness of who knows what and who does what may then be activated to become an actual tie. When seeking advice, it is unlikely that team members contact other people at random. It is more likely that they will contact team members who they perceive as having relevant expertise. Based on the above discussion, I argue that expertise recognition *precedes* retrieval coordination (in this study, knowledge seeking) and information allocation (or, in Hollingshead and Brandon’s term, “encoding”). The above discussion leads to the following hypotheses:

Hypothesis 7. Expertise recognition leads to knowledge seeking.

INSERT FIGURE 4 ABOUT HERE

Hypothesis 8. Expertise recognition leads to information allocation.

INSERT FIGURE 5 ABOUT HERE

Transitivity. Supported by balance theory (Heider, 1958), transitivity is an important network mechanism, explaining how actors form triadic relationships: e.g., my friend's friend could become my friend. The concept of transitivity has its origins in cognitive theory, which explains how people perceive other people's relationships: e.g., if person *i* knows that person *j* is acquainted with person *l* and that person *l* is acquainted with person *k*, then *i* might expect that *j* and *k* will become acquainted with one another (Heider). Ties formed and developed among three parties may generate favorable outcomes such as friendships, information-sharing, and project collaboration (Louch, 2000). The relationship between transitivity and trust is even observed in social contexts with low generalized trust (Batjargal, 2007). Batjargal has suggested that transitivity facilitates interpersonal trust that is formed in investment decisions of venture capitalists in transitional economies (e.g., China and Russia).

Extending this cognitive balance mechanism to general social relationships, the literature has shown that people have a tendency to maintain balanced relationships (Freeman, 1992). Cognitive balance is an underlying cause of transitive triadic relationships (Monge & Contractor, 2003). People tend to be cognitively balanced in perceiving others' relationships (Kilduff & Tsai, 2003). In explaining the difference between a contagion network perspective and a cognitive consistency perspective, Monge and Contractor emphasize that the attributes of actors are influenced not by the attributes of others but by the network configuration of transitive triads.

The tendency to prefer cognitively balanced attitudes towards making relationships may also pertain to organizational information-sharing. People retrieve information from a third party when their contact person retrieves information from the third party (Palazzolo, 2005). They prefer balance when one person has relevant expertise or knowledge that other people possess. A classic example of transitivity shows that person *i* may feel uncomfortable when person *j*—with whom he or she is acquainted—has a friendship with person *k*, with whom he or she has yet to be acquainted. Applying this logic to an organizational setting, it is argued that *i* may experience unease when he or she does not have a knowledge-sharing communication tie with *k*, but *j* does. Because of this unease, *i* may forge a tie with *k* to balance the flow of information.

It is noteworthy to see that the conventional understanding of transitivity is predicated on a single type of tie among actors. For example, if *i* has a knowledge-sharing tie with *j*, and if *j* has a knowledge-sharing tie with *k*, then *i* would likely come to forge a knowledge-sharing tie with *k*. In other words, new ties that are created transitively are assumed to be of the same type as previous ties (in this case, ties for knowledge-sharing). Given that individuals are embedded in organizations and develop multiple ties, the following question captures what a single-tie network analysis lacks: does one type of a tie lead to the formation of ties of other types?

Multiplex transitivity. It is worth noting that conventional balance theories explain the formation of transitive ties by focusing on the tendency to maintain cognitive consistency (Heider, 1958). However, Feld (1981) has argued that the conventional understanding of transitivity does not adequately explain why people with common interests (or foci) tend to form ties with one another, which in turn causes other ties to be formed. Feld explained that the formation of transitive ties depends on the extent and types of pre-existing foci that define the relationships. *Foci* have been defined as “any social, psychological, or physical entity around which joint activities of individuals are organized" (Feld, p. 1025). Foci may include people, places, social positions, social and personal activities, and groups. If people are focused on common activities, then they will tend to have similar interactions and sentiments that occur around foci where they form and in which they engage. Although one might be tempted to define foci in terms of physical entities such as workplaces, foci are not limited to physical locations. Rather, foci include anything that might link individuals, such as common interests. For example, in the context of virtual work arrangements, if an individual perceives that another person has expertise and knowledge that is useful for completing his or her task, he or she may forge a tie with that person defined by their focus on completing that particular task. Then, once these individuals are connected, they may be more likely to form other ties, such as advice-seeking or collaborative ties.

According to Feld's perspective on transitivity, an individual who perceives another person as having a common interest will tend to forge a tie based on that interest, paving the way for other ties between them. This idea is closely related to the concept of multiplexity, which refers to the degree to which individuals who interact in one focused context also interact in another context (Monge & Eisenberg, 1987). By measuring the number of relationships that two people share, multiplexity captures the multifaceted nature of their exchange relationship (Ibarra, 1993; Marsden). Individuals' patterns of interaction may not be limited to only one type of tie; rather, they may occur across discrete types of relations (Lee & Monge, 2011). This is congruent with the fact that in organizational settings, ties that are relevant to one another—such as creative-interaction, advice-seeking, friendship, and knowledge-sharing ties—often evolve in tandem (Robins

& Pattison, 2006; Lee & Lee, 2012). For example, Lee and Lee have shown that if *i* has a creative-interaction-seeking tie (measured by generating new ideas) with *j*, then *i* is likely to seek advice from *k* with whom *j* has an advice-seeking tie. Given such a tendency, and further extending the logic of multiplexity to transitivity, it is plausible to speculate that individuals are more likely to form a transitive relationship that includes multiple types of ties rather than just a single type of tie. It also is reasoned that if someone perceives another person as having relevant expertise, this may be a precursor to joint attention between these people (in Feld's perspective). That is, based on the individual's awareness of the other person's expertise, he or she may forge a collaborative tie with them. Then, once a collaborative relationship is formed, the individual may learn more about the other person's expertise, which may cause additional ties to form in the future. This leads to my speculation that if one's network will likely entail multiple ties, then an individual will be more likely to form a bivariate transitive relationship between discrete ties (e.g., expertise-recognition and knowledge-seeking in this study) *via* multiple individuals rather than one individual.

I also argue that the formation of the bivariate transitive relationships between expertise recognition and knowledge seeking and between expertise recognition and information allocation would be more likely to occur *via* an individual's perceptions of the expertise of multiple individuals. That is, a bivariate transitive relationship is likely to form between expertise recognition and knowledge seeking ties *via* multiple individuals rather than one individual. In other words, if person *i* has an accurate perception of the expertise of persons *k*, *l*, and *m* who are already aware of person *j*'s expertise, then *i* would likely develop a knowledge-seeking tie with *j*, even if *i* initially does not retrieve information from *j*. Likewise, if *i* has an accurate perception of the expertise of *k*, *l*, and *m* who are aware of *j*'s expertise, then *i* would be likely to develop an information-allocation tie with *j*, even if *i* initially does not currently forward information to *j*. In sum, expertise recognition is predicted to foster other types of knowledge-sharing ties (e.g., information allocation and knowledge seeking as a result of retrieval coordination/information retrieval). The aforementioned discussion leads to the following hypotheses:

Hypothesis 9. There is an alternating transitive relationship between expertise recognition and knowledge-seeking ties: if individuals k, l, and m perceive person j's expertise accurately, and if person i has an accurate perception of the expertise of direct contacts k, l, and m, this will lead to the formation of a knowledge-seeking tie between i and j.

INSERT FIGURE 6 ABOUT HERE

Hypothesis 10. There is an alternating transitive relationship between expertise recognition and information-allocation ties: if individuals k, l, and m perceive person j's expertise accurately, and if person i has an accurate perception of the expertise of direct contacts k, l, and m, this will lead to the formation of an information-allocation tie between i and j.

INSERT FIGURE 7 ABOUT HERE

Chapter 4. Methods

This study's research design was primarily shaped by a variable analytic approach. Its main purpose was to examine a series of hypotheses and research questions that were formulated to test the relationships between virtuality and expertise recognition, between expertise recognition and knowledge seeking, and between expertise recognition and information allocation. To investigate these relationships, the first step was to measure the above concepts based on data obtained through a structured survey questionnaire. This survey consisted of two parts: one part measured virtuality, while the other part measured knowledge-seeking and information-allocation networks. The main aspects of virtuality were measured on a five point scale, and the two network properties (network diversity and network closure) were calculated from data obtained through name-generating network questions. As a next step, this study used established statistical methods—hierarchical multiple regression and bivariate exponential random graph modeling (ERGM)—to examine the relationships among the variables and concepts. What follows is a detailed description of the research site, the sample, procedures, and measures.

Research Site

The data used for this study were collected through a survey of employees in a U.S.-based company called "BizTech" (a pseudonym). A member of the S&P 500, BizTech develops computer hardware and computer software, and it provides IT services and IT consulting across the world. Its business ranges from IT solutions (IT integrated systems, service oriented architecture, smarter computing, business analytics, business strategy, e-Commerce consulting, cloud computing, data management, and data warehousing) to products (business analytic tools, collaboration, websphere, IT systems, and storage). According to its 2012 year-end financial report, BizTech earned over $100 billion in revenue, with roughly $15 billion in net income, and it possesses nearly $125 billion in total assets. The company employs hundreds of thousands of people. As a global company, BizTech was a reasonable site for studying virtuality.

The focus of this study was on BizTech's inside sale representatives. Instead of conventional sales, which are made face-to-face, inside sales representatives mostly use telephones and web-based communication (Krogue, 2013). Inside sales representatives use a personalized website to sell BizTech's brands and services and to interact, via video or text chat, with their colleagues and with prospective clients. BizTech's inside sale representatives represent BizTech's offering and provide clients with solutions that incorporate BizTech's hardware and software, such as servers, networking devices, and options for offsite data storage (e.g., in the "cloud"). They work on generating and developing leads (i.e., sparking prospective customers' interest in BizTech and/or encouraging existing customers to make additional inquiries into products or services) or client relations. Inside sales representatives who participated in this study can largely be categorized into two groups: brand-focused representatives (type A) and client-focused representatives (type B). The former (type A) identify and manage new business opportunities through outbound marketing campaigns and inbound web and telephone inquiries; they promote sales by catching prospective customers' interest, and/or they encourage past customers to purchase more products or services. The latter (type B) help clients to understand how BizTech's offerings could meet the needs of their organization (e.g., identity management, data protection, and the maintenance of their information infrastructure).

Like employees in most organizations, inside sales representatives in BizTech work in teams. For example, according to organizational charts, BizTech Latin America had 18 managers who each supervised an average of 10 individuals (*SD* = 7.31). When it comes to interaction, which is closely related to TMS, these immediate teams might not be the most meaningful unit of interaction. Rather, extended teams explained most of the variation in BizTech representatives' interactions. For client-focused representatives, for example, routine tasks such as marketing software did not involve heavy interaction with their immediate team. However, client-focused representatives often teamed up with specialists, including brand-focused representatives to handle complicated tasks, such as providing consulting to a specific business about an optimal IT system, resulting in multiple inside sales representatives' involvement. Since inside sales representatives' job entails helping client businesses to better understand how BizTech could provide solutions to their diverse challenges and needs, sales representatives with different areas of expertise routinely coordinated their efforts. And the necessity for teaming up was not limited to client representatives. For example, brand-focused representatives (say, software brand specialists) also teamed up with other BizTech sales representatives, partners, and consultants and marketing specialists to meet their clients' needs. In sum, the degree to which inside sales representatives' interactions center on their immediate team or extended team may vary on a task-by-task basis. When working as part of an extended team, knowing the expertise of other inside sales representatives is particularly important, so they will interact with one another to a greater extent. Note that the present study used individuals' relations within and/or across teams as the unit of analysis. Though it used teams (both immediate and extended) as the context for capturing interactions among individuals in a knowledge network, this study mainly has implications for individuals' relations within and/or across teams.

Given BizTech's interest in optimizing individual inside sales representatives' job performance, it routinely encourages them to take advantage of communication technologies. Not only does it promote the use of publicly available electronic communication tools (like LinkedIn, Twitter, and Skype); it also encourages them to use proprietary tools. To this end, the company designed a program called *Digital Matters* (a pseudonym) to single out high-performance employees who use electronic communication tools. By highlighting these success stories, BizTech hopes to encourage other employees to boost their own performance by adopting the same tools and using them effectively.

Sample

Participants came from the three regional centers of BizTech: Australia and New Zealand (abbreviated ANZ), Colombia and Argentina (Latin America), and France and Ireland (France). As of the time the survey was conducted, the number of inside sales representatives was as follows: ANZ (n = 132), Latin America (n = 180), and France (n = 120). Those who asked for their names to be removed or who did not hold the position of inside sales representatives were removed from the list of the survey respondents. This led to the following potential numbers of survey participants: ANZ (n = 114), Latin America (n = 177), and France (n = 116). In the end, the response rate was 52% for ANZ (n = 59), 75% for Latin America (n = 132), and 41% for France (n = 47).

With respect to demographics, it should be noted that, due to BizTech's concerns about the privacy of its employees, respondents' information was collected on a categorical basis. Further, respondents could freely opt out of answering demographic questions. Regarding gender, the ANZ sample contained an equal number of males and females; the Latin American sample was 56.6% male and 43.4% female; and the French sample was 57.9% male and 42.1% female. Regarding age, the distribution of ANZ respondents was as follows: 18–24 (16.7%), 25–35 (31.3%), 36–46 (35.4%), 47–57 (16.7%), and 58 or older (0%). For Latin America, the age distribution was as follows: 18–24 (11.7%), 25–35 (69.4%), and 36–46 (18.9%), and 47 or older (0%). For France, the age distribution was as follows: 18–24 (5.3%), 25–35 (36.8%), 36–46 (36.8%), and 47–57 (21.1%), and 58 or older (0%). The Latin American respondents were the youngest while the French respondents were the oldest.

Regarding highest level of education, ANZ respondents were broken down as follows: high school degree (6.1%), some college (8.2%), associate's degree (4.1%), bachelor's degree (61.2%), master's degree (18.4%), and PhD, MD, or other advanced degree (2.0%). For Latin America: high school degree (0.9%), some college (3.6%), associate's degree (42.0%), bachelor's degree (26.8%), master's degree (25.9%), and PhD, MD, or other advanced degree (0.9%). For France: high school degree (2.7%), some college (8.1%), associate's degree (10.0%), bachelor's degree (24.3%), master's degree (45.9%), and PhD, MD, or other advanced degree (2.7%). The French respondents were most highly educated while Latin American and ANZ respondents showed similar education levels in terms of advanced degrees.

Procedures

The data for this study were collected in tandem with one of BizTech's internal research projects. As discussed, BizTech was very interested in assessing the effect of its program, Digital Matters, on the way that its inside sales representatives use electronic communication tools to interact with their clients and coworkers. One of my dissertation committee members helped me to set up a meeting in mid-January 2013 with researchers at BizTech. Following that meeting, my survey questionnaire was revised multiple times with input from BizTech's researchers; these interactions greatly improved the clarity of its content and wording and helped to accommodate the specific situation of the research site. For example, to take into account the fact that BizTech's inside sales representatives interact with people on extended teams rather than their immediate team, some of the survey wording was revised as follows: "Please think about the BizTechers you work with on your extended team. Rate how strongly you agree with each of the following statements."

Compared with collecting data from one region, using multiple regions better represents the organization, which is globally distributed. Further, I anticipated that using multiple regions would produce more variability in terms of virtuality. Although inside sales representatives rarely interact across these regions, using multiple regional centers provides more variance in terms of geographic dispersion, electronic dependence, cultural diversity, and dynamic structure.

To adequately perform network analysis, this study needed to obtain a bounded network from each regional center. A problem associated with the name-generating method is that it often produces open-ended networks; for example, an ego might list an individual for a given network question who does not belong to the organization. Such open-ended networks would not represent any meaningful interactions among the organization's members. Using region-based data helped ensure that respondents' networks were bounded by their regional centers. Given that the present study used a name-generating network measure, this means that an inside sales representative operating at, say, Latin America would presumably list his or her fellow inside sales representatives who also work at Latin America. To ensure that the network would be bounded—meaning that the network would include only BizTech employees—the network question required respondents to limit their responses to BizTech employees.

