The Impact of Awareness and Accessibility on Expertise Retrieval: A Multilevel Network Perspective

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Building on the major premises of transactive memory (TM) theory as well as the recent multilevel extension to the original theory, this study examined the influence of perceived social accessibility of expertise providers, technological accessibility, and awareness of expertise distribution on expertise retrieval. Using social network data collected from a large global sales team, the study found that all three variables had significant impact on expertise retrieval at both the dyadic and individual levels. Our study confirmed the conceptual and theoretical value of approaching TM from a multilevel network perspective.

To stay competitive in a knowledge economy, knowledge workers must be able to quickly access and retrieve needed expertise (Argote, 1999). Scholars across multiple disciplines (Kanawattanachai & Yoo, 2007; Lewis, Lange, & Gillis, 2005; Majchrzak, Jarvenpaa, & Hollingshead, 2007; Moreland & Argote, 2003; Zhang, Hempel, Han, & Tjosvold, 2007) have found Wegner’s (1987, 1995) theory of transactive memory (TM) a useful framework within which to study how individuals retrieve expertise. According to TM, the major barrier to retrieving expertise is a lack of awareness of “who knows what.” If members are aware of where the expertise lies, they can retrieve it. Across a range of tasks, laboratory studies have shown that teams with well-developed TM systems outperform teams without such systems and that better expertise retrieval and work coordination were observed in teams having higher awareness of each other’s expertise (e.g., Hollingshead, 1998a; Liang, Moreland, & Argote, 1995; Moreland, 1999).

However, the simple proposition that equates awareness of expertise with access to expertise has been challenged by recent field studies (Casciaro & Lobo, 2008; Faraj & Sproull, 2000). For instance, Faraj and Sproull (2000) demonstrated that team performance was a function of access to expertise rather than the mere presence of expertise in the team, indicating that awareness of expertise by itself may not adequately explain performance. Yuan, Fulk, Monge, and Contractor (in press) found that awareness of “who knows what” needs to be supported by strong relationships to obtain actual access to expertise. Existing knowledge management research also has found that employees experiencing a knowledge-sharing dilemma (Cabrera & Cabrera, 2002) may be unwilling to share their expertise with people with whom they do not share common characteristics (Argote & Ingram, 2000) or positive affective relations (Casciaro & Lobo, 2008; Szulanski, 1996). Findings such as these suggest that accessibility may be an important factor contributing to effective expertise retrieval.

The primary objective of the present study therefore is to expand the research focus of TM theory by examining whether expertise retrieval is impacted by a combination of awareness of expertise distribution, source accessibility, and technological accessibility. This issue is addressed using both a social network and a multilevel perspective for the following reasons. First, taking a network perspective allows us to study TM at a dyadic level where the actual expertise-retrieval activities take place. TM is usually defined as a collective expertise directory (Wegner, 1987, 1995). Increasingly, this directory is conceptualized as a cognitive social network of expertise. Even at group meetings when multiple members seek expertise from one single expert, the basic unit of analysis is still at a dyadic level. It simply means that multiple dyadic expertise-retrieval activities have happened simultaneously.

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distributed expertise (Monge & Contractor, 2003). Such a conceptualization calls for the use of social network analysis method to better capture microlevel differences in expertise retrieval relationships as well as source accessibility and technological accessibility. For example, Team Member A may be socially accessible to Team Member B, but not to Team Member C. In addition, Team Member B may use face-to-face interaction, e-mail, and telephone calls to communicate with Team Member A, but use e-mail only when communicating with Team Member C. Thus, Team Member B may find Team Member A both socially and technologically more accessible than does Team Member C. Such a network perspective can capture differences in these dyadic interactions that traditional individual-level or group-level data cannot.

Second, we take a multilevel perspective to address the nested nature of social interactions. As Brass (2008) recently noted, dyadic relationships are nested within individuals such that individual differences (e.g., Team Member B’s choice of communication when interacting with Team Member A versus Team Member C) may cast contextual influence on dyadic interaction (e.g., Team Member A or C’s choice of communication media when interacting with Team Member B). A multilevel approach that considers both individual- and dyadic-level characteristics can tease out the influence of individual difference from specific dyadic interactions.

In summary, although previous research has supported our argument that awareness of expertise distribution and accessibility may each relate to expertise retrieval (Borgatti & Cross, 2003), to our knowledge, no study has approached these issues from both network and multilevel perspectives simultaneously. We argue that approaching the issue from network and multilevel perspectives provides both conceptual and methodological contributions to the field.

The article is organized as follows. In the next section, we provide a review of related literature, propose a multilevel model of dyadic expertise retrieval, and identify specific hypotheses. We then describe an empirical test of the proposed hypotheses using hierarchical linear modeling (HLM) techniques. Individual- and dyadic-level perceptions and exchange data were collected in the field from a global sales team. The article concludes with a discussion of results and their theoretical and practical implications.