Inside sales representatives from the three regional centers were invited to participate in the survey. To accommodate Spanish- and French-speaking participants, the survey questionnaire was translated into Spanish and French by a native Spanish speaker and two native French speakers. Another native French speaker checked the French version for accuracy. These translators also helped translate the invitation emails. All of them were doctoral students at a U.S. university and were thus familiar with academic research.

The survey was administered over six weeks, from March 8 through April 15, 2013 at an online survey site, Qualtrics.com. Given the Internet-intensive nature of inside sales representatives' jobs, they were expected to be comfortable with taking online surveys. Based on the list of active inside sales representatives in the three regions provided by BizTech Inside Sales, the first round of invitation emails was sent during the first week of March 2013, and four reminder emails were sent out through mid-April. These emails were sent using the message-sending function of Qualtrics. Those who expressed their unwillingness to receive these emails were all removed from the contact list saved at Qualtrics.

Measures

Expertise recognition. The list of expertise was collected from research participants' LinkedIn pages. In a previous study, participants' expertise was assessed by interviewing supervisors (Austin, 2003). Despite the advantages of third-person evaluations, there are two issues with using interview-induced expertise. First, there is no guarantee that the supervisors selected for an interview are good judges of their subordinates' expertise. Second, even if they manage to accurately report the expertise of their subordinates, there is the question of how well this represents the expertise of the entire organization. Instead, to develop the list of expertise used in the survey questionnaire, the list of expertise was obtained directly from information about skills or knowledge that BizTech's inside sale representatives had themselves listed on LinkedIn. There were merits to exploring the expertise that inside sales representatives listed on social networking sites. In a sense, conducting an additional survey would be redundant, since potential survey respondents have already made their expertise public. Also, given that their supervisors, colleagues, and clients may have access to their LinkedIn page, it is assumed that there is little, if any, incentive to manipulate their expertise. Further, using information regarding expertise on LinkedIn allowed the researcher to collect specific types of expertise rather than the broader domains of expertise that have been used in most research.

The researcher looked up all publicly accessible expertise-related information on BizTech's inside sales representatives' LinkedIn pages and used this to generate overall categories of expertise that might be relevant to inside sales representatives. These categories were used to create a master list of expertise domains. At the time of data collection, the number of inside sale representatives who had a LinkedIn account was 35 for ANZ, 28 for Latin America, and 15 for France. Note that not all representatives are included on BizTech's official websites, so the number of those with LinkedIn pages did not match the number of representatives that was confirmed by the list provided by BizTech. Further, the actual survey participants may or may not have publicized their information on LinkedIn. Given that this study's respondents were also performing the same/similar jobs as inside sales persons, it is assumed that the list of expertise generated from publicly accessible information on LinkedIn reasonably represented the actual respondents' expertise.

To narrow down each BizTech inside sales representative's areas of expertise, the researcher only included those areas of expertise that the rep's LinkedIn visitors had endorsed. Among the areas of endorsed expertise (see Table 1 for the entire list), the top 20 areas which were endorsed more than three times overall by LinkedIn visitors were selected: account management; business analysis/business development; channel/channel partners; collaboration solutions; client financing, client relationship management; cloud computing; customer service; data analysis/data center; disaster recovery; demand generation; lead generation/lead development/lead management; network security; new business development; online commerce; project management; sales/sales management; solution selling; storage/storage solutions; and virtualization. Finally, BizTech's research team added three more areas of expertise: marketing, digital technology, and digital selling. From this list of 23 areas, respondents were asked to select their areas of expertise and to identify the main area of expertise for each of the individuals they had contacted for knowledge seeking and information allocation.

INSERT TABLE 1 ABOUT HERE

Expertise recognition was measured in terms of whether a research participant accurately perceived the expertise of the BizTech colleagues he or she contacted for knowledge seeking and information allocation. Note that respondents' expertise can be known only if they participated in the survey and someone else who had participated in the survey had listed them as a contact for knowledge seeking and information allocation. The researcher matched an individual's perceptions of another person's expertise with that person's self-reported area(s) of expertise (Su, 2012). For example, if *j* reported his/her expertise as "client financing" and *i* associated *j* with the same area of expertise, then *i* was assigned a 1, otherwise 0.

Previous studies have measured expertise recognition by asking respondents to rate others' expertise on a numerical scale and have then determined the accuracy of expertise recognition by comparing those subjective assessments with self-reported expertise (Austin, 2003; Su, 2012). But in this study, respondents directly selected their contacts' expertise from a dropdown menu of the 23 pre-sorted domains of expertise. This method aimed to gauge whether respondents accurately recognized others' expertise as classified by a series of specific domains existing in the company. This is a more straightforward and accurate way to determine expertise recognition, because perceptions may be subject to bias. Further, it is well-suited to network analysis, which requires constructing ties that are binary (1 for accurate recognition, 0 otherwise). People are naturally subjective, so it is important to understand bias in expertise recognition.

Because knowing others' expertise tends to be determined by the degree to which one interacts with the person whom he or she perceives to be an expert, expertise recognition is indeed an outcome of one's subjective perceptions. Of course, the longer and deeper the interaction, the more objectively accurate one's perception will be. The aforementioned way of measuring expertise recognition was intended to minimize bias stemming from subjectivity.

In testing hypotheses 1, 2, 3, 4, 5, and 6 and addressing research questions 1, 2, 3, and 4, the measure of expertise recognition for each participant was calculated by dividing the number of experts that he or she correctly identified by the total number of experts that he or she attempted to identify (e.g., if someone associated 12 people with particular areas of expertise but only 6 of them were actually experts in those areas, he or she was assigned .5). The average score was .14 (*SD* = .15). Since individuals who listed more experts tended to record higher scores of expertise recognition, the measure was normalized by dividing by the total number of experts each respondent attempted to identify. In testing hypotheses 7 and 8, an adjacency matrix was created to represent individuals' identification of others' expertise. To use the bivariate ERGM, the measure of expertise recognition needed to be arrayed in an adjacency matrix that included each individual's accurate identification of others' expertise in a dyadic fashion.

In using a self-reported measure of expertise as a reference point in measuring accuracy of expertise recognition, it was assumed that self-reports of expertise accurately represent one's true expertise. Self-reported measures of expertise have been shown to be reliable (Littlepage & Silbiger, 1992). When respondents assess their own expertise or knowledge in their natural work environment, compared to a performance-measuring experiment, self-reported measures of expertise more accurately reflect their true expertise (Sue, 2012). Furthermore, self-reported measures of expertise are less biased and less prone to exaggeration when individuals do not feel pressured in their ordinary work environment (Austin, 2003). Unlike a previous study (Austin), this research was conducted in a naturally occurring situation. Therefore, it is unlikely that the survey caused respondents to fake or exaggerate their expertise.

Virtuality measures. The elements of virtuality (geographic dispersion, electronic dependence, cultural diversity, and dynamic structure) were measured by five items on a five-point scale, with values ranging from strongly agree to strongly disagree. These items were slightly modified from those used by Gibson and Gibbs (2006) and Chudoba et al. (2005). *Geographic dispersion* was measured by agreement with statements like "my colleagues are in different geographic locations" (M = 4.17, SD = 0.71, Cronbach's α = 0.64). *Electronic dependence* was measured by agreement with statements like "I rely on electronic communication tools to communicate with my colleagues on a daily basis" (M = 4.27, SD = 0.61, Cronbach's α = 0.80). *Cultural diversity* was measured by agreement with statements like "I work with colleagues whose cultural backgrounds differ from my own" (M = 3.65, SD = 0.86, Cronbach's α = 0.59). *Dynamic structure* was measured by agreement with statements like "there is high turnover among the colleagues I work with" (M = 3.09, SD = 0.99, Cronbach's α = 0.94).

Network measures. This study used a name-generated network. Two network questions, which asked survey respondents to list the names of coworkers, were designed to measure the two main elements of TMS: knowledge seeking and information allocation. The knowledge-seeking communication networks question came from

Reagans & McEvily (2003) but was modified to reflect the research site's situation. Based on theories of information allocation (Monge & Contractor, 2003), the researcher created the question for information allocation.

Knowledge-seeking communication networks. Guided by their knowledge of others' expertise (i.e., their "directory" of expertise), individuals can allocate relevant knowledge to others (transactive encoding) or receive it from them (transactive retrieval) (Hollingshead & Brandon, 2003). In Wegner's terms, transactive retrieval/information retrieval is conceptually equivalent to "retrieval coordination"—a process by which individuals are aware of the specific knowledge that is necessary for their tasks and, using their directory of others' expertise, contact those who possess that knowledge (Wegner, 1987; 1995). A key aspect of retrieval coordination is that humans do not have the capacity to possess all necessary knowledge on their own, so they form TMS to be aware of the information that others possess and use that awareness to seek relevant information (Hollingshead & Brandon). Focusing on the extent to which individuals seek knowledge from their colleagues, the current study used the following name-generating network question to measure knowledge-seeking communication networks within BizTech: "Think about the BizTech colleagues who have acted as a critical source of knowledge for your work during the past six months. These are the people you reached out to when you needed help with your job, whether you work directly with them or not."

Information-allocation communication networks. Information allocation refers to a process by which individuals, based on their directory of expertise, transfer information to others who might find it relevant (Wegner, 1995). Palazzolo (2005) has explained that the underlying reason why humans allocate information to others, rather than storing it all themselves, is that they can reserve more of their cognitive capacity for information that they feel is most relevant to their own activities. According to TMS theories, once an individual transfers his or her information to someone who is deemed better qualified to handle that information, he or she is no longer responsible for storing that information and can preserve his or her cognitive capacity for other tasks (Wegner, 1987). A key aspect of information allocation is that individuals forward information to others who they think might find it more relevant or who are better able to process it, regardless of whether the other person specifically requested the information. Emphasizing the importance of forwarding unsolicited knowledge to others as the most significant aspect of information allocation, the present study used the following name-generating network question to measure information-allocation communication networks within BizTech: “Think about the BizTech colleagues with whom you have shared unsolicited knowledge (e.g., advice or information that you thought they would find helpful in their jobs) during the past six months, whether you work directly with them or not.” In measuring knowledge-seeking and information-allocation communication networks, “knowledge” was used as a general term to refer to any information-sharing related to the creation, furthering, or closing of business opportunities.

It should be noted that, unlike a complete network, networks created by using a name-generating questionnaire typically do not capture all of the possible connections among individuals. For example, someone might list five people whom he or she has contacted for knowledge, but it cannot be known whether these five people know one another unless these people are surveyed and list one another. The name-generating technique could thus lead researchers to underestimate the number of ties among contacts. Two things were done to attenuate these limitations.

First, to overcome this limitation of egocentric networks, a bounded network was obtained. A bounded network can be created by ensuring that survey respondents consider and list individuals who come from the same pool to which survey respondents belong (e.g., same kinship unit, organization, or community). One premise here is that if survey respondents list contacts who come from the same pool, then contacts may be listed more than one time. Because organizational members tend to develop ties with those who have relevant information and skills, it is reasonable to expect that several of BizTech's inside sales representatives might be seeking expertise from the same individual. While informal friendship ties tend to be more diverse and expansive, work-based ties may be limited to relatively few individuals. Another premise is that if the survey respondents who are listed as contacts by other survey respondents themselves *actually* list their contact(s), it is more likely that potential ties among contacts could be captured. For example, if inside sales representative *i* lists representatives *j*, *k*, *l*, and *m* as his/her contacts, one cannot know if there is a communication tie between *j* and *k*, unless *j* or *k* lists the other as a contact. But if *j* lists any other of *i*'s contacts (*k*, *l*, and *m*) as his or her contact(s), it is then possible to know how *i*'s contacts are connected. This is a key factor about addressing the aforementioned underestimation issue in an egocentric network's problem. So to maximize the number of inside sales representatives who completed the survey, it was important for *j* to answer the network questions, regardless of whether *j* actually had a tie with *k*. Thus, when using bounded networks, achieving a high response rate matters.

To do so, the survey respondents were asked to list only those people who they had contacted for knowledge seeking and information allocation within the context of a professional relationship; more specifically, the survey questionnaire asked them to list people in their company who had helped them to identify, progress, or close business opportunities during the past six months. Second, unlike conventional egocentric networks, the survey respondents were not limited to listing a specified number of contacts; rather, they were asked to list as many contacts as possible.

According to Kossinets (2006), a network might contain missing data for any of the following three reasons: fixed-choice design, boundary specification, and survey non-response. A fixed-choice design effect occurs when researchers limit the number of contacts that respondents can report (Kossinets). As mentioned previously, this study did not employ a fixed-choice design; rather, it encouraged each survey respondent to list as many of their contacts as possible.

The boundary specification issue arises when a researcher sets a rule regarding who to include in and exclude from a network (Laumann, Marsden, & Prensky, 1983). An improper boundary specification might cause a researcher to miss important ties (Kossinets). Laumann, Marsden, & Prensky (1983) have suggested that there are two strategies for boundary specification: the realist approach and the nominalist approach. According to Laumann et al., the realist approach rests on the assumption that individuals who constitute a network view it as a social fact and are aware of the other individuals who constitute their network. From the realist standpoint, the researcher’s assessment of how confidently actors define their network plays a key role in setting a network boundary (Everton, 2012). According to the nominalist approach, however, networks do not exist as objective social facts, and individuals are not expected to be aware of who the members of their network are. Thus, this approach emphasizes that setting the boundary of a network is related to the researcher's theoretical interest (Wasserman & Faust, 1994) and what they aim to study (Laumann et al.). As a result, a network might end up having arbitrary boundaries.

Wasserman and Faust (1994) have emphasized the importance of the population of the interest in setting the boundary of a network. The present study attempted to make inferences about individuals who work in virtual work arrangements and who actively engage in knowledge sharing. To that end, I focused on the knowledge-sharing communication ties of BizTech inside sales representatives—virtual workers who actively share knowledge with one another. Even though some BizTech representatives might have significant knowledge-sharing communication ties with individuals beyond the context of their inside sales center (possibly even outside of the company), it was speculated that most if not all of their communication ties centered on their fellow inside sales representatives. This was reasonable because knowledge-sharing communication ties are more likely to emerge within a particular organization than across organizations.

Missing data from non-responses (either missing actors or missing ties) are present in most network studies. The possible negative effects of missing data in network analysis have been well-documented (Knoke & Yang, 2008). Despite the obvious problems posed by missing data, Knoke and Yang have reported that there is no effective solution, except to attain the highest possible response rate. Out of the three regions examined in this study, only Latin America showed a relatively high response rate (about 73%), so the other two regions (ANZ and France) were eliminated from analysis.

As mentioned previously, although missing data are believed to negatively impact network analysis, no robust remedy has been developed. Each of the potential solutions—imputing the unconditional mean, reconstruction, preferential attachment, and hot deck imputation—has its advantages and disadvantages (Huisman, 2009). According to Huisman's simulation-based study of directed networks, missing data most affected degree and inverse geodesic measure; interestingly, ignoring missing data performed better than imputation for measures such as reciprocity, transitivity, and assortativity.

For this study, the decision to ignore missing data rested on the finding that ERGMs work with moderate amounts of missing data (Robins, Pattison, & Woolcock, 2004). By artificially creating a network with non-responses and comparing ERGM results from a complete network and a network with non-responses, Robins et al. showed that in case of ERGMs, missing data may not seriously distort the analysis. According to Robins et al., conventional network analysis is prone to missing data because it focuses on *measured* network structures. However, ERGMs "adduce the global structure of a network as the aggregation of local sub-structure" (p. 278). Based on the notion that ERGMs can adequately test local social neighborhoods, despite any gaps stemming from non-responses, the researcher chose to ignore missing data rather than reconstruct it through imputation or discard particular cases.

Network diversity and network closure were obtained from the name-generated networks. First, the name-generated network data were stored in the form of edgelists for knowledge-seeking networks and information-allocation networks. On average, each survey respondent listed 5.20 names (*SD* = 3.47) for knowledge seeking and 3.90 names (*SD* = 2.45) for information allocation. Then, following a recommended routine (Borgatti, Everett, & Freeman, 2002a), name-generated network data were converted into adjacency matrices using a UCINET procedure. To use the bivariate ERGM software XPnet, which only processes square matrices, the network data for knowledge seeking and information networks were converted into square matrices.