Theoretical Background

Awareness of Expertise Distribution: A Multilevel Revision

Wegner (1987) defined group TM as “a set of individual memory systems in combination with the communication that takes place between individuals” (p. 186). He stated that in work groups, people usually use a lot of external memory devices such as notepads, books, computer disks, souvenirs, or other artifacts to help them remember things. But most important, they use people—fellow group members—as external memory devices. Group members, being specialized knowledge depositories for group knowledge, can actively engage in transactive encoding, storage, and retrieval of information for specialized knowledge. Through social interactions, these individual memory devices are brought together to form a group memory system. The system is transactive in the sense that group cognitive activities are distributed among group members, yet connected through collaborative efforts. As long as team members know (a) how a piece of knowledge is referred to and, more important, (b) who has the needed knowledge, they can retrieve expertise from one another as needed instead of acquiring all needed expertise by themselves (Wegner, 1987, 1995). A well-developed TM system thus promises higher team effectiveness through pooling distributed expertise. Therefore, the central theme of TM theory is to develop and increase awareness of expertise distribution to facilitate expertise retrieval among team members.

While the theory has informed studies on such diverse topics as turnover, training, and coordination, confusion remains about whether TM should be approached as a collective-level construct only or whether it also could be treated as an emergent collective concept that still has its roots in microlevel dynamics (Larson & Christensen, 1993). Originally, TM was defined as a collective concept describing group cognition (Moreland, 1999; Wegner, 1987). Yet, as noted by Simon (1991) and Larson and Christensen (1993), among others, group cognition should not be perceived in isolation from individual cognitions because a group relies upon its individual members to create, share, and retain knowledge. That is, a group is both a collective and a collection of interacting individuals.

Following this logic, Yuan (2009) and colleagues (Yuan et al., 2009; Yuan, Monge, & Fulk, 2005) proposed approaching TM from a multilevel perspective. More specifically, they argued that collective awareness of expertise distribution also has a counterpart in individual-level awareness of expertise distribution. They considered the addition of individual-level awareness of expertise distribution a crucial extension to TM theory because collective awareness of expertise distribution, which measures how much a team as a whole is aware of its members’ expertise, does not necessarily grow automatically with the growth of individual-level awareness, which measures an individual team member’s knowledge of his or her team members’ expertise. When team members choose to hoard their individual knowledge of who knows what, as has been observed in studies on knowledge-sharing dilemma (Cabrera & Cabrera, 2002), the collective TM system can remain underdeveloped despite the growth of individual-level awareness of expertise distribution. Using HLM techniques, Yuan et al. (2009) demonstrated that both individual and collective levels of awareness of expertise distribution had a positive influence on individual expertise retrieval such that individuals who had a better knowledge of “who knows what” engaged in more expertise exchange and that teams with well-developed TM systems also reported higher average expertise exchanges among team members.

Given the nested nature of social interactions, we believe that it is important to study TM from a multilevel perspective to avoid the problems of ecological fallacy or the fallacy...
of hasty generalization. Both are common mistakes in logical reasoning when people erroneously use observations made at one level of analysis to make predictions about relationships at a different level of analysis. Ecological fallacy happens when collective-level observations are used to infer individual-level behavior. Hasty generalization happens when insufficient individual-level observations are generalized to the collective level. In addition to these fallacies, failure to specify the level of analysis has caused confusion in TM research about how the concept should be measured (Yuan, 2009). Some studies (e.g., Liang et al., 1995) have inferred the existence of a collective TM from aggregating individual-level data, and others (Hollingshead, 1998b; Wegner, 1987) did not measure TM directly at all. A multilevel perspective offers a clear alignment of TM theory and measurement to avoid this confusion.

Despite advances made by taking a multilevel perspective on TM (Yuan et al., 2005), previous research has not considered the impact of dyadic levels of awareness which captures “who knows whose expertise” on expertise retrieval. If awareness of expertise distribution is only considered at the individual level, differences in specific dyadic relationships are ignored. Such differences can have a huge impact on expertise retrieval. For example, if Person A is aware of the knowledge held by Person B, and Person C is aware of the knowledge held by Person D, both Persons A and B have the same individual-level of awareness (which equals 1). However, if Person B has more expertise to distribute to Person A than does Person D to Person C, Person A will retrieve much more information than will Person C as a result of differences in dyadic levels of awareness, despite the same number used to measure individual-level awareness. Therefore, in addition to individual-level awareness, dyadic awareness also should be considered when examining expertise retrieval. Furthermore, dyadic awareness is directional in that Person A's awareness of Person B’s expertise does not implicate Person B’s awareness of Person A's expertise. Such asymmetry in awareness again calls for the adoption of social network analysis theories and method to study transactive memory.