To test the interaction effect of network diversity and network closure on the relationship between virtuality and expertise recognition, the knowledge-seeking and information-allocation networks were combined into one network. This was done because a combined network of knowledge seeking and information allocation can fully represent one's knowledge-sharing communication network. To investigate the relationships among expertise recognition, knowledge seeking, and information allocation, the knowledge-seeking and information-allocation networks were not merged; instead, they were used separately in order to reflect the two main elements of TMS, knowledge seeking and information allocation.

Network diversity. Network diversity was operationalized in terms of the degree to which one has nonredundant ties. Redundancy has been understood as the degree to which "one's contacts are connected to each other" (Borgatti, 1997, p. 35). In networks with nonredundant ties, some people are only connected with one another indirectly or not at all (Burt, 1992). Network efficiency was used to measure network diversity. To calculate the efficiency of a network, I started by measuring effective size.

The original concept of i's effective size was proposed by Burt (1992) as follows:

$$\sum_j [1 - \sum_q p_{iq} m_{jq}],\ q \neq i, j$$

where p_{iq} is defined by dividing i's tie with i's contact q by the total number of i's linkages with every other one of his/her contacts, and m_{jq} is defined by dividing j's linkage with his or her contact q by the maximum value of *j*'s ties, $\max(z_{jk} + z_{kj})$. If one treats the network as consisting of 1 (tie) and 0 (no tie), the maximum value of a tie is 1, which makes max $(z_{jk} + z_{kj})$ equal to the interaction of *j* with *k* that has a maximum value of 1. This allows one to focus on degree of redundancy due to overlapping ties rather than redundancy caused by a strong tie.

According to Borgatti (1997), redundancy is understood as the average number of ties that alters forge with one another, excluding their ties to ego. Then, the degree of nonredundancy can be seen as the portion of all ties among alters minus redundancy, which is equivalent to the definition of effective size (and further applying to efficiency). Along this logic, Borgatti defined effective size by excluding the average number of ties that alters form with each other from the total number of alters that exist in one's network, which measures nonredundancy. Guided by Borgatti's definition of effective size, UCINET 6.0 (Borgatti, Everett, & Freeman, 2002a) calculates effective size as $n - \frac{2t}{n}$, where *t* is the average number of ties among the alters in one's network (ties with ego are excluded) and *n* is the number of alters. However, effective size tends to increase as one has more contacts (Burt, 1992). To normalize the effect of the number of contacts in one's network on effective size, effective size was divided by the number of other actors in one's network, which produces the following formula: $\text{efficiency} = 1 - \frac{2t}{n^2}$. Given the above logic of obtaining a measure of nonredundancy, efficiency was used to measure network diversity.

Network closure. Existing studies (e.g., Reagans & McEvily, 2003) have used Burt's measure of social cohesion: $\sum_{q=1}^{N} p_{iq} p_{qj\ q \neq j}$, where p_{iq} is the tie from individual *i* to individual q and p_{qj} is the tie from q to *j*. This measure reflects a triadic density that indicates whether there are strong third-party connections around a focal relationship (Reagans & McEvily). However, it may not reflect the fact that network closure needs to explain the degree to which one is tied to surrounding others. To take this into account, UCINET 6.0 was used to calculate cluster coefficients for each actor. Unlike density or clique, cluster coefficients measure an individual's level of network closure. They are defined as the proportion of the number of alters who are connected to each other to the possible maximum number of pairs of alters (Borgatti, Everett, & Freeman, 2002a). For example, if actor *i* has 5 neighbors, then there are a total of 10 pairs of neighbors because $\binom{5}{2} = \frac{5!}{3!2!} = 10$. And actor *i* would have four neighbors who are connected to each other. Thus the local clustering coefficient for actor *i* would be 4/10 = .40. So actor *i* would not be highly clustered, because just about 40% of all the possible ties among these neighbors would be present. If actor *i* had a local cluster coefficient of .80, this would indicate that he or she was embedded in highly clustered neighborhoods.

Control variables. Perceptions of other people's expertise are by nature subjective, resulting in bias in expertise recognition. As discussed, this study minimized this subjective bias by employing a direct measure of expertise recognition. In addition, this study controlled for individuals' perceptions of their coworkers' expertise by asking four questions (e.g., "I am aware of the skills and expertise that my colleagues have," $M = 4.07$, $SD = 0.62$, Cronbach's $\alpha = 0.68$) using a five-point scale from 1 = strongly disagree to 5 = strongly agree (Kanawattanachai & Yoo, 2007). This study also controlled for how long individuals had worked in their current role, which would presumably be correlated with expertise recognition. Regarding respondents' tenure in their current job roles, ANZ respondents were broken down as follows: 6–12 months

(32.8%), 1–2 years (32.8%), 2–4 years (27.6%), 4–6 years (5.2%), and more than 6 years (1.7%). For Latin America: 6–12 months (44.0%), 1–2 years (32.8%), 2–4 years (20.0%), 4–6 years (2.4%), and more than 6 years (0.8%). For France: 6–12 months (22.4%), 1–2 years (20.4%), 2–4 years (26.5%), 4–6 years (10.2%), and more than 6 years (20.4%). The French respondents had longer tenures in their current job roles than the ANZ and Latin American respondents. Latin American respondents were more likely to have entered into their current roles quite recently.

Data Analysis

Hierarchical multiple regression. The proposed relationships between virtuality and expertise recognition were tested (see Figure 3) using hierarchical multiple regression analysis with a stepwise procedure. Before running regression models, histograms and Q-Q plots were used to examine the normality and linearity of virtuality, network diversity, and network closure. Only network closure looked positively skewed, but since the skew was reasonably moderate, the data were not transformed.

Hierarchical multiple regression was performed as follows. As a first step, expertise recognition was regressed on the control variables (perception of expertise and tenure at the current job role). In step 2, the main effect of virtuality on expertise recognition was adjusted for control variables (geographic dispersion, electronic dependence, cultural diversity, and dynamic structure). To examine the main effect of network diversity and network closure on expertise recognition, in step 3, controlling for the control variables and the main effects of geographic dispersion, electronic dependence, cultural diversity, and dynamic structure, I tested network diversity and network closure, separately. In step 3, two hierarchical multiple regression models were created: model 1 with network diversity as a moderator and model 2 with network closure as a moderator. In step four, controlling for the aforementioned factors in the previous steps, interaction terms for network diversity and the four virtuality dimensions were examined, and interaction terms for network closure and the four dimensions of virtuality were examined in model 1 and model 2.

Exponential random graph modeling (ERGM). To test hypotheses 7, 8, 9, and 10 regarding the relationship between expertise recognition and the two knowledge sharing networks, the bivariate ERGM programs PNet and XPNet were used (Wang, Robins, & Pattison, 2009). For hypotheses 7 and 8, the multiple link parameter (Arc AB) was estimated for expertise-recognition and knowledge-seeking ties, and expertise-recognition and information-allocation ties; for hypotheses 9 and 10, the alternating bivariate transitivity parameter (TKT-ABA in XPNet terms) was estimated for alternating bivariate transitivity of expertise-recognition and knowledge-seeking ties, and expertise-recognition and information-allocation ties (Koehly & Pattison, 2005). ERGM uses a randomly-generated set of graphs to test whether a specific network configuration of interest is found in the observed network by chance (Snijders, Steglich, & van de Bunt, 2010). *P*-values were used to determine whether the presence of the proposed network configuration was statistically significant. Estimated parameters are considered converged when the t-ratio for convergence is less than 0.1 (Robins, Snijders, Wang, Handcock, & Pattison, 2007). When models were converged, a goodness-of-fit (GOF) test was used to examine whether the observed statistics differed significantly from the simulated statistics induced by the fitted model. An estimated parameter is said to converge when the t-ratio is smaller than 0.1, but non-estimated parameters are said to converge when the t-ratio is less than 2.0 (Robins, Pattison, & Wang, 2009).

It is recommended that, for bivariate ERGM, one starts by estimating baseline parameters for univariate networks; the target parameters (in the current study, the two bivariate parameters) should only be estimated when these univariate parameters converge adequately (Huitsing, van Dujin, Snijders, Wang, Sainio, Salmivalli, & Veenstra, 2012). Since the main objective of bivariate ERGM is to test for the presence of bivariate configurations (e.g., bivariate transitivity between tie A and tie B), the significance of the fit of each bivariate parameter was tested while controlling for univariate parameters. The first step for bivariate ERGM analysis was to construct a parsimonious model for the two univariate networks: expertise recognition and knowledge seeking, and expertise recognition and information allocation. To determine the parsimonious univariate parameters for each network, the univariate ERGM was fitted to the expertise-recognition and knowledge-seeking networks (and later the information-allocation network).

The models (the univariate ERGM and the bivariate ERGM) were fitted a stepwise manner; that is, one parameter was added at a time, beginning with the link parameter (Arc) and examining its GOF. Not surprisingly, the GOF for the model that contains only the Arc parameter was not satisfactory so reciprocity was added in the second model. Parameters were added until a model yielded acceptable levels of GOF (t-ratios less than 0.1 for fitted parameters and less than 2.0 for nonfitted parameters) (see Tables 2, 3, 4, 5, 6, & 7 for details). When the univariate ERGMs for expertise recognition and knowledge seeking, and expertise recognition and information allocation reached an acceptable GOF, the researcher began to fit the bivariate ERGM. The following univariate parameters were estimated: arc, reciprocity, A-In-S, A*k*T and A2P-T. These univariate parameters were controlled for while estimating bivariate parameters.

INSERT TABLE 2 ABOUT HERE

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Chapter 5. Results

Table 8 shows descriptive statistics for the variables of interest. Network diversity and network closure were positively correlated with expertise recognition ($r = .49$, $p < .001$; $r = .43$, $p < .001$). With regard to the relationships among each of the elements of virtuality, geographic dispersion was positively correlated with electronic dependence ($r = .21$, $p < .05$) and cultural diversity ($r = .46$, $p < .01$). Cultural diversity was positively correlated with dynamic structure ($r = .24$, $p < .05$).

INSERT TABLE 8 ABOUT HERE

The results from step 2 did not support hypotheses 1 or 2; there was no statistically significant relationship between geographic dispersion and expertise recognition or between dynamic structure and expertise recognition in either model 1 or model 2. Thus, hypotheses 1 and 2 were not confirmed. With respect to research question 1, the relationship between electronic dependence and expertise recognition was not statistically significant. In response to research question 2, the relationship between cultural diversity and expertise recognition was not statistically significant. In support of hypothesis 3, network diversity was positively associated with expertise recognition ($\beta = 0.43$, $p < .001$). With respect to hypothesis 4, the interaction effect between network diversity and geographic dispersion on expertise recognition was statistically significant ($\beta = –0.32$, $p < .05$), supporting hypothesis 4-a, but, contrary to hypothesis 4-b, the interaction effect between network diversity and dynamic structure on expertise recognition was only marginally significant ($\beta = –0.19$, $p < .10$). Regarding research question 3, the interaction effect between network diversity and electronic dependence on expertise recognition was not statistically significant, and there was no significant interaction effect between network diversity and cultural diversity on expertise recognition. In support of hypothesis 5, network closure was positively related to expertise recognition ($\beta = 0.39$, $p < .001$). With respect to hypothesis 6, the interaction effect between network closure and geographic dispersion on expertise recognition was statistically significant ($\beta = -0.41$, $p < .05$), supporting hypothesis 6-a, but, with regard to hypothesis 6-b, the interaction effect between network closure and dynamic structure on expertise recognition was only marginally significant ($\beta = -0.22$, $p < .10$). In response to research question 4, the interaction effect between network closure and electronic dependence on expertise recognition was not statistically significant, nor was the interaction effect between network closure and cultural diversity, indicating that network closure does not moderate the relationship between cultural diversity and expertise recognition.

INSERT TABLE 9 ABOUT HERE

INSERT TABLE 10 ABOUT HERE

Plots are useful for interpreting the interaction effects. As such, I plotted the relationships between geographic dispersion and expertise recognition at one unit below the mean of network diversity and at one unit above the mean (Aiken & West, 1991). Likewise, I plotted the relationships between geographic dispersion and expertise recognition and between dynamic structure and expertise recognition at one unit below the mean of network closure and at one unit above the mean.

Figure 8 shows that those who exhibited the higher level of network diversity tended to perceive others' expertise more accurately than those who exhibited the lower level of network diversity, regardless of levels of geographic dispersion. When geographic dispersion was larger, both those with higher levels of network diversity and with lower levels of network diversity recognized expertise less accurately. However, the relationship between expertise recognition and geographic dispersion was less negative at higher levels of network diversity. That is, those with the higher level of network diversity perceived others' expertise more accurately than those with the lower level of network diversity, even when the degree of geographic dispersion is higher. This indicates that when individuals work in situations where geographic dispersion exists, network diversity is helpful in perceiving others' expertise. Figure 9 shows the same pattern for the relationship between network closure and expertise recognition. That is, those with the higher level of network closure perceived others' expertise more accurately than those with the lower level of network closure, even when the degree of geographic dispersion was higher. This indicates that network closure is helpful in perceiving others' expertise when they work in a situation where geographic dispersion exists.

INSERT FIGURE 8 ABOUT HERE

INSERT FIGURE 9 ABOUT HERE

Tables 11 and 12 show how the estimated model fits the data. The GOF t-ratios for fitted statistics need to be smaller than 0.1, while the GOF t-ratio for nonfitted statistics should be less than 2.0 (Robins & Lusher, 2013). The bivariate ERGM with expertise recognition and knowledge seeking yielded several graph statistics whose GOF t-ratios did not meet the suggested criteria (0.12 for A2P-TA; 0.13 for Arc B; 0.18 for A2P-TB; and 0.12 for Reciprocity B). Since these were all fitted statistics, the failure to meet the suggested criteria could be problematic. However, three of the four GOF t-ratios were only slightly greater than 0.10 (A2P-TB was a bit higher). Furthermore, acknowledging that it is highly unlikely to have all statistics meet satisfactory criteria for the GOF test for ERGM, Robins and Lusher have recommend focusing on fitting those statistics that are most relevant to a particular research question. For example, if a researcher is particularly interested in degree, he or she would want to have the degree-related statistics fit very well. This study focused on the presence of bivariate parameters, and these univariate graph statistics were used as controls for the bivariate ERGM, meaning that they were not used to test hypotheses.

INSERT TABLE 11 ABOUT HERE

INSERT TABLE 12 ABOUT HERE

Tables 13 and 14 show the results of the bivariate ERGM. The first model estimated a total of ten univariate parameters, which were used as controls, and two bivariate configurations (Arc AB and TKT-ABA). The negative univariate link parameter for expertise recognition (Arc A) indicates that expertise-recognition ties are sparse (–6.13, *SE* = 0.44, $p < .05$). And the negative univariate link parameter for knowledge seeking (Arc B) indicates that knowledge-seeking ties also are sparse (–6.27, *SE* = 0.43, $p < .05$). With respect to the negative link parameters, it is worth noting that social networks with densities less than 0.5, out-degree parameters (Arc parameter) tend to be negative (Steglich, Snijders, & Pearson, 2010). In this study, respondents might have had sparse expertise-recognition ties because they underreported their coworkers' expertise or because they perceived others' expertise incorrectly. Likewise, respondents might have had sparse knowledge-seeking ties because they underreported the number of times they sought out knowledge or because they rarely sought out knowledge from their coworkers.

The second model, which focused on expertise recognition and information allocation, estimated a total of six univariate parameters and three bivariate parameters (Arc AB, Reciprocity AB, and TKT-ABA). The univariate arc parameters for expertise recognition and information allocation were both negative (–7.50, *SE* = 0.52, $p < .05$; –7.08, *SE* = 0.42, $p < .05$). The interpretation of the negative parameter is the same as the case of knowledge seeking.

Interestingly, the multiplex reciprocal relationship between expertise recognition and information also turned out to be statistically significant (5.61, *SE* = 1.18, $p < .05$). This indicates that if person *i* perceives person *j*'s expertise correctly, then *j* will tend to forward unsolicited information to *i*. However, since this graph statistic was not the focus of this study (but was merely included to improve the fitness of the model), the researcher did not develop a theory to explain the relationship.