Dyadic-level awareness focuses on expertise awareness between pairs of people; however, expertise retrieval also may be influenced by a person's individual-level general awareness of how expertise is distributed within the group. While one specific expertise-retrieval activity involves only two people (hence, the importance of dyadic relationships), individual-level awareness may exert an additional contextual influence that affects multiple relationships (Klein, Tosi, & Cannella, 1999). Individuals who have a greater general awareness of expertise distribution may be more likely to retrieve expertise from their team members because with a better sense of which team member to approach for expertise, they may feel more confident in raising the right questions to the right experts and at the right time. They also may retrieve expertise from multiple sources when there are multiple experts in the same expertise domain, which may in turn trigger additional rounds of expertise seeking when different sources provide different information. Such iterative expertise seeking is unlikely to be characteristic of a team member who is aware of fewer experts. Therefore, in addition to dyadic-level expertise awareness, it is important to consider the individual’s general level of awareness. While the dyadic level focuses on expertise awareness between pairs of people, the individual level focuses on how many team members’ expertise an individual is aware of. More formally, we propose that:

**H1:** Dyadic expertise awareness is positively related to dyadic expertise retrieval.

**H2:** Individual expertise awareness is positively related to dyadic expertise retrieval.

**Social Accessibility**

As discussed earlier, TM theory emphasizes the importance of knowing “who knows what” for expertise retrieval. Because the theory focuses mainly on developing better TM systems through fostering higher levels of specialization in different expertise domains, the underlying assumption is that people will prefer to retrieve expertise from high-quality sources. Yet, early information-seeking research has found that people rank accessibility as one of the most important factors influencing their choice of information sources (Culnan, 1984, 1985; O’Reilly, 1982). Coworkers seem to be preferred sources of information, relative to documents or other external sources, because they are perceived as more accessible (Hertzm & Pejtersen, 2000; Leckie, Pettigrew, & Sylvain, 1996; Moreland & Levine, 2001), even when better quality information is known to exist elsewhere (Carlson & Davis, 1998; O’Reilly, 1982). More recently, Cross and Sproull (2004) found that a source’s willingness to cognitively engage (i.e., be socially accessible) was positively related to receipt of actionable information. These findings have suggested that accessibility is a key predictor of expertise retrieval in addition to expertise awareness. Given the existence of empirical evidence that supports the importance of both awareness of expertise distribution (the focus of TM theory) and source accessibility for expertise retrieval, we think it is important to explore how the two factors may interact to influence expertise retrieval.

Perceived social accessibility of experts is crucial for successful expertise retrieval. As noted by Kim and Mauborgne (1997), expertise is a special type of resource that cannot be forced out of people. Further, it may be difficult to know exactly how much expertise a person holds (or withholds) because expertise is invisible to expertise seekers. Given these intrinsic characteristics of expertise, perceiving someone to be socially accessible may be crucial for gaining full access to their expertise. A few studies have demonstrated the importance of social relationships in determining perceived source accessibility and, in turn, expertise retrieval. For example, Borgatti and Cross (2003) found that relational accessibility of an information source had significant impact on retrieving information. Yuan et al. (2009)
also found that the strength of communication ties, which support social accessibility, was directly related to expertise exchange.

However, these studies suffer from the same shortcoming because they consider accessibility at either the dyadic or individual level and fail to fully explore the multilevel nature of expertise retrieval activities. Specifically, in Borgatti and Cross’s (2003) study, the research focus was on dyadic-level information seeking, and there was no discussion about how individual-level characteristics can influence the information-seeking process. In contrast, Yuan et al.’s (2009) study aggregated dyadic-level expertise exchange activities to the individual level and used individuals as the lowest level of analysis. However, as discussed earlier, aggregation across dyadic ties provides a more coarse-grained analysis and makes it difficult to study variations across dyad ties nested within one individual. To address limitations in the earlier studies, it is therefore proposed that:

H3: Dyadic accessibility is positively related to dyadic expertise retrieval.

H4: Individual accessibility is positively related to dyadic expertise retrieval.

In addition, an interaction effect is proposed because it is anticipated that the expertise retrieval will be more successful between two persons in a dyad who not only know about each other’s expertise but also are socially accessible to each other. Hence, it is hypothesized that:

H5: Dyadic expertise awareness positively interacts with dyadic accessibility to influence dyadic expertise retrieval.

Technological Accessibility: The Impact of Media Multiplexity

When distributed team work becomes more common in contemporary organizations, social accessibility needs to be supported by technological accessibility (Alavi & Tiwana, 2002; Straub & Karahanna, 1998). Otherwise, the expertise of a socially accessible expert may still fail to be successfully retrieved. Technological accessibility focuses on the technical affordances of communication technologies to support communication and social interactions. Extensive research has been conducted investigating how communication technology is used in organizations to support communication and information exchange (Carlson & Davis, 1998; Dennis, Fuller, & Valacich, 2008; Dennis, Wixom, & Vandenberg, 2001; Straus & McGrath, 1994), particularly among distributed employees (Rice, 1992).