Hypothesis 7 predicted that expertise recognition leads to knowledge seeking. In testing hypothesis 7, the parameter estimate of interest was the multiplex link parameter (Arc AB in XPnet terms). Whereas the arc parameter represents the propensity to form a tie (Robins & Lusher, 2013), the multiplex arc parameter captures the tendency to form two different ties between actors. The hypothesized parameter converged properly (t-ratio for convergence = −0.03) and was positive and statistically significant (7.98, *SE* = 0.33, $p < .05$). Hypothesis 8 predicted that expertise recognition leads to information allocation. In testing hypothesis 8, the parameter estimate of interest was the multiplex link parameter containing expertise recognition and information allocation. The hypothesized parameter converged properly (t-ratio for convergence = −0.06) and was positive and statistically significant (10.16, *SE* = 0.69, $p < .05$).

Hypothesis 9 predicted alternating bivariate transitivity of expertise-recognition and knowledge-seeking ties, so the parameter estimate of interest was the alternating bivariate transitivity parameter (TKT-ABA in XPnet terms). The hypothesized parameter was not statistically significant. Hypothesis 10 predicted alternating bivariate transitivity of expertise-recognition and information-allocation ties. To test hypothesis 10, the bivariate transitivity parameter TKT-ABA was estimated but was not statistically significant. Therefore, hypotheses 9 and 10 were not supported, indicating that there were no alternating bivariate transitive relationships between expertise recognition and knowledge seeking or between expertise recognition and information allocation.

INSERT TABLE 13 ABOUT HERE

INSERT TABLE 14 ABOUT HERE

Chapter 6. Discussion

Virtual work arrangements have become increasingly prevalent with the rise of the knowledge economy. Organizations introduce and manage virtual collaborations in order to take advantage of diverse sources of information, knowledge, and expertise. Oftentimes, this entails building up TMS among workers. Reflecting this context, this study attempted to understand TMS in relation to virtuality and networks. To this end, this study used network analysis to analyze TMS in actual virtual work arrangements. It specifically addressed (a) the relationship between virtuality and expertise recognition, which is a key element of TMS, (b) the effects of an emergent knowledge-sharing communication network's properties on the relationship between virtuality and expertise recognition, and (c) the extent to which TMS explains the specific patterns of interaction that emerge in knowledge-sharing communication networks.

In this study, the relationship between virtuality and expertise recognition was not confirmed. Instead, the effect of virtuality on expertise recognition should be understood in light of the fact that network mechanisms, network diversity and network closure, moderated the relationship. The results show that when network diversity interacts with geographic dispersion, it can moderate the relationship between expertise recognition and geographic dispersion. As described previously, those who were high on network diversity perceived others' expertise more accurately than those who were low on network diversity, even when the degree of geographic dispersion was higher. When focusing on geographic dispersion as a barrier to connections, it could be reasoned that geographic dispersion might hinder people's perceptions of expertise. However, even if people feel that they are geographically distant from their coworkers, if they form and maintain higher levels of nonredundant ties, then they will not necessarily feel that geographic dispersion hampers their perceptions of others' expertise. Perhaps individuals who feel physically and geographically distant from one another can still feel connected if they maintain nonredundant ties.

On the other hand, network closure, which was measured by the degree to which one is embedded in a clustered network, moderated the relationship between expertise recognition and geographic dispersion. Though being physically distant from coworkers would likely make a virtual worker feel distant and even isolated (Gibson & Gibbs, 2006), the results of this study show that such feelings may be attenuated if the individual is embedded in a highly clustered network. Redundant but intertwined relationships may thus be helpful in alleviating a feeling of being distant from coworkers that may hinder their perceptions of others' expertise. By being in a dense network, people can sustain their relationships with team members or coworkers who work at different sites.

Consistent with previous theoretical discussions, this study suggests that network diversity and network closure may play a vital role in accurately perceiving others' expertise. Interestingly, network diversity and network closure can both contribute to expertise recognition. As discussed in the literature review, theorists of network diversity (Burt, 1992) and network closure (Coleman, 1988) emphasize, respectively, the benefits of weak yet diverse ties and redundant yet solid ties. It is tempting to think about these two network mechanisms as being in conflict; however, subsequent studies have shown otherwise. After analyzing the relationships between structural holes and performance, and between network closure and performance, Burt (2000) argued that "structural holes and network closure can be brought together in a productive way" (p. 398). Burt illustrated that performance is maximized when organizational members develop nonredundant ties beyond their immediate workgroups, while simultaneously maintaining cohesive relationships within those groups.

To measure network closure, Burt used network density, which is the proportion of actors who are linked with another actor to all possible dyadic linkages, and hierarchy. These two types of network closure were both positively associated with performance. Reagans and McEvily (2003) demonstrated that network range, an indicator of network diversity, and cohesion were contributing together when predicting knowledge transfer. Reagans and McEvily used triadic density to focus on the presence of strong third-party connections. As discussed in the methods section, there were continuities and discontinuities in using clustering coefficients to measure network closure. Network density and clustering coefficients are both indicators of network closure. Burt stated that network density is one of the measures of network closure, not the only way. Further, because network density is a group-based measure, it did not fit well with this study's research context. While clustering coefficients capture the degree of cohesion within a network, they are individual-based measures. Thus, it is reasonable to attempt to measure network closure in another way (clustering coefficient in this study).

Extending a perspective that does not see network diversity and closure as conflicting, I suggest that network diversity and network closure can *both* be seen as making information-seeking and knowledge-sharing more effective. Consistent with the main point of each of these two perspectives, network diversity grants people access to diverse information and expands the boundaries of personal networks (Burt, 1992), whereas network closure enables individuals to develop more precise knowledge of others along multiple dimensions. While network diversity provides individuals with various sources of information about others' expertise and skills, network closure allows individuals to perceive others' knowledge and skills from various angles. This is important because in networks with less closure, virtual workers might experience limited aspects of a person's expertise and might misconstrue the actual nature of his or her expertise. In some cases, an individual's perceptions of other people's expertise may reflect what he or she *wants* one to perceive (Leonardi & Treem, 2012). But if multiple third-party individuals corroborate his or her impressions, then he or she may be able to make more accurate assessments through *triangulation*. In sum, overlapping ties may be redundant in terms of the sources of information, but they may bring additional ways of understanding others' expertise.

In an effort to better understand the relationship between the main elements of TMS, I used bivariate ERGM to investigate the relationships between expertise recognition and knowledge seeking and between expertise recognition and information allocation. The results of this study indicate that expertise recognition forms a multiplex relationship with knowledge-seeking ties and information-allocation ties.

Theoretical Implications

This study has illuminated the relationships between one's perception of expertise and (a) virtuality, (b) virtuality when taking into account the effect of network diversity and network closure, and (c) knowledge-seeking and information allocation ties. Given that TMS can be best understood in the light of a network (Lewis, 2003; Wegner, 1995), this study examined the relationship between virtuality and expertise recognition in terms of the two main network properties, network diversity and network closure. By doing so, it focused on interactions between virtual collaborators who operate in virtual work arrangements rather than on the structural aspects of those arrangements.

Implications for virtuality theory. This study suggests that TMS needs to be studied in relation to virtual work arrangements, which are becoming more prevalent in the workplace. Building up TMS among workers is critically related to what virtual work arrangements aim to achieve: diverse sources of information, knowledge, and expertise. This study examined how expertise recognition, the prominent element of TMS, is related to virtuality, which may make a well-functioning TMS more difficult to establish. The results of this study counter previous assumptions by showing that the structural barriers inherent in virtuality do not necessarily hinder expertise recognition because two prominent network properties, network diversity and network closure, may moderate some of the structural effects of virtuality on expertise recognition.

This study sought to better understand the emergence of communication networks in virtual work arrangements. To get a better understanding of the effect of communication on expertise recognition and, potentially, on TMS, this study adopted a communication network approach. Whereas previous TMS studies focused on the content of communication (Leonardi & Treem, 2012) or the strength of communication ties (Yuan et al., 2010), this study examined communication ties themselves (specifically, knowledge-sharing communication ties). By focusing on the *relational* aspects of communication, this study contributes to the understanding of the emergent communication network perspective—in particular, the meaning of emergence in a network. It is important to focus on the relational aspect of communication, because it allows one to understand the emergence of patterned interactions in the network of interest through self-organization mechanisms of the network structure.

According to Contractor (1994), self-organizing systems theory aims “to explain the emergence of patterned behavior in systems that are initially in a state of disorganization or in a different state of organization” (p. 51). Further, Contractor proposed that “organizational members’ coordinated activity and their shared interpretations are, in part, self-generating” (p. 53). Drawing on self-organizing systems theory, Contractor and Grant (1996) showed that initial levels of communication and patterns of interaction in semantic networks predict ensuing patterns of interaction. In explaining the emergence of communication networks, the multi-theoretical and multi-level (MTML) framework (Monge & Contractor, 2003) is a useful tool. In the MTML framework, the endogenous elements of networks are represented by various graph configurations, such as links, reciprocity, transitivity, and clustering. These endogenous components help explain how the relational aspects of networks affect the self-organizing process (Contractor, Wasserman, & Faust, 2006). According to Contractor et al., the endogenous elements of a network, which reflect its relational characteristics, affect the chance that particular linkages are present in the network. The present study shows that such endogenous patterns of communicative interaction constitute the overall structure of the communication network, which is the essential part of understanding emergence in the context of networks. That is, endogenous network configurations, such as links, reciprocity, and triangles, are basic components of networks that eventually combine to shape what the network will be like.

This study reminds us that understanding the potential benefits of network diversity and network closure requires a balanced approach. One should be cautioned against assuming that diverse ties will always promote expertise recognition or that network closure will always inhibit it. The present study tells us why such overgeneralizations are not always the case. Although weak yet diverse ties can promote expertise recognition, being embedded in a network with overlapping ties—which the measure of network closure used in the present study aimed to capture—may also promote expertise recognition. This study demonstrates that network diversity and network closure are not mutually exclusive, but can work together to promote expertise recognition, which is a key factor in TMS. The benefits of network diversity—more efficient access to information resources (Burt, 1992)—can be achieved through weak ties (Granovetter, 1973). Nonredundant and diverse communication ties can give people a better sense of who in their network has what specialized knowledge. Network closure, which is associated with fewer nonredundant ties, provides people with an increased chance to look at others' expertise from different angles.

Implications for TMS theory. Ever since Wegner (1995) conceptualized the main elements of TMS, there have not been serious attempts to examine potential relationships among expertise recognition, knowledge retrieval, and information allocation. If these relationships exist, what kind of relationships might they be? This study helps to answer this question and suggests some mechanisms responsible for establishing relationships among the elements of TMS. By showing the presence of the multiplex links between expertise recognition and knowledge seeking, and between expertise recognition and information allocation, this study attempted to answer the above question. The findings show that individuals in an organization tend to form multiplex ties, rather than just uniplex relationships (based on a single type of linkage). If someone perceives another person as having relevant expertise, this may be a precursor to joint attention between these people. That is, based on the individual's awareness of the other person's expertise, he or she may forge a knowledge-sharing tie with them. Then, once a knowledge-sharing relationship is formed, the individual may learn more about the other person's expertise, which may cause additional ties to form in the future.

What this study showed is congruent with literature that emphasizes the multifaceted nature of individuals' relationship—that is, that people's relationships tend to be defined by multiple ties rather than just a single type of a tie (Ibarra, 1993; Robins & Pattison, 2006). An individual who perceives another person as having a common interest will tend to forge a tie based on that interest, paving the way for other ties (Feld, 1981). Individuals' patterns of interaction may not be limited to only one type of tie; rather, they may occur across discrete types of relations (Lee & Monge, 2011).

The above discussion supports my speculation that individuals who share one tie will tend to form other ties (e.g., expertise recognition and knowledge seeking in this study). For example, in the context of virtual work arrangements, if an individual perceives that another person has expertise and knowledge that is useful for completing his or her task, he or she may forge a tie with that person defined by their focus on completing that particular task. Then, once these individuals are connected, they may be more likely to form other ties, such as advice-seeking or collaborative ties. This study showed that individuals seek knowledge from, and/or allocate information to, others in their organization who they view as experts. It is interesting to see that such a tendency within general interpersonal relationships is also evident in the relationships among the elements of TMS. This may have to do with the fact that people's perceptions of one another's expertise, and possibly ensuing knowledge-sharing behaviors, may reflect their relationships.

The above discussion leads to the conclusion that a network approach is useful for examining TMS. According to Wegner's (1987) definition, a TMS is "a set of individual memory systems in combination with the communication that takes place between individuals" (p.186). TMS can be understood in network terms because network ties exist and operate between individuals (Lewis, 2003). Thus, I would argue that TMS can be a perceived network—formed and shaped in individuals' minds, reflecting their perceptions of who knows what and who knows who knows what, and, further, who knows who does what. In other words, one can project his or her mental representation of *who knows who knows what* (expertise recognition, Wegner, 1987) and *who knows who does what* (task-knowledge coordination, Brandon & Hollingshead, 2003) onto a network. What needs to be emphasized, of course, is the fact that one's social interaction influences this process of developing perceptions of expertise. The above mentioned mental representations of others' expertise are an outcome of interactions, instead of individuals' independent efforts.

This study has attempted to go beyond rational approaches to TMS (Austin, 2003; Kanawattanachai & Yoo, 2007), which implicitly assume that if the pre-conditions of TMS are met—namely, individuals develop and possess specialized expertise and are able to correctly identify experts—then an individual will reach out to those experts when their expertise is needed. This approach neglects the social reasons that individuals may knowingly reach out to non-experts. Focusing on *vicarious* learning patterns that emerge among people who use and adapt technology in their organization, social influence models (Fulk, Schmitz, & Steinfield, 1990) argue that social context and influence play a critical role in shaping one's perception of technology and technology uses in organizations. This study emphasizes the social features of expertise recognition. Identifying and contacting the right person(s) may not solely depend on an individual's rationality or judgment; instead, an individual's awareness of others' expertise and actual contact with the right person(s) may be guided and shaped by his or her social interactions with others. In this matter, a network approach provides an alternative in that it views TMS as an outcome of social connections.

Practical Implications

As discussed, accurate recognition of expertise helps relevant knowledge and information to be shared among employees. Thus, for managers to promote more active knowledge sharing in their companies or organizations, they might wish to foster work environments where employees are more aware of one another's expertise in terms of not only their general domains of expertise (i.e., the kinds of expertise they possess) but also their task-specific expertise (i.e., the kinds of tasks/projects that they use their expertise to complete). In this matter, managers might wish to increase the degree to which their employees develop nonredundant ties. Again, nonredundant ties are significantly related to coworkers' ability to perceive one another's expertise, which is a key element of TMS. Because building more diverse networks is an ideal way to foster expertise recognition, management might be able to provide some opportunities for employees to connect with those they otherwise would not know (e.g., introducing more formal and/or informal social meetings inside and/or outside of work).

Given the finding that network diversity and network closure played a significant role in perceiving others' expertise, management may wish to focus on how their employees' networks evolve during the process of TMS formation. For organizations to know whether they have TMS operating among their employees, they need to have a clear sense of the types of employee communication networks that are operating at various levels of work units. Managers should regularly observe how their employees' local communication networks (i.e., work units) evolve in relation to the organization's overall communication network. To do so, it is recommended that companies conduct regular network surveys that focus on their employees' expertise recognition and knowledge sharing. Based on the results of these surveys, managers and supervisors could map the flow of knowledge among their employees and better identify sources of expertise.

Managers may wish to know if there are discrepancies between an individual's actual expertise and what others perceive as his or her expertise or between the expertise that an individual wants to be known for and what others end up perceiving as their expertise. It has been documented that digital expert databases in an organization are a useful way to inform coworkers about one another's expertise (Fulk, Heino, Flanagin, Monge, & Bar, 2004). However, although such databases function as a convenient means for helping an organization's members to identify expertise, managers should be aware that what individuals display and share on these repositories may not fully and accurately reflect their actual expertise. To address such discrepancies, companies should regularly conduct surveys of expertise. Such surveys should be similar to those that were administered for this study. They should compare “actual” expertise (through self-reported expertise, which was used in this study, or perhaps through a supervisor’s evaluation) with what coworkers perceive. By doing so, management may be able to better identify the degree to which their organizational members are aware of others’ expertise accurately.

Limitations and Future Research

Some limitations stem from this study’s use of a name-generating technique to construct networks. Since this study was unable to employ a full network method to measure knowledge sharing and information allocation, survey respondents were not given a list of people that defined the range of their network. A general limitation of name generators is that they might not fully capture all ties, but are limited to those that were recalled and listed by egos. This could have led to underestimation of the number of ties among BizTech’s inside sales representatives.

While this study asked respondents to list their own multiple areas of expertise, it only asked them to state one main area of expertise for the people they listed. There were reasons for doing this. First, there was a need to avoid making the survey too lengthy. For many if not all respondents, asking them to identify multiple areas of expertise for each contact could lead to fatigue for the remaining survey questions. However, it should be noted that it constrained respondents’ choices for reporting others’ expertise. Related to this limitation, this study was unable to measure expertise recognition in terms of consensus about an individual’s area(s) of expertise.

To surmount the above mentioned limitations, future studies could employ a full network measure. This would avoid underestimation of possible ties among research participations. Though there have been previous attempts to measure expertise recognition (Austin, 2003; Lewis et al., 2007), there is no agreed upon method for doing so. Future studies may wish to come up with a new idea for how to boost the validity of measuring expertise recognition. Following other studies (Austin, 2003; Su, 2012), this study adopted self-reported expertise as a benchmark for determining whether others perceive one's expertise correctly. However, one might wonder whether self-reported expertise is the best benchmark. To address this concern, future studies could use others' consensus about a particular individual's expertise.

To avoid confusion, it is important to note this study's complexity in terms of the unit of analysis. This study collected data from *individuals* in virtual work arrangements, but drew conclusions about *the relations among individuals* who work in a team and/or across teams. This complexity—which ultimately prompted me to use both network analysis and regression analysis—might obfuscate the unit of analysis of this study. For regression analysis, data collected from individuals were used to describe the relationships between expertise recognition and each of the elements of virtuality; the unit of analysis was thus individuals who were working in a team. However, in network analysis, it is not the individual, but *the relations among individuals* (people, groups, or organizations), that is the unit of analysis (Emirbayer & Goodwin, 1994; Wasserman & Faust, 1994). I used network diversity and closure to examine the moderating effect of network properties on the relationship between virtuality and expertise recognition. Further, the bivariate ERGM analysis was based on network measures and network analysis. In sum, I collected data from teams, and drew implications about their relations in that team and/or across teams.

Conclusion

In knowledge-based economies, one cannot over-emphasize the importance of knowledge sharing. Better known as one's perception of who knows what, TMS is widely considered a prerequisite of knowledge sharing and coordination in organizations (Hollingshead & Brandon, 2003). TMS is critically related to what managers actually aim to gain by using virtual work arrangements: diverse sources of information, knowledge, and expertise. TMS not only helps to reduce each individual's burden of maintaining and processing information but also enables people to access to diverse information (Monge & Contractor, 2003). For management to attain these benefits of virtual work arrangements, it is crucial that TMS exist among their employees.

To better understand TMS in relation to virtuality, this study used a network approach. Specifically, this study examined the relationship between virtuality and expertise recognition, and the relationships between expertise recognition and (a) knowledge seeking and (b) information allocation. The two main network properties—network diversity and network closure—not only influenced expertise recognition positively but also moderated the effects of the structural aspects of virtuality on expertise recognition. This study expanded the focus of the relationship between virtuality and TMS beyond expertise recognition. Although awareness of other people's expertise indeed is a key element of TMS (Palazzolo, 2005; Wegner, 1987), it is not the only element. In this vein, this study used a cutting-edge statistical network method to examine the relationships among the three main elements of TMS: expertise recognition, knowledge seeking, and information allocation.

Appendices

Survey Questionnaire

This research is part of a study being conducted by researchers at Rutgers University in partnership with BizTech (a pseudonym) Inside Sales. All data will be collected by researchers at Rutgers, and results will be de-identified and aggregated before they are shared with BizTech. This survey is designed to assess your use of information technology in the workplace, and specifically looks at the impact of the Digital Matters (a pseudonym) program within BizTech Inside Sales. The survey is broken into four primary sections, with a few demographic questions at the end.

Section I: The first section asks about your experiences with the social selling champion program. If you have not participated in the Digital Matters program, indicate this by selecting “no”.

Are you a Digital Matters member?

(1 = no, 2 = yes)

The following questions ask you about your interactions with Digital Matters members.

1a. How often have you talked with a Digital Matters member within BizTech Inside Sales?

(1 = never, 2 = less than once a month, 3 = monthly, 4 = weekly, 5 = daily, 6 = NA)

1b. How useful has the information shared by the Digital Matters member been to you?

(1 = not at all, 2 = minimally, 3 = somewhat, 4 = moderately, 5 = greatly, 6 = NA)

1c. Has a Digital Matters member been assigned to mentor you? *(1 = no, 2 = yes)*

You indicated that you are a Digital Matters member. The following questions ask about your experience in the program.

2a. What tools do you use to communicate in your role as a Digital Matters member?

- eContact
- Twitter
- BizTech Connections External version
- LinkedIn
- Viadeo
- Facebook
- BizTech SmartCloud for Meetings (formerly Lotus Live)
- Rep Page
- Skype
- VSEE
- Sametime Text Chat
- Sametime Meetings (with video)
- Sametime Meetings (without video)
- Other (enter text)

2b. In your opinion, what are the major benefits of the Digital Matters program? (open-ended)

Section II: The next set of questions asks about your current job role, and your use of technology in that role. Answer each question to the best of your ability.

3. What is your job role?

4. How long have you been a member of your current sales role?

- Fewer than 6 months
- 6 – 12 months
- 1 – 2 years
- 2– 4 years
- 4 – 6 years
- More than 6 years

5. **What are your primary areas of business expertise? Select all that apply, choosing the categories that best match your expertise.**

- Account management
- Business analysis / business development
- Channel / Channel partners
- Collaboration solution
- Client financing
- Client relationship management
- Cloud computing
- Customer service
- Data analysis / data center
- Digital technology
- Digital selling

- Disaster recovery
- Demand generation
- Lead generation / lead development / lead management
- Marketing
- Network security
- New business development
- Online commerce
- Project management
- Sales / direct sales / pre-sales / Sales enablement / Sales management
- Solution selling
- Storage / storage solutions
- Virtualization

Section III: The following questions ask you to identify the people with whom you work closely. Your answers to these questions will be used to map the informal communication networks within the organization. As you think about the questions below, keep in mind that "knowledge" is a general term that refers to any information-sharing related to identifying, progressing, or closing business opportunities. **It is important for the following that you provide the first name and last name for each person that you identify.** This will allow the researchers running the study to create an accurate "map" of connections within BizTech. **Remember that ALL DATA provided in this section will be de-identified by the researchers at Rutgers University, and no identifying data about you or anyone else will be shared back with BizTech.**

6. Think about the BizTechers who “acted as a critical source of knowledge” for your work (i.e., they help you to identify, progress, or close business opportunities) during the past six months. These are the people you reached out to when you needed help with your job, whether you work directly with them or not (Adapted from Reagans & McEvily, 2003, p. 253). Please list the names of as many of these people as possible, and for each person, report their main area of expertise (select their expertise as you understand it). Select the ways you usually communicate with them.

7. Think about the BizTechers with whom you have shared unsolicited knowledge (e.g. advice or information that you thought they would find helpful in their jobs) during the past six months, whether you work directly with them or not. Please list the names of as many of these people as possible, and for each person, report their main area of expertise (select their expertise as you understand it).

8. On a scale of 1 to 5, how often do you use the following communication tools in a given month? (1 indicates no usage, and 5 indicates daily usage)

(1 = never, 2 = less than once a month, 3 = monthly, 4 = weekly, 5 = daily)

- eContact
- Twitter
- BizTech Connections External version
- LinkedIn
- Viadeo
- Facebook
- BizTech SmartCloud for Meetings (formerly Lotus Live)
- Rep Page

- Skype
- VSEE
- Sametime Text Chat
- Sametime Meetings (with video)
- Sametime Meetings (without video)
- Other (enter text)

9. Of the following Sametime applications, select those that you use for internal and external purposes. Check all that apply.

(Internal and External columns as choices)

- Sametime Text Chat
- Sametime Meetings (with video)
- Sametime Meetings (without video)

10. Which of the following digital tools do you use to communicate with clients? Select all that apply.

- eContact
- Twitter
- BizTech Connections External version
- LinkedIn
- Viadeo
- Facebook
- BizTech SmartCloud for Meetings (formerly Lotus Live)
- Rep Page
- Skype

- VSEE
- Sametime Text Chat
- Sametime Meetings (with video)
- Sametime Meetings (without video)
- Other (open ended)

11. Based on a scale of 1 to 5, where 1 indicates no training and 5 indicates extensive training, how much training have you received for each of the following tools that you selected in the previous question?

(1 = none, 2 = a little training, 3 = some training, 4 = a moderate amount of training, 5 = extensive training)

- eContact
- Twitter
- BizTech Connections External version
- LinkedIn
- Viadeo
- Facebook
- BIZTECH SmartCloud for Meetings (formerly Lotus Live)
- Rep Page
- Skype
- VSEE
- Sametime Text Chat
- Sametime Meetings (with video)
- Sametime Meetings (without video)

- Other (open ended)

12. On a scale of 1 to 5, to what degree would you consider yourself an expert user of each of the following tools? (1 indicates that you have no expertise, while 1 indicates that you are definitely an expert,)

(1 = not at all, 2 = minimally, 3 = somewhat, 4 = moderately, 5 = definitely)

- eContact
- Twitter
- BizTech Connections External version
- LinkedIn
- Viadeo
- Facebook
- BizTech SmartCloud for Meetings (formerly Lotus Live)
- Rep Page
- Skype
- VSEE
- Sametime Text Chat
- Sametime Meetings (with video)
- Sametime Meetings (without video)
- Other (open ended)

13. When learning about a new digital tool (i.e. Rep Pages), how important is each of the following in helping you to learn about best practices for using the tool in your sales role? (1 indicates that a tool is not at all important, whereas 5 indicates that a tool is definitely important in helping you to learn)

(1 = not at all, 2 = minimally, 3 = somewhat, 4 = moderately, 5 = definitely)

- From my manager
- From the people sitting near me
- From other colleagues in the office
- Through informal BizTech training sessions (lunch & learn; coffee, etc.)
- Through BizTech Connections (Communities such as Social Seller Showcase)
- From a Digital Matter member

14. To what degree do the following tools contribute to your ability to generate new leads and to meet your sales quota/objectives? (1 indicates that the tool does not contribute at all, while 5 indicates that the tool contributes greatly)

(1 = not at all, 2 = minimally, 3 = somewhat, 4 = moderately, 5 = greatly)

- eContact
- Twitter
- BizTech Connections External version
- LinkedIn
- Viadeo
- Facebook
- BizTech SmartCloud for Meetings (formerly Lotus Live)
- Rep Page
- Skype
- VSEE
- Sametime Text Chat
- Sametime Meetings (with video)

- Sametime Meetings (without video)
- Other (open ended)

15. Of the following, how likely is each to motivate you to use a new social and digital selling tool? (1 indicates that it would not have any impact, while 5 indicates that it would definitely lead you to use a new tool)

(1 = not at all, 2 = minimally, 3 = somewhat, 4 = moderately, 5 = definitely)

- My colleagues sitting around me use a tool
- Encouragement from my manager to use a tool
- A Digital Matter member who I speak to regularly recommends that I use a tool
- A successful Digital Matter Member uses a tool
- The tool is a great way to identify business opportunities
- The tool is an easy way to access news, blogs, trends
- The tool is a good way for me to get connected with my colleagues

Section IV: The final section asks you to think a bit more about how you use digital tools at work, and about your general work environment. Please think about the BizTecher you work with on your extended team, that is, those people with whom you interact to identify, progress, or close business opportunities, regardless of whether they have the same manager as you.

16. Think about the digital tools in the questions above that you used to interact only with BizTechers on your extended team (e.g., Sametime Internal text chat, BizTech W3 Connections, etc.). Rate how strongly you agree with each of the following statements. (1 indicates that you strongly disagree, while 5 indicates that you strongly agree) *(1 = strongly disagree, 2 = somewhat disagree, 3 = neither agree* *nor disagree, 4 = somewhat agree, 5 =strongly agree)* (Modified from Gibson & Gibbs, 2006).

- I rely on these communication tools to communicate with BizTech coworkers on a daily basis
- I rely on these communication tools to seek my coworkers' advice
- I rely on these communication tools to generate new ideas
- I rely on these communication tools for decision making
- I rely on these communication tools for collaboration

17. Please think about the BizTechers you work with on your extended team. Rate how strongly you agree with each of the following statements. (1 indicates that you strongly disagree, while 5 indicates that you strongly agree)

(1 = strongly disagree, 2 = somewhat disagree, 3 = neutral, 4 = somewhat agree, 5 =strongly agree)

- We collaborate across time zones
- We often work extended days in order to communicate with each other
- We rarely communicate in real-time (As a result, we have to send emails or another form of message)
- My colleagues' job functions differ from my own
- My colleagues are experts in different areas
- Working with my colleagues whose expertise differs from my own poses challenges

18. Please think about the BizTechers you work with on your extended team. Rate how strongly you agree with each of the following statements. (1 indicates that you

strongly disagree, while 5 indicates that you strongly agree) *(1 = strongly disagree, 2 = somewhat disagree, 3 = neutral, 4 = somewhat agree, 5 =strongly agree) (*modified from Chudoba et al. , 2005; Gibson and Gibbs, 2006).

- My colleagues are in different geographic locations
- My colleagues work with people in different geographic locations
- My colleagues and I rarely have face-to-face interactions
- I work with colleagues whose cultural background differs from my own
- I work with colleagues whose native language or dialect differs from my own
- Working with my colleagues whose culture differs from my own poses challenges

19. Please think about the BizTechers you work with on your extended team. Rate how strongly you agree with each of the following statements. (1 indicates that you strongly disagree, while 5 indicates that you strongly agree) *(1 = strongly disagree, 2 = somewhat disagree, 3 = neutral, 4 = somewhat agree, 5 =strongly agree)* (Adapted from Gibson & Gibbs, 2006).

- There is high turnover among the colleagues I work with
- My colleagues' roles change frequently
- Due to high turnover among my colleagues, it is difficult to maintain a consistent pattern of collaboration
- Due to high turnover among my colleagues, I often have to seek out new people to give me advice.

20. Please think about the BizTechers you work with on your extended team. Rate how strongly you agree with each of the following statements. (1 indicates that you strongly disagree, while 5 indicates that you strongly agree) *(1 = strongly disagree, 2*

= somewhat disagree, 3 = neutral, 4 = somewhat agree, 5 =strongly agree) **(**Adapted from Lewis, 2003).

- I am aware of the skills and expertise that my colleagues have
- It is clear that my colleagues all know who has expertise in specific areas (e.g., 'who knows what' on our extended team)
- Different individuals are responsible for having expertise in different areas
- When I need assistance, I know who I need to turn to

The following questions ask for basic demographic information that will be helpful in our analysis of the data. Please remember that all answers are kept confidential by the researchers at Rutgers University. These questions are all optional.