Early research on technology use can be classified into two camps: those based on trait theories of technology and those based on theories of social influence. Studies based on trait theories of technology focus on explaining technology use through examining the technical features of different technologies. Representative theories include media richness theory (Daft & Lengel, 1986; Mollica, Gray, & Trevino, 2003) and social presence theory (Short, Williams, & Christie, 1976). Trait theories describe how particular traits of a given communication technology influence the preference for one medium over another to accomplish certain tasks. E-mail messages, for instance, are considered inappropriate for the completion of complicated tasks because text-based messages are incapable of conveying rich nonverbal cues, which is best expressed in face-to-face communications. The social influence camp, in contrast, argues that the use and adoption of information and communication technology is not dependent on the features of the technology alone (Kraut, Rice, Cool, & Fish, 1998; Markus, 1994). Instead, socially constructed norms also can influence the adoption and usage of a communication technology (Contractor & Eisenberg, 1990; Fulk, Steinfield, & Schmitz, 1990). As a result, it is argued that e-mail can be used to convey rich emotions and strong social connections.

Recent studies on the use of communication technology in organizations have demonstrated two trends. First, research on this topic has moved beyond the debate between the two camps about the relative importance of technical features or social norms in determining how a technology is used. More recent theories and research have embraced both perspectives (DeSanctis & Poole, 1994; Walther, 1996; Webster & Trevino, 1995). The current perspective holds that technologies provide basic affordances which are augmented by the creative ways in which people use them, making the fit between a task and a particular communication technology less relevant for task performance (Fuller & Dennis, 2009).

Second, while earlier trait theories have focused on selecting a particular medium to fulfill a communication need, new studies have paid more attention to how multiple media can be used in combination to support communication needs. For instance, Haythornthwaite and Wellman (1998) found that pairs engaged in intense work relationships and closer friendships tended to use more kinds of media to communicate than did pairs that were not so engaged. They noted that frequent communicators seldom relied on one single medium to satisfy their communication needs. Watson-Manheim and Belanger (2007) also observed that in contemporary organizations, employees often work on multiple groups simultaneously, and each group may favor a different communication technology. As a result, they tend to rely upon a range of communication technologies or, media multiplexity, to meet their communication needs for accomplishing a task. We argue that technological accessibility can be fruitfully explored via media multiplexity.

Existing research on the usage of communication technology in organizations has provided ample suggestions about how different communication technologies can be used in combination to serve the communication needs for completing a task (Haythornthwaite & Wellman, 1998; Stephens, 2007; Stephens, Sornes, Rice, Browning, & Saetre, 2008). For instance, certain expertise is difficult to share because it is tacit and hard to articulate (Hansen, 1999; Polanyi, 1967; Uzzi, 1996). Face-to-face communication may therefore provide better access to this type of expertise because it allows the
expertise seeker to learn through observations, even when the expertise provider encounters difficulties in verbalizing his or her thoughts. In contrast, when expertise can be easily codified, sharing expertise through documents or e-mail may improve both accuracy and efficiency in expertise sharing. Other aspects of technology suggest that media multiplexity facilitates greater flexibility in fulfilling communication needs. Asynchronous communication technology, for example, allows expertise holders and retrievers to carry out their tasks at their own pace (Kalman, Monge, Fulk, & Heino, 2002). As long as expertise holders have communicated or shared their information at any time prior to the request for that expertise, for example, through e-mail or a common electronic expertise repository (e.g., intranet), it will be available on demand to expertise seekers. Some communication technologies such as e-mail or podcasts also allow expertise holders to satisfy multiple expertise-seeking requests by a single post, which can greatly improve communication efficiency.

Given these findings, it is reasonable to assume that media multiplexity will improve expertise retrieval because expertise seekers can reap the benefits of each communication medium by using the different media in an integrated fashion to obtain different types of expertise from different experts to accomplish a task. While the importance of media multiplexity for expertise retrieval may be greater among team members who are distributed across multiple locations, co-located team members also may find communication technology crucial for expertise seeking. E-mail, for example, is commonly used by both co-located and distributed workers to facilitate work collaboration (Haythornthwaite & Wellman, 1998).

Like social accessibility, we anticipate that the impact of technological accessibility, as supported by media multiplexity, can be partitioned into both dyadic- and individual-level effects. Within a dyad, the larger the number of different communication technologies used for communication, the greater flexibility in gaining access to the other person and the higher likelihood of success of expertise retrieval. Furthermore, an individual’s overall level of competence and familiarity with using multiple media for communication may make it easier for them to select the media technology that is most suited for the (a) type of expertise being retrieved and/or (b) preferences of the specific individual from whom expertise is desired to increase the likelihood of success in dyadic expertise retrieval. Hence, it is proposed:

H6: Dyadic media multiplexity is positively related to dyadic expertise retrieval.

H7: Individual media multiplexity is positively related to dyadic expertise retrieval.

Finally, since media multiplexity provides technical support for communication, it is proposed that expertise retrieval will be more frequent between members of a dyad when the expertise seeker not only knows about the provider’s expertise but also has the technical flexibility to successfully retrieve the expertise from the provider. Similarly, it is anticipated that members of a dyad will retrieve expertise more frequently when the expertise seeker not only feels that the provider is socially accessible but also has the technical flexibility to successfully communicate with the expertise provider. Hence, two interaction effects are proposed:

H8a: Dyadic media multiplexity positively interacts with dyadic expertise awareness to increase dyadic expertise retrieval.