21. What is your gender? M / F

22. Where is your office located?

23. Which of the following best represents your age?

- 18-24
- 25-35
- 36-46
- 47- 57
- 58 or older

24. What is the highest level of education you have achieved?

- Less than high school
- High School degree
- Some college
- Associate's Degree

- Bachelor's Degree
- Master's Degree
- PhD, MD, or other advanced degree

25. What is your country of origin? _________________

26. What is or are your native language(s)? _______________

27. Do you have any other comments about the Digital Matters program?

____

Tables

Table 1. BizTech Inside Sales Representatives' Expertise (n = 142)

Account Management
B2B Online Commerce Solutions
Brand Solution-Websphere Software
Budget
Business Analysis
Business Continuity and Resiliency
Business Development
Business Intelligence
Business Process
Business Relationship Management
Business Services
Channel
Channel Brand Sales
Channel Partners
Channel Sales
Cisco Technologies
Client Financing
Client Relationship Management
Client Financing
Cloud Computing
Cognos
Collaboration Solution
Computer Hardware
Computer Software
Consultive & Solution Sales
CRM (Customer Relationship Management)
C-Suite
Customer Engagement
Customer Experience
Customer Satisfaction
Customer Service
Data Analysis
Data Center
Demand Generation
Digital Marketing
Direct Sales
Disaster Recovery
Email Marketing
Engineering
Enterprise Architecture

Enterprise Sales
Enterprise Software
Enterprise Software Inside Sales
Finance
Forecasting
Information Management
Information Management Software
Information Security
Infrastructure Management
Infrastructure Services
IT Service Management
IT Strategy
Lead Development
Lead Management
Managed Services
Management
Marketing
Marketing Campaign Lead
Marketing Communications
Marketing Project Manager
Marketing Strategy
Mobile Technology
Negotiation
Network Infrastructure Architecture
Network Sales
Network Security
Networking
New Business Development
Online Advertising
Online Commerce Web Solutions
Online Marketing
Oracle Systems Sales
Pre & Post Sales Support
Pre-sales
Process Improvement
Process Management
Product Lifecycle Management
Product Marketing
Professional & Outsourcing Solutions
Program Management
Project Management
Project Planning
Rational Software

Relationship Management
Renewals
Revenue Forecasting
Routing
Sales
Sales Account
Sales Enablement
Sales Management
Sales Operations
Sales Process
Sales, Business Development
Security
Security & End User Services
Security Brand
Selling
Siebel
Small Business Sales
SMB (Server Message Block)
SOA (Service-Oriented Architecture)
Social Media Marketing
Social Networking & Collaboration
Software Brand /Business Analytics
Software Business development
Software Industry
Software Lead Development
Software Project Management
Software Renewal
Software Sales
Solution Architecture
Solution Development
Solution Sales
Solution Selling
Solutions Marketing
SQL
Stakeholder Management
Storage
Storage Architecture
Storage Solutions
Storage Virtualization
Strategic Alliances
Strategic Leadership
Strategic Partnerships
Strategic Planning

Strategic Sales
System X
Target Account Selling
Team Leadership
Team Management
Technical Support Services Sales
Telecommunications
Telepresence
Territory Sales
Tivoli & Security
Unified Communications
Value Based Selling
Vendor Management
Virtualization
VMware Infrastructure
Wireless Networking

Table 2. Goodness-of-Fit Model Selection for the Univariate ERGM for Expertise Recognition in Latin America

Graph Statistics	Census	Model1	Model2	Model3	Model4	Model5
Arc	178.00	**-0.05**	**-0.05**	**0.08**	**0.02**	**-0.08**
Reciprocity	5.00	2.88	**-0.07**	**0.09**	**-0.02**	**-0.01**
In-2star	272.00	4.85	4.67	0.68	0.74	0.23
Out-2star	158.00	0.37	0.39	0.40	-0.16	-0.60
In-3star	385.00	10.90	10.08	1.54	1.49	0.43
Out-3star	89.00	0.30	0.32	0.35	-0.41	-0.83
Mixed-2-star	191.00	-2.31	-2.16	-1.49	0.16	-0.07
T1	0.00					
T2	0.00					
T3	1.00					
T4	3.00					
T5	1.00					
T6	0.00					
T7	22.00	3.52	0.62	-0.25	0.35	-0.17
T8	12.00	1.65	-0.60	-0.38	-0.10	-0.28
T9(030T)	29.00	10.96	9.23	5.46	7.63	-0.12
T10(030C)	2.00					
Sink	25.00	2.79	2.44	4.08	1.84	1.16
Source	35.00	6.18	6.04	1.11	0.29	0.89
AinS	154.30	2.39	2.32	**0.10**	0.03	**-0.05**
AoutS	121.44	0.39	0.39	0.41	0.02	-0.36
Ain1out-star	128.36	-2.86	-2.68	-1.25	0.21	0.06
1inAout-star	131.13	-2.80	-2.51	-1.84	-0.42	-0.31
AinAout-star	86.27	-3.70	-3.29	-1.68	-0.35	-0.23
AT-T	28.50	10.91	9.14	5.48	7.67	**-0.06**
AT-C	6.00	0.50	0.24	0.28	2.04	0.19
AT-D	24.50	9.06	7.65	4.55	6.41	-0.15
AT-U	28.00	10.67	8.96	5.35	7.49	-0.04
AT-TD	26.50	9.99	8.40	5.03	7.05	-0.10
AT-TU	28.25	10.80	9.06	5.42	7.59	-0.05
AT-DU	26.25	9.87	8.31	4.96	6.96	-0.09
AT-TDU	27.00	10.22	8.59	5.14	7.20	-0.08
A2P-T	186.50	-2.40	-2.25	-1.54	**0.07**	**-0.07**
A2P-D	148.69	0.04	0.06	0.22	-0.41	-0.74
A2P-U	260.50	4.51	4.31	0.52	0.55	0.21
A2P-TD	167.59	-1.61	-1.54	-0.98	-0.17	-0.38
A2P-TU	223.50	0.03	0.01	-0.71	0.40	0.08
A2P-DU	204.59	2.42	2.34	0.41	0.19	-0.18
A2P-TDU	198.56	0.03	0.02	-0.50	0.17	-0.15

Note. Fitted graph statistics are bold. Otherwise, nonfitted graph statistics. Nonexistent or rare graph statistics remain blank.

Table 3. Goodness-of-Fit Model Selection for the Univariate ERGM for Knowledge Seeking in Latin America

Graph Statistics	Census	Model1	Model2	Model3	Model4	Model5	Model6
Arc	176.00	**0.09**	**0.03**	**0.31**	**-0.05**	**0.01**	**-0.09**
Reciprocity	5.00	-0.22	**0.05**	**0.07**	**-0.15**	**-0.13**	**0.00**
In-2star	284.00	5.10	5.05	3.77	0.56	0.59	0.34
Out-2star	149.00	0.42	0.46	-0.45	0.26	-0.12	-0.70
In-3star	451.00	10.54	11.31	5.92	1.68	1.33	0.79
Out-3star	67.00	0.23	0.35	-0.77	0.22	-0.38	-0.96
Mixed-2-star	181.00	-2.19	-2.10	0.68	-1.49	0.12	-0.01
T1	0.00						
T2	0.00						
T3	1.00						
T4	3.00						
T5	1.00						
T6	1.00						
T7	18.00	0.47	0.59	1.59	-0.38	0.13	-0.06
T8	14.00	-0.62	-0.39	-0.07	-0.54	-0.12	-0.32
T9(030T)	26.00	8.88	10.14	11.98	5.48	9.74	0.11
T10(030C)	2.00						
Sink	26.00	2.91	2.49	0.41	4.13	2.03	1.29
Source	34.00	5.58	5.84	3.12	0.93	0.11	0.66
AinS	152.92	2.66	2.52	2.19	**-0.10**	**-0.06**	**-0.10**
AoutS	119.50	0.48	0.48	-0.10	0.26	0.06	-0.43
Ain1out-star	122.89	-2.76	-2.67	-0.29	-1.21	0.27	0.10
1inAout-star	127.19	-2.67	-2.47	-0.09	-1.81	-0.52	-0.38
AinAout-star	84.25	-3.64	-3.30	-1.12	-1.57	-0.36	-0.23
AT-T	25.50	8.84	10.01	11.95	5.46	9.72	**0.11**
AT-C	6.00	0.41	0.41	2.50	0.15	2.42	0.56
AT-D	21.75	7.37	8.36	9.91	4.55	8.16	-0.05
AT-U	26.00	8.69	9.80	11.73	5.34	9.45	0.21
AT-TD	23.63	8.11	9.19	10.93	5.02	8.95	0.08
AT-TU	25.75	8.77	9.91	11.85	5.40	9.60	0.20
AT-DU	23.88	8.03	9.09	10.82	4.95	8.82	0.08
AT-TDU	24.42	8.30	9.40	11.21	5.13	9.13	0.12
A2P-T	178.50	-2.27	-2.18	**0.54**	-1.53	**0.03**	**-0.04**
A2P-D	141.38	0.09	0.12	-0.76	0.08	-0.37	-0.84
A2P-U	275.00	4.73	4.68	3.48	0.39	0.42	0.25
A2P-TD	159.94	-1.48	-1.47	-0.17	-1.05	-0.17	-0.48
A2P-TU	226.75	0.17	0.15	2.54	-0.82	0.30	0.14
A2P-DU	208.19	2.52	2.56	1.55	0.27	0.14	-0.23
A2P-TDU	198.29	0.15	0.15	1.40	-0.63	0.12	-0.18

Note. Fitted graph statistics are bold. Otherwise, nonfitted graph statistics. Nonexistent or rare graph statistics left blank.

Table 4. Goodness-of-Fit Model Selection for the Bivariate ERGM with Expertise Recognition and Knowledge Seeking in Latin America

Graph Statistics	Census	Model1	Model2
ArcA	178.00	0.04	**0.03**
ReciprocityA	5.00	0.56	**0.04**
2-In-StarA	272.00	0.35	0.10
2-Out-StarA	158.00	-0.64	-1.11
3-In-StarA	385.00	0.48	0.08
3-Out-StarA	89.00	-1.04	-1.69
Mixed-2-StarA	191.00	0.29	0.15
030TA	29.00	0.55	-0.07
030CA	2.00	0.73	0.81
SinkA	25.00	1.28	1.49
SourceA	35.00	0.72	1.02
K-In-StarA	154.30	0.04	**0.00**
K-Out-StarA	121.44	-0.35	-0.57
K-L-StarA	86.27	-0.14	-0.22
K-1-StarA	128.36	0.17	0.30
1-L-StarA	131.13	-0.01	-0.46
AKT-TA	28.50	0.63	**0.04**
AKT-CA	6.00	0.75	0.85
AKT-DA	24.50	0.25	-0.19
AKT-UA	28.00	0.57	0.08
A2P-TA	186.50	0.26	**0.12**
A2P-DA	148.69	-0.87	-1.31
A2P-UA	260.50	0.21	0.03
ArcB	176.00	0.03	**0.13**
ReciprocityB	5.00	0.36	**0.12**
2-In-StarB	284.00	0.70	0.39
2-Out-StarB	149.00	-0.78	-1.21
3-In-StarB	451.00	1.33	0.49
3-Out-StarB	67.00	-1.56	-2.09
Mixed-2-StarB	181.00	0.17	0.16
030TB	26.00	0.54	-0.05
030CB	2.00	0.93	0.98
SinkB	26.00	1.47	2.08
SourceB	34.00	0.12	0.45
K-In-StarB	152.92	-0.01	**0.08**
K-Out-StarB	119.50	-0.24	-0.38
K-L-StarB	84.25	-0.06	-0.07
K-1-StarB	122.89	0.17	0.43
1-L-StarB	127.19	-0.03	-0.48
AKT-TB	25.50	0.59	**0.03**

AKT-CB	6.00	0.93	1.02
AKT-DB	21.75	0.24	-0.23
AKT-UB	26.00	0.69	0.20
A2P-TB	178.50	0.19	**0.18**
A2P-DB	141.38	-0.97	-1.38
A2P-UB	275.00	0.61	0.38
ArcAB	156.00	0.07	**0.06**
ReciprocityAB	10.00	0.50	0.09
ReciprocityAAB	9.00	0.42	-0.10
ReciprocityABB	9.00	0.32	-0.05
ReciprocityAABB	3.00		
In2StarAB	522.00	0.12	-0.06
Out2StarAB	312.00	-0.64	-1.11
Mix2StarAB	187.00	0.20	0.17
Mix2StarBA	190.00	0.37	0.27
TABA	28.00	0.59	-0.04
TABB	28.00	0.66	0.07
TBBA	26.00	0.50	-0.16
TBAB	24.00	0.11	-0.41
TAAB	25.00	0.04	-0.43
TBAA	26.00	0.34	-0.28
CAAB	6.00	0.84	0.89
CBBA	6.00	0.92	0.95
TKT-ABA	27.50	0.67	**0.07**
CKT-ABA	6.00	0.86	0.93
DKT-ABA	21.00	-0.26	-0.59
UKT-ABA	25.50	0.43	-0.11
TKT-BAB	24.00	0.67	0.07
CKT-BAB	6.00	0.86	0.93
DKT-BAB	21.75	-0.26	-0.59
UKT-BAB	27.50	0.43	-0.11

Note. Fitted graph statistics are bold. Otherwise, nonfitted graph statistics. Nonexistent or rare graph statistics left blank.

Table 5. Goodness-of-Fit Model Selection for the Univariate ERGM for Expertise Recognition in Latin America

Graph Statistics	Census	Model1	Model2	Model3
Arc	116.00	**-0.07**	**-0.09**	**0.11**
Reciprocity	7.00	6.70	**0.01**	**0.01**
In-2star	97.00	0.94	0.88	0.67
Out-2star	96.00	0.87	0.87	0.69
In-3star	46.00	0.51	0.50	0.21
Out-3star	62.00	1.62	1.50	1.02
Mixed-2-star	169.00	0.23	0.22	0.15
T1	0.00			
T2	0.00			
T3	0.00			
T4	1.00			
T5	1.00			
T6	0.00			
T7	21.00	6.15	0.16	-0.03
T8	16.00	4.46	-0.37	-0.47
T9(030T)	8.00	2.60	2.75	0.01
T10(030C)	2.00			
Sink	14.00	-0.46	-0.11	-0.20
Source	19.00	1.20	1.52	1.36
Isolates	10.00	2.16	1.82	1.21
AinS	76.88	1.02	0.94	0.82
AoutS	71.88	0.53	0.55	0.51
Ain1out-star	111.94	-0.25	-0.28	-0.15
1inAout-star	115.41	-0.05	-0.10	-0.01
AinAout-star	75.52	-0.72	-0.80	-0.50
AT-T	8.00	2.66	2.78	**0.03**
AT-C	6.00	0.88	1.14	0.32
AT-D	8.00	2.66	2.78	0.04
AT-U	8.00	2.65	2.80	0.04
AT-TD	8.00	2.66	2.78	0.03
AT-TU	8.00	2.65	2.79	0.03
AT-DU	8.00	2.65	2.79	0.04
AT-TDU	8.00	2.66	2.79	0.04
A2P-T	167.00	0.20	0.19	0.14
A2P-D	93.50	0.76	0.76	0.61
A2P-U	94.75	0.85	0.79	0.60
A2P-TD	130.25	0.41	0.40	0.30
A2P-TU	130.88	0.44	0.42	0.31
A2P-DU	94.13	0.87	0.83	0.64
A2P-TDU	118.42	0.55	0.52	0.39

Note. Fitted graph statistics are bold. Otherwise, nonfitted graph statistics. Nonexistent or rare graph statistics left blank.

Table 6. Goodness-of-Fit Model Selection for the Univariate ERGM for Information Allocation in Latin America

Graph Statistics	Census	Model1	Model2	Model3
Arc	124.00	**0.07**	**-0.02**	**-0.09**
Reciprocity	13.00	10.37	**0.04**	**-0.03**
In-2star	106.00	0.79	0.73	0.23
Out-2star	113.00	1.09	1.06	0.59
In-3star	50.00	0.30	0.32	-0.23
Out-3star	81.00	1.94	1.86	0.99
Mixed-2-star	179.00	-0.07	-0.18	-0.33
T1	0.00			
T2	0.00			
T3	1.00			
T4	1.00			
T5	2.00			
T6	1.00			
T7	34.00	8.45	-0.26	-0.55
T8	31.00	6.74	-0.52	-0.64
T9(030T)	11.00	3.59	3.26	-0.11
T10(030C)	3.00			
Sink	14.00	-0.11	0.35	0.28
Source	16.00	0.52	0.99	0.74
Isolates	10.00	2.77	1.79	1.47
AinS	83.88	0.90	0.82	0.41
AoutS	82.84	0.78	0.73	0.41
Ain1out-star	119.56	-0.40	-0.52	-0.52
1inAout-star	121.22	-0.34	-0.43	-0.49
AinAout-star	80.10	-0.88	-0.95	-0.83
AT-T	11.00	3.64	3.33	**-0.08**
AT-C	8.50	1.85	1.47	0.06
AT-D	11.00	3.64	3.29	-0.07
AT-U	11.00	3.63	3.30	-0.07
AT-TD	11.00	3.64	3.31	-0.07
AT-TU	11.00	3.64	3.31	-0.08
AT-DU	11.00	3.64	3.30	-0.07
AT-TDU	11.00	3.64	3.31	-0.07
A2P-T	177.00	-0.09	-0.20	-0.34
A2P-D	110.00	0.99	0.95	0.52
A2P-U	103.25	0.69	0.63	0.16
A2P-TD	143.50	0.30	0.19	-0.05
A2P-TU	140.13	0.18	0.09	-0.18
A2P-DU	106.63	0.89	0.84	0.36
A2P-TDU	130.08	0.41	0.32	0.01

Note. Fitted graph statistics are bold. Otherwise, nonfitted graph statistics. Nonexistent or rare graph statistics left blank.