H8b: Dyadic media multiplexity positively interacts with dyadic accessibility to increase dyadic expertise retrieval.

Method

Sample

Data were collected from a global sales team within Pinnacle (a pseudonym), a large, multinational information technology product and service company. The team was composed of 43 people who came from different divisions within the company representing sales and specialized technical and service-delivery functions. Team members were geographically distributed to provide local support for the customer’s global operations. The sales team provided a set of integrated products and services to a large, international financial services customer. The ability to exchange information across the brands, divisions, and geographies and to build and maintain coordinated and shared understandings of information and group activities was critical for the overall success for the team and the enterprise. Although individuals were assigned to formal roles and responsibilities, in practice, there was a lot of dependence on informal communication for coordination. Communication among members of the team was mostly about the customer, e.g., updates in requirements, coordinating and discussing the details of a particular sale.

Team members had access to a variety of communication tools including e-mail, telephone, conference calls, and instant messaging (chat). Since team members worked in different offices and were frequently away from the office visiting the customer, it was important for them to have access to a variety of tools for communication.

The data collection was part of a larger internal initiative to improve collaboration and knowledge sharing in global sales teams. The team in this study was selected on the basis of its similarity to other teams with regard to its diverse composition, revenue model, structure of its sales coverage model, and its dependence on effective collaboration for performance. Data were collected via a Web-based survey. All team members were asked to complete the survey during their workday to obtain the highest possible response rate. Questionnaires were completed by 31 members, for a 71% response rate. Altogether, the final sample contains 31 individuals which, when multiplied by the number of members they evaluated (n = 43), generates a total of 1,290 dyadic ties for the final analysis. In addition, participants also were encouraged to add names of their expertise sources from outside the team. As a result, the datasets used for analysis included 1,559 dyadic ties nested within 31 individuals.
Measurements

Following the convention of social network studies (Scott, 1991/2004; Wasserman & Faust, 1994), we used one network question to measure each of the study variables. Although the team we studied was large in size, which is typical of teams in big organizations handling complicated tasks (Majchrzak, Malhotra, Stamps, & Lipnack, 2004), we did not observe any fragmentation of the team into smaller cliques. As depicted in Figure 1, team members were well connected overall in their expertise retrieval network. The size of a node reflects the level of awareness that a member has of his or her team member’s expertise, with large size corresponding to higher awareness. The width of a line depicts frequency of expertise retrieval.

The primary dependent variable, individual expertise retrieval, was measured by asking respondents to report on a scale of 1 (very infrequently) to 4 (very frequently) how frequently each of their team members had provided information or advice that the respondent would need to do his or her job.

Awareness of expertise distribution was measured by asking respondents to self-report the extent to which he or she agreed with the statement that he or she was aware of each of his or her team members’ knowledge and skills. The responses were on a scale of 1 (strongly disagree) to 4 (strongly agree). Each data point in the awareness matrix was used to measure dyadic expertise awareness. Individual expertise awareness was set as equal to the mean of the dyadic responses provided by each person.

Social accessibility was measured by asking respondents to rate the extent to which each of their team members was accessible to solve his or her problems within a reasonable time frame. The responses were on a scale of 1 (very infrequently) to 4 (very frequently). Each data point in the awareness matrix was used to measure dyadic accessibility. The mean of the dyadic responses provided by each person was used to measure individual accessibility.

Media multiplexity was derived from media-usage matrices. Media usage was captured by asking respondents to indicate (0 = no, 1 = yes) if they had used the following communication media to communicate at least once a week with each of their team members: face-to-face interactions,
instant messaging, e-mail, one-to-one telephone calls, and conference calls. These responses were put into five binary matrices such that a cell value of 1 in each matrix indicated that a member (row) had used that medium at least once a week to communicate with a specific member (column). Following Haythornthwaite and Wellman (1998), media multiplexity was measured by summing these matrices to create a single matrix with cell values ranging from 0 (no communication media usage once a week) to 5 (all communication medium used). The summed responses were used to measure dyadic media multiplexity. The row mean of the summed media-usage matrix was used to measure individual media multiplexity.

In addition to the primary variables of interest, two control variables also were included in the modeling: proximity and tenure. A long line of research has established that expertise retrieval is more likely when employees are geographically close to each other (Rice & Aydin, 1991; Rice, Collins-Jarvis, & Zydney-Walker, 1999). Proximity was measured at the dyadic level only. Respondents were asked to use a 3-point scale (1 = same building, 2 = different buildings in the same area, and 3 = different countries) to report the physical proximity of each of their interactive partner. It also was expected that people who had been on the project longer might be perceived as knowing more than would newer members and therefore may have better awareness of expertise distribution (Wegner, 1987). To control for this, a second variable, tenure, was included in all analyses. Respondents were asked to use a 3-point scale (1 = <6 months, 2 = 6 months–2 years, and 3 = >2 years) to report how long they had been working on the project team.

Descriptive statistics and zero-order correlations of research and control variables are reported in Table 1. The Level-1 dyadic-level correlation coefficients are reported in the lower triangle of the table. They were calculated based on the whole sample, using data that had been centered by individual means to control for clustering/interdependence of the data. Correlations among Level-2 individual-level variables are reported in the upper triangle of the table. Tenure was measured at the individual level only; therefore, there was no dyadic-level counterpart. Proximity was measured at the dyadic level only; there was no individual-level counterpart.

**Analysis**

The hypotheses were tested using HLM, as dyadic relationships were clustered by each individual person; therefore, HLM analysis was needed to obtain unbiased estimates of standard errors for hypothesis testing that could not be obtained using ordinary least squares hierarchical regression (Raudenbush & Bryk, 2002). Whereas two popular network-analysis procedures, QAP (Krackhardt, 1987) and p* analyses (e.g., Monge & Contractor, 2003) also can correct for interdependence in observations, the HLM procedure does not require researchers to fill missing values in the network matrices with either zeros or other numbers that are more prone to researchers’ subjective judgment. In other words, using HLM, we did not need to generate a 43 × 43 matrix from the data we had to conduct the analysis, as would have been required had the other two software packages been used.

Essentially, HLM analysis takes a two-step procedure in which the intercepts and slopes of Level-1 predictors (in this case, the dyadic relationships that a focal respondent has) are first estimated for each Level-2 unit and then used as outcome variables for Level-2 predictors (i.e., each individual person). In this research, an intercepts-as-outcomes model was conducted (Raudenbush & Bryk, 2002, pp. 80–85) because Hypotheses 2, 4, and 7 aimed to study whether these Level-2 characteristics about individual team members would influence their mean dyadic expertise retrieval from each expertise provider. Instead of entering all the research variables in the model at the same time, the analysis was conducted in steps to evaluate the unique contribution of each set of variables. This procedure also allows us to calculate differences in deviance scores between nested models to evaluate improvement in fit between two nested models. Differences in deviance scores between a pair of nested models follow a $\chi^2$ distribution, and can be used to conduct likelihood ratio tests to evaluate significant improvement in model fit (Raudenbush & Bryk, 2002; Snijders & Bosker, 1999), analogous to an evaluation of changes in $R^2$ in regression analysis.

**Table 1.** Descriptive statistics and zero-order correlations.

<table>
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<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>M</th>
<th>SD</th>
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<tbody>
<tr>
<td>1. Proximity</td>
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<td>2.629</td>
<td>1.220</td>
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<td>2. Tenure</td>
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<td></td>
<td>2.515</td>
<td>1.174</td>
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<td>3. Expertise retrieval</td>
<td>−0.313*</td>
<td></td>
<td></td>
<td>0.612*</td>
<td>0.733*</td>
<td>0.399*</td>
<td>2.477</td>
<td>0.587</td>
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<td>4. Awareness</td>
<td>−0.241*</td>
<td>0.537*</td>
<td></td>
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<td>3.361</td>
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<td>5. Accessibility</td>
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<td>0.640*</td>
<td>0.606*</td>
<td></td>
<td>0.408*</td>
<td>2.928</td>
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<td>6. Media multiplexity</td>
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<td>0.430*</td>
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<tr>
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The lower triangle of the table reports the zero-order correlation and descriptive statistics of individual-level variables. The upper triangle reports the zero-order correlation and descriptive statistics of dyadic-level variables.

* Significant at the 0.05 level (two-tailed).
Following Raudenbush and Bryk’s (2002) suggestion, both variables were “group-mean centered” by centering Level-1/dyadic-level variables around the mean of each individual person. Theoretically, this centering procedure is preferred when the focus is on generating reliable estimates of Level-1/dyadic-level coefficients, independent of the clustering effect of Level-2/individual-level variables (Hofmann & Gavin, 1998). Moreover, according to Enders and Tofighi (2007), this mean-centering method is the only appropriate way to examine interaction effects between a pair of Level-1 variables. Therefore, given that our models contained both Level-1 variables and their Level-2 counterparts as well as interaction terms between two Level-1 variables, all of the Level-1 variables—including the control and research variables—were centered prior to running the HLM models. Also following Enders and Tofighi’s recommendation, Level-2 variables were all grand-mean centered prior to analysis (p. 121). Following the convention of HLM analysis, only unstandardized regression coefficients are reported.

Results

Initial intraclass correlation analysis yielded high coefficients, which supported the use of HLM. Following the recommendation by Raudenbush and Bryk (2002), a hierarchical null model with no predictors, which is equivalent to a random effects ANOVA test, was conducted to decompose the variance of Level-1 variables (p. 136). Therefore, given that our models contained both Level-1 variables and their Level-2 counterparts as well as interaction terms between two Level-1 variables, all of the Level-1 variables—including the control and research variables—were centered prior to running the HLM models. Also following Enders and Tofighi’s recommendation, Level-2 variables were all grand-mean centered prior to analysis (p. 121). Following the convention of HLM analysis, only unstandardized regression coefficients are reported.