Table 7. Goodness-of-Fit Model Selection for the Bivariate ERGM with Expertise Recognition and Information Allocation in Latin America

Graph Statistics	Census	Model1	Model2	Model3
ArcA	117.00	**0.07**	**0.04**	**-0.09**
ReciprocityA	8.00	**-0.04**	**0.09**	**0.01**
2-In-StarA	99.00	1.02	0.68	0.46
2-Out-StarA	96.00	0.66	0.36	0.41
3-In-StarA	47.00	0.24	0.24	-0.05
3-Out-StarA	62.00	1.08	-0.06	0.49
Mixed-2-StarA	169.00	0.37	0.19	0.14
030TA	10.00	-0.18	0.41	0.06
SinkA	13.00	-1.03	-0.37	-0.38
SourceA	19.00	1.12	1.93	1.13
IsolatesA	10.00	1.70	1.83	1.23
K-In-StarA	78.38	1.33	0.85	0.69
K-Out-StarA	71.88	0.42	0.48	0.31
K-L-StarA	77.02	-0.94	-0.87	-0.65
K-1-StarA	113.44	-0.37	-0.36	-0.18
1-L-StarA	117.41	0.08	-0.14	-0.14
AKT-TA	10.00	**-0.55**	**0.08**	**-0.09**
AKT-CA	6.00	-0.02	0.77	0.42
AKT-DA	8.00	-1.04	-0.26	-0.28
AKT-UA	10.00	-0.47	0.14	-0.08
A2P-TA	169.00	0.33	0.18	0.13
A2P-DA	93.50	0.70	0.42	0.37
A2P-UA	96.75	1.06	0.69	0.42
ArcB	125.00	**0.04**	**0.11**	**-0.06**
ReciprocityB	14.00	**-0.02**	**0.24**	**-0.02**
2-In-StarB	108.00	0.57	0.50	0.23
2-Out-StarB	113.00	0.85	0.61	0.47
3-In-StarB	51.00	-0.17	0.00	-0.31
3-Out-StarB	81.00	1.28	0.19	0.59
Mixed-2-StarB	179.00	-0.31	-0.24	-0.32
030TB	13.00	-0.34	0.31	-0.02
SinkB	13.00	-0.23	-0.05	0.13
SourceB	16.00	0.61	1.33	0.64
IsolatesB	10.00	1.87	1.93	1.23
K-In-StarB	85.38	0.92	0.70	0.48
K-Out-StarB	82.84	0.61	0.69	0.39
K-L-StarB	81.60	-1.32	-1.05	-0.86
K-1-StarB	121.06	-0.77	-0.66	-0.52
1-L-StarB	123.22	-0.64	-0.48	-0.51
AKT-TB	13.00	**-0.59**	**0.09**	**-0.11**

AKT-CB	8.50	-0.23	0.30	0.16
AKT-DB	11.00	-0.92	-0.16	-0.24
AKT-UB	13.00	-0.51	0.13	-0.11
A2P-TB	179.00	-0.32	-0.24	-0.32
A2P-DB	110.00	0.90	0.67	0.42
A2P-UB	105.25	0.57	0.51	0.18
ArcAB	112.00	**0.05**	**0.04**	**-0.08**
ReciprocityAB	22.00	0.22	0.37	**-0.01**
ReciprocityAAB	14.00	-0.04	0.09	0.02
ReciprocityABB	20.00	0.01	0.22	-0.01
ReciprocityAABB	7.00	-0.04	0.09	0.02
In2StarAB	209.00	0.93	0.65	0.41
Out2StarAB	210.00	0.83	0.56	0.49
Mix2StarAB	180.00	0.09	0.01	-0.03
Mix2StarBA	173.00	-0.26	-0.25	-0.22
TABA	10.00	-0.85	0.04	-0.16
TABB	11.00	-0.91	-0.05	-0.24
TBBA	10.00	-1.02	-0.16	-0.26
TBAB	13.00	-0.42	0.15	-0.03
TAAB	9.00	-1.13	-0.31	-0.34
TBAA	12.00	-0.34	0.19	0.00
CAAB	9.00	-0.05	0.67	0.37
CBBA	8.00	-0.08	0.51	0.29
IsolatesAB	10.00	2.39	2.57	1.47
TKT-ABA	10.00	-0.81	**0.09**	**-0.11**
CKT-ABA	7.00	-0.03	0.70	0.40
DKT-ABA	9.00	-1.09	-0.27	-0.27
UKT-ABA	12.00	-0.17	0.31	0.09
TKT-BAB	13.00	-0.81	0.09	-0.11
CKT-BAB	7.50	-0.03	0.70	0.40
DKT-BAB	10.00	-1.09	-0.27	-0.27
UKT-BAB	11.00	-0.17	0.31	0.09

Note. Fitted graph statistics are bold. Otherwise, nonfitted graph statistics.

Table 8. Inter-Item Correlation Matrix

Variable	Mean	S.D.	1	2	3	4	5	6
1.Geographic dispersion	4.17	.72						
2.Electronic dependence	4.26	.60	.21*					
3.Cultural diversity	3.64	.86	.46**	.13				
4.Dynamic structure	3.08	.99	.01	–.04	.24*			
5.Network diversity	.04	.03	.01	.14	–.01	–.07		
6.Network closure	.15	.18	.04	.14	.01	–.10	.74*	
7.Expertise recognition	.14	.15	–.02	.10	–.03	.03	.49***	.43***

* $p < .05$, ** $p < .01$, *** $p < .001$

Table 9. Regression of Expertise Recognition on Virtuality with Network Diversity as a Moderator

Variable	Step 1	Step 2	Step 3	Step 4
Expertise perception	.06	.06	.03	.00
Tenure	–.11	–.12	–.17	–.21
Geographic dispersion		–.02	–.00	–.03
Electronic dependence		.11	.02	.03
Cultural diversity		–.07	–.07	–.04
Dynamic structure		.07	.10	.14
Network diversity			.43***	.49***
Geographic dispersion × Network diversity				–.32*
Electronic dependence × Network diversity				.10
Cultural diversity × Network diversity				–.03
Dynamic structure × Network diversity				–.19†
ΔR^2	.01	.02	.17	.09
ΔF	.63	.37	19.06***	2.79*
Total R^2	.01	.03	.20	.29
F	.63	.45	3.19**	3.20**
D.F.	2, 95	6, 91	7, 90	11, 86

Note. Reported values are standardized regression coefficients.
† $p < .10$, * $p < .05$, ** $p < .01$, *** $p < .001$

Table 10. Regression of Expertise Recognition on Virtuality with Network Closure as a Moderator

Variable	Step 1	Step 2	Step 3	Step 4
Expertise perception	.06	.06	.02	.00
Tenure	–.11	–.12	–.16	–.21
Geographic dispersion		–.02	–.01	–.09
Electronic dependence		.11	.03	.04
Cultural diversity		–.07	–.08	–.05
Dynamic structure		.07	.12	.14
Network closure			.39***	.48**
Geographic dispersion × Network closure				–.41*
Electronic dependence × Network closure				.13
Cultural diversity × Network closure				–.02
Dynamic structure × Network closure				–.22†
ΔR^2	.01	.02	.14***	.10*
ΔF	.63	.37	15.17	2.88
R^2	.01	.03	.17	.27
F	.63	.45	2.61*	2.85**
D.F.	2, 95	6, 91	7, 90	11, 86

Note. Reported values are standardized regression coefficients.
† $p < .10$, * $p < .05$, ** $p < .01$, *** $p < .001$

Table 11. Goodness-of-Fit Results for the Bivariate ERGM with Expertise Recognition and Knowledge Seeking in Latin America

Graph Statistics	Sample Mean	Std. Error	GOF t-ratio
Arc A	177.62	11.63	**0.03**
Reciprocity A	4.95	1.53	**0.04**
2-In-Star A	266.35	56.33	0.10
2-Out-Star A	185.17	24.56	–1.11
3-In-Star A	371.59	171.45	0.08
3-Out-Star A	146.73	34.09	–1.69
Mixed-2-Star A	186.19	31.24	0.15
030TA	29.59	8.52	–0.07
Sink A	21.09	2.62	1.49
Source A	31.43	3.48	1.02
K-In-Star A	154.36	18.17	**–0.00**
K-Out-Star A	129.73	14.48	–0.57
K-L-Star A	88.33	9.48	–0.22
K-1-Star A	123.02	18.02	0.30
1-L-Star A	139.70	18.80	–0.46
AKT-TA	28.21	7.74	**0.04**
AKT-CA	3.31	3.15	0.85
AKT-DA	25.78	6.72	–0.19
AKT-UA	27.44	7.28	0.08
A2P-TA	182.91	29.62	**0.12**
A2P-DA	177.85	22.26	–1.31
A2P-UA	258.69	52.92	0.03
Arc B	174.21	11.19	**0.13**
Reciprocity B	4.81	1.56	**0.12**
2-In-Star B	262.39	55.47	0.39
2-Out-Star B	177.60	23.66	–1.21
3-In-Star B	367.65	170.45	0.49
3-Out-Star B	139.86	34.91	–2.09
Mixed-2-Star B	176.60	28.15	0.16
030T B	26.41	7.64	–0.05
Sink B	21.19	2.32	2.08
Source B	32.39	3.57	0.45
K-In-Star B	151.50	17.89	**0.08**
K-Out-Star B	124.99	14.33	–0.38
K-L-Star B	84.83	8.69	–0.07
K-1-Star B	115.63	16.78	0.43
1-L-Star B	135.36	16.90	–0.48
AKT-TB	25.32	6.99	**0.03**
AKT-CB	3.04	2.91	1.02
AKT-DB	23.13	6.12	–0.23
AKT-UB	24.71	6.65	0.20
A2P-TB	173.66	26.67	**0.18**
A2P-DB	170.96	21.39	–1.38

A2P-UB	255.44	52.07	0.38
Arc AB	155.34	10.60	**0.06**
Reciprocity AB	9.75	2.91	0.09
Reciprocity AAB	9.29	2.99	–0.10
Reciprocity ABB	9.15	3.05	–0.05
In-2-Star AB	528.32	110.07	–0.06
Out-2-Star AB	362.27	45.42	–1.11
Mix-2-Star AB	182.28	27.32	0.17
Mix-2-Star BA	181.74	30.36	0.27
TABA	28.32	7.88	–0.04
TABB	27.45	7.61	0.07
TBBA	27.25	7.82	–0.16
TBAB	27.25	7.92	–0.41
TAAB	28.45	8.02	–0.43
TBAA	28.29	8.32	–0.28
CAAB	3.32	3.03	0.89
CBBA	3.22	2.93	0.95
TKT-ABA	26.99	7.14	**0.07**
CKT-ABA	3.25	2.95	0.93
DKT-ABA	24.73	6.37	–0.59
UKT-ABA	26.25	7.18	–0.11
TKT-BAB	23.49	7.14	0.07
CKT-BAB	3.25	2.95	0.93
DKT-BAB	25.48	6.37	–0.59
UKT-BAB	28.25	7.18	–0.11

Note. Fitted graph statistics are bold. Otherwise, nonfitted graph statistics.

Table 12. Goodness-of-Fit Results for the Bivariate ERGM with Expertise Recognition and Information Allocation in Latin America

Graph Statistics	Sample Mean	Std. Error	GOF t-ratio
Arc A	117.88	10.19	–**0.09**
Reciprocity A	7.96	2.89	**0.01**
2-In-Star A	91.18	17.17	0.46
2-Out-Star A	88.10	19.50	0.41
3-In-Star A	47.94	19.86	–0.05
3-Out-Star A	49.13	26.34	0.50
Mixed-2-Star A	164.67	30.97	0.14
030TA	9.72	4.85	0.06
Sink A	13.96	2.52	–0.38
Source A	15.90	2.75	1.13
Isolates A	6.32	3.00	1.23
K-In-Star A	71.14	10.54	0.69
K-Out-Star A	68.31	11.52	0.31
K-L-Star A	83.73	10.30	–0.65
K-1-Star A	116.65	17.75	–0.18
1-L-Star A	119.94	17.81	–0.14
AKT-TA	10.42	4.50	**–0.09**
AKT-CA	4.19	4.32	0.42
AKT-DA	9.21	4.35	–0.28
AKT-UA	10.36	4.35	–0.08
A2P-TA	164.99	30.59	0.13
A2P-DA	86.41	19.02	0.37
A2P-UA	89.70	16.67	0.42
Arc B	125.73	11.56	–**0.06**
Reciprocity B	14.11	4.66	**–0.02**
2-In-Star B	103.50	19.79	0.23
2-Out-Star B	102.50	22.61	0.47
3-In-Star B	58.21	23.51	–0.31
3-Out-Star B	63.07	30.67	0.59
Mixed-2-Star B	191.21	28.10	–0.32
030T B	13.09	6.40	–0.02
Sink B	12.67	2.55	0.13
Source B	14.19	2.84	0.64
Isolates B	6.30	3.02	1.23
K-In-Star B	79.55	12.07	0.48
K-Out-Star B	77.62	13.40	0.39
K-L-Star B	91.39	11.40	–0.86
K-1-Star B	131.99	20.93	–0.52
1-L-Star B	133.69	20.64	–0.51
AKT-TB	13.66	5.82	**–0.11**
AKT-CB	7.54	5.86	0.16
AKT-DB	12.38	5.71	–0.24
AKT-UB	13.60	5.74	–0.11

A2P-TB	190.96	37.45	–0.32
A2P-DB	100.66	22.15	0.42
A2P-UB	101.81	19.30	0.18
Arc AB	112.80	9.84	**–0.08**
Reciprocity AB	22.09	7.36	**–0.01**
Reciprocity AAB	13.91	5.79	0.02
Reciprocity ABB	20.05	7.20	–0.01
Reciprocity AABB	6.95	2.90	0.02
In-2-Star AB	194.24	35.94	0.41
Out-2-Star AB	190.02	40.72	0.49
Mix-2-Star AB	180.95	34.38	–0.03
Mix-2-Star BA	180.50	33.85	–0.22
TABA	10.77	4.91	–0.16
TABB	12.36	5.66	–0.24
TBBA	11.40	5.38	–0.26
TBAB	13.16	5.80	–0.03
TAAB	10.89	5.50	–0.34
TBAA	11.99	5.18	0.00
CAAB	7.30	4.62	0.37
CBBA	6.47	5.23	0.29
Isolates AB	5.71	2.92	1.47
TKT-ABA	10.49	4.56	**–0.11**
CKT-ABA	5.22	4.50	0.40
DKT-ABA	10.33	4.94	–0.27
UKT-ABA	11.60	4.66	–0.09
TKT-BAB	13.49	4.56	–0.11
CKT-BAB	5.72	4.50	0.40
DKT-BAB	11.33	4.94	–0.27
UKT-BAB	10.60	4.66	0.09

Note. Fitted graph statistics are bold. Otherwise, nonfitted graph statistics.