The results provided evidence of significant between-subject variance in individual expertise exchange, \( r_0 = 0.218, df = 29, \chi^2 = 115.038, p < 0.01. \) An intraclass correlation (ICC), which measures the amount of variance in the outcome variable that can be accounted for by between-subject differences, was calculated using the following formula:

\[
ICC = \frac{r_{00}}{(r_{00} + \sigma^2)}
\]

where \( r_{00} \) measures the variance of \( \pi_{ij} \), and the \( \sigma^2 \) measures the variance of Level-1 residuals, \( e_{ij} \). The ICC = 0.218/(0.218 + 1.194) = 0.154 indicated that 15.4% of the total variance in dyadic expertise retrieval could be explained by between-individual differences, showing a moderate clustering effect of the data and therefore the need for using HLM data-analysis techniques.

The coefficient for the fixed effect (\( \beta_{00} \)) in this null model was 2.504, representing the grand mean of dyadic expertise retrieval across individuals (range = 1–4). The deviance score (-2 log likelihood) of this model was 1706.143, which was used as a baseline to evaluate significance in model improvement. The Model fit results for the null model effects are summarized under Model 1 in Table 2.

In the second step of hypothesis testing, expertise retrieval was regressed on the two control variables, proximity at the dyadic level (Level 1) and tenure at the individual level (Level 2) in Model 2. The results showed a significant negative relationship between proximity and expertise retrieval, \( \pi_{\text{proximity}} = -0.362, t = -7.380, p < 0.05, \) indicating that people were more likely to retrieve expertise from individuals who were physically close. The impact of tenure on dyadic expertise retrieval also was significant, \( \beta_{\text{tenure}} = -0.362, t = -3.194, p < 0.05, \) indicating that senior members were less likely to retrieve expertise from others. The Level-1 residual variance \( e_{it} \), which measures within-subject unexplained variance in the outcome variable, dropped from 1.194 for the null model to 1.028, meaning that the two control variables explained 13.903% variance in the outcome variable. The deviance score (-2 log likelihood) of this model was 1506.411. A comparison of the deviance scores of Models 1 and 2, \( \chi^2(3) = 1706.144 - 1506.411 = 199.733, p < 0.05, \) indicates that the improvement in model fit was significant. Model fit results are reported under Model 2 in Table 2. Proximity and tenure were included as control variables in all remaining analyses.

H1 and H2 proposed that both dyadic and individual awareness would positively influence expertise retrieval. Both hypotheses were fully supported. Dyadic and individual awareness were included in Model 3 at Levels 1 and 2, respectively, and both were found to have significant impact on dyadic expertise retrieval. At Level 1, \( \pi_{\text{dyadic awareness}} = 1.007, t = 15.135, p < 0.05. \) At Level 2, \( \beta_{\text{individual awareness}} = 0.525, t = 5.987, p < 0.05. \) The Level-1 residual variance \( e_{it} \) dropped from 1.042 for the control-only model to 0.701, meaning that awareness at both levels explained an additional 28.559% of the variance in the outcome variable. Comparing the deviance scores of Models 2 and 3, \( \chi^2(4) = 1506.411 - 1270.719 = 235.692, p < 0.05, \) indicates that the improvement in model fit was significant. Model fit results are reported under Model 3 in Table 2. They suggest that individuals tend to retrieve expertise from individuals of whom they have a greater awareness of their expertise; and individuals who have higher levels of awareness of expertise distribution are more likely to successfully retrieve expertise. The multilevel model identifies these as distinct effects.

H3 and H4 proposed that both dyadic and individual social accessibility would positively influence expertise retrieval. Again, both hypotheses received full support. Both dyadic, \( \pi_{\text{dyadic accessibility}} = 0.667, t = 10.972, p < 0.05, \) and individual social accessibility, \( \beta_{\text{individual accessibility}} = 0.419, t = 2.226, p < 0.05. \) had a significant impact on expertise retrieval. It seems that individuals tend to retrieve expertise from individuals they perceived as socially accessible. In addition, individuals who tended to perceive others as social...
As shown in Model 5 in Table 3, results fully supported H5, the interaction effect between dyadic awareness and dyadic social accessibility also was significant, $\beta_{\text{Individual Accessibility} \times \text{Individual Awareness}} = 0.181, t = 3.164, p < 0.05$. This means that when dyadic awareness and dyadic social accessibility were both high, the combination increased expertise retrieval more than either one individually did. As Table 3 shows, the Level-1 residual variance, $e_{1i}$, dropped from 0.701 for Model 3 to 0.433, meaning that perceived social accessibility at both levels explained an additional 22.446% of the variance in the outcome variable. A comparison of the deviance scores of Models 3 and 4, $\chi^2(7) = 1270.719 - 1027.986 = 242.733, p < 0.05$, indicates a significant improvement in model fit. The multilevel method identifies all of these as significant effects that are distinct from the effects of expertise awareness. Model fit results are reported under Model 4 in Table 2.