Table 13. Bivariate ERGM for Expertise Recognition and Knowledge Seeking

Graph Statistics	Est.(S.E.)	t-ratio
Arc A	–6.13(0.44)*	–0.03
Reciprocity A	0.46(1.07)	–0.09
In-k-Star A	–0.23(0.24)	–0.03
AkT-TA	1.15(0.63)	0.09
A2P-TA	–0.19(0.09)	–0.10
Arc B	–6.27(0.43)*	0.00
Reciprocity B	0.96(1.09)	–0.10
In-k-Star B	0.38(0.23)	–0.00
AkT-TB	0.49(0.43)	–0.09
A2P-TB	–0.20(0.09)	–0.11
Arc AB	7.98(0.33)*	–0.03
TKT-ABA	–0.00(0.80)	–0.09

Note. t-ratio indicates t-ratios for convergence. Network A is expertise recognition and network B is knowledge seeking.
* $p < .05$

Table 14. Bivariate ERGM for Expertise Recognition and Information Allocation

Graph Statistics	Est.(S.E.)	t-ratio
Arc A	–7.50(0.52)*	–0.05
Reciprocity A	–7.44(1.48)*	–0.03
AkT-TA	1.18(1.11)	–0.02
Arc B	–7.08(0.42)*	–0.06
Reciprocity B	–1.48(1.18)	–0.02
AkT-TB	0.83(0.42)	–0.01
Arc AB	10.16(0.69)*	–0.06
TKT-ABA	–1.19(1.22)	–0.02
Reciprocity AB	5.61(1.18)*	–0.02

Note. t-ratio indicates t-ratios for convergence. Network A is expertise recognition and network B is information allocation.
* $p < .05$

Figures

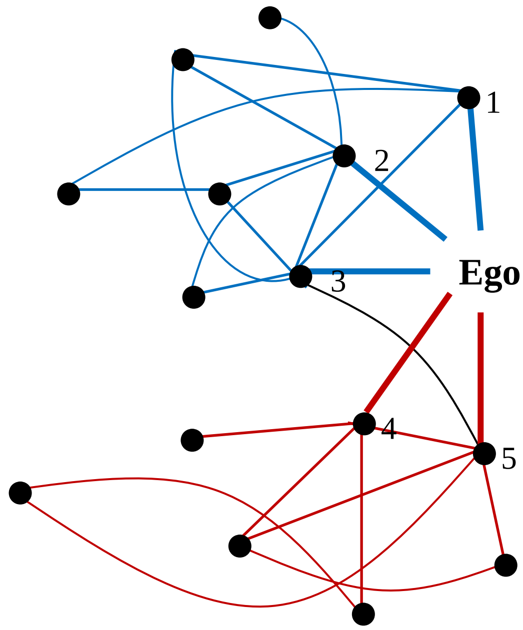

Figure 1. A Cohesive but Redundant Communication Network That Includes Two Clusters (Burt, 1992)

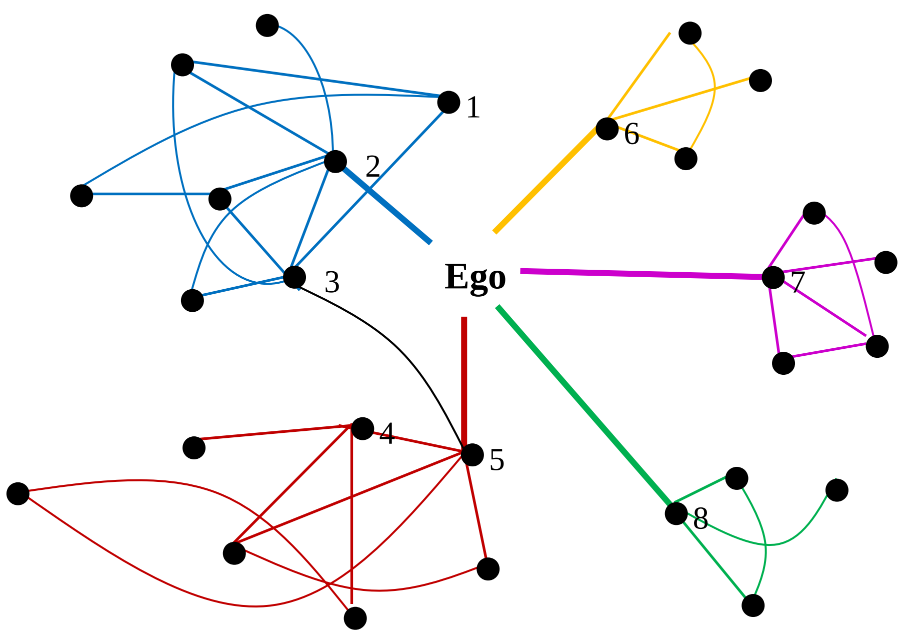

Figure 2. A Less Redundant Communication Network That Includes Two Cohesive Clusters and Multiple Structural Holes (Burt, 1992)

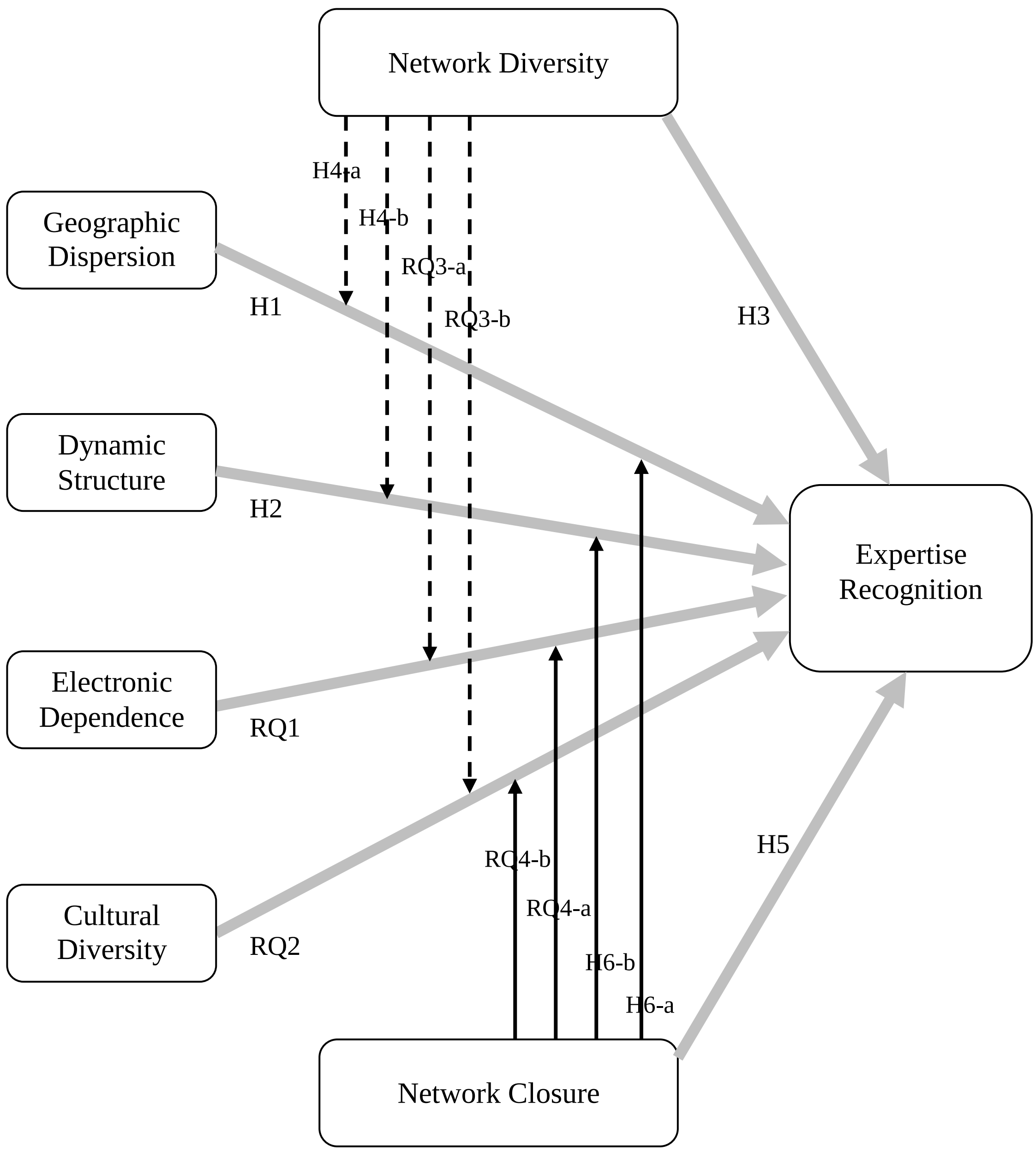

Figure 3. The Moderating Effect of Network Diversity and Network Closure on the Relationship between Virtuality and Expertise Recognition

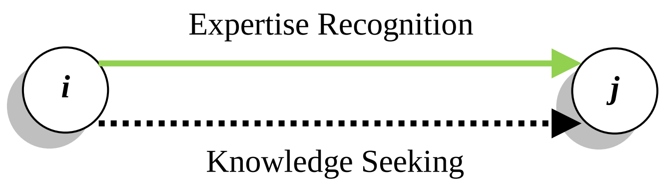

Figure 4. Multiplex Link (Arc AB)

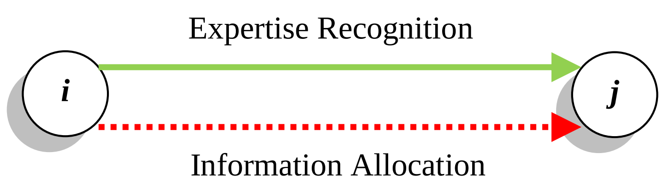

Figure 5. Multiplex Link (Arc AB)

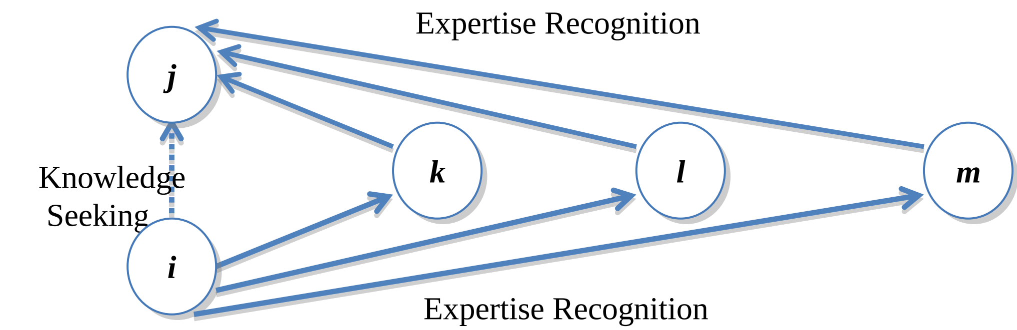

Figure 6. Alternating Bivariate Transitivity of Expertise-Recognition and Knowledge-Seeking Ties

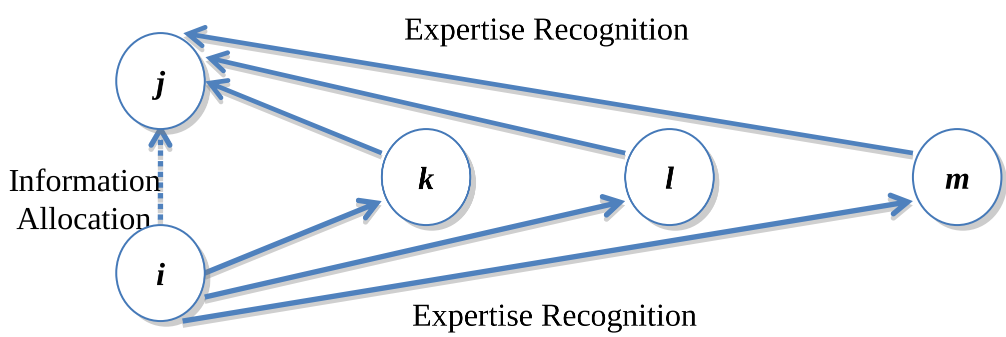

Figure 7. Alternating Bivariate Transitivity of Expertise-Recognition and Information-Allocation Ties

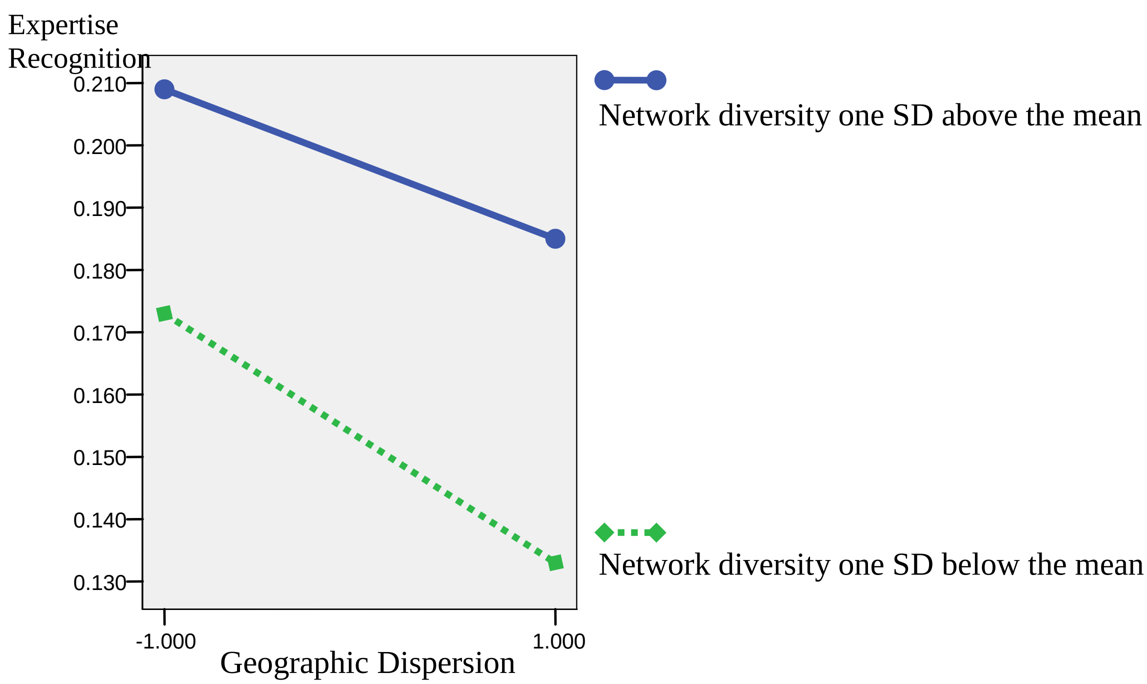

Figure 8. Moderating Effect of Network Diversity on the Relationship between Geographic Dispersion and Expertise Recognition

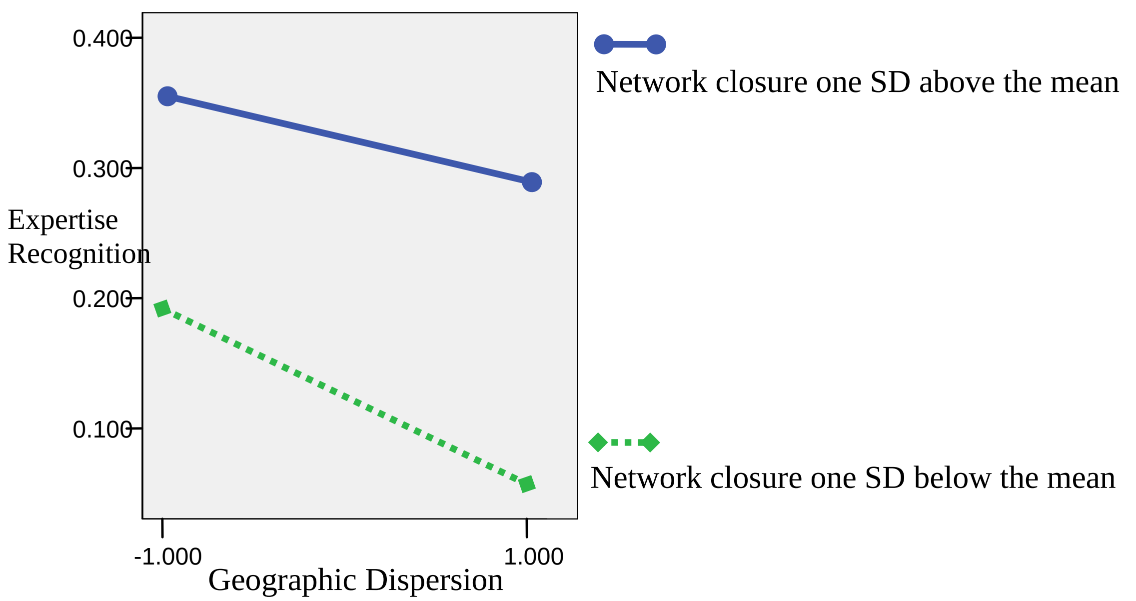

Figure 9. Moderating Effect of Network Closure on the Relationship between Geographic Dispersion and Expertise Recognition

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