H6 and H7 proposed that both dyadic and individual media multiplexity would positively influence expertise retrieval. As shown in Model 5 in Table 3, results fully supported both H6, $\pi_{\text{dyadic multiplexity}} = 0.138, t = 3.373, p < 0.05$, and H7, $\beta_{\text{Individual multiplexity}} = 0.165, t = 2.638, p < 0.05$. Individuals tend to retrieve expertise from those individuals with whom they use multiple media, and individuals who tend to use multiple media are more likely to successfully retrieve expertise.

H8a and H8b proposed that dyadic media multiplexity would interact with dyadic awareness and dyadic social accessibility to influence expertise retrieval. As can be seen in Model 5 (Table 3), neither hypothesis was supported, with $\pi_{\text{Awareness} \times \text{Multiplexity}} = -0.007, t = -0.057, p > 0.05$, rejecting H8a, and $\pi_{\text{Accessibility} \times \text{Multiplexity}} = -0.013, t = -0.480, p > 0.05$, rejecting H8b. The impact of high dyadic awareness and social accessibility on expertise retrieval did not become stronger when media multiplexity was high.

As seen in Table 2, Model 5 was a significant improvement over Model 4. The two media multiplexity variables and the two interaction variables were included in Model 5, in addition to those variables in Model 4. The Level-1 residual variance $e_{1i}$ of Model 5 dropped from 0.443 for Model 4 to 0.335, meaning that the Level-1 and Level-2 multiplexity variables explained an additional 9.045% of the variance in the outcome variable. A comparison of the deviance scores of Models 4 and 5, $\chi^2(6) = 1027.986 - 948.283 = 79.703, p < 0.05$, indicates that the improvement in model fit was significant.

Random slope analysis of Model 5 showed significant variance in the slope of the impact of dyadic expertise awareness on expertise retrieval across Level-2 unit (individual persons). Follow-up analysis found that individual expertise awareness had a significant positive impact on this slope, meaning that for those individuals who had high awareness of expertise distribution in the team, the dyadic-level relationship between expertise awareness and retrieval became stronger. The complete results of Model 5 are reported in Table 3.

**Discussion**

Successful expertise retrieval is crucial for job performance in a knowledge economy. While TM theory has provided some insightful propositions about how developing awareness of expertise distribution facilitates expertise retrieval among team members, more work is needed to study under what situations such awareness can combine with access to expertise to result in actual retrieval. Few TM studies have explicitly examined accessibility. Implied in its exclusion is the assumption that accessibility to expertise will happen automatically as long as people know who has the needed expertise. However, the sparse research on accessibility and awareness (Borgatti & Cross, 2003; Yuan et al., 2009) has reinforced the need for further studies that...
will evaluate access as an independent factor in expertise retrieval. Studies of this nature also can help address one of the central challenges in organizational knowledge management: how to overcome the knowledge-sharing dilemma (Cabrera & Cabrera, 2002) and to actualize expertise sharing within organizations.

In this research, we explored how accessibility, both social and technological, would interact with awareness of expertise distribution to influence expertise retrieval. Our study extends earlier research on awareness and accessibility by examining the effects of awareness and accessibility on expertise retrieval at both individual and dyadic levels within the same model. We believe that taking such a multilevel approach to segment effects at different levels has important implications when studying the impact of awareness and accessibility on expertise retrieval. Failure to segment effects at different levels of analysis may result in erroneous conclusions. Ecological fallacy may happen when people assume that a team member with a generally high level of awareness of expertise distribution knows the expertise differentials within each pair of team members engaged in expertise exchange. In contrast, hasty generalization can happen when an individual team member’s high awareness of expertise distribution between two parties in a dyadic exchange will be used to evidence his or her overall awareness of expertise distribution across the whole team.

We found that individual and dyadic levels of expertise awareness, perceived social accessibility, and media multiplexity influenced expertise retrieval. This means that expertise retrieval is more likely to happen within a dyad when (a) Member A knows Member B’s expertise (H1), (b) Member A perceives Member B as socially accessible (H3), and (c) Member A can reach Member B via multiple communication media (H6). Above and beyond dyadic-level dynamics, successful expertise retrieval is more likely to happen to those individual team members who (d) have a high awareness of expertise distribution of the whole team (H2), (e) have a larger pool of accessible experts in their social network (H4), and (f) are reachable via diverse media (H7). In addition, dyadic-level expertise awareness and perceived social accessibility demonstrated a significant interaction effect on expertise retrieval (H5), highlighting the importance of incorporating social accessibility in TM theory when studying expertise retrieval. Contrary to prediction, dyadic-level media multiplexity did not interact with either dyadic-level expertise awareness or dyadic-level perceived social accessibility. Specific implications of these findings will be discussed in the remainder of this section.

### TABLE 3. Results for Model 5: The full model.

<table>
<thead>
<tr>
<th>Fixed effect</th>
<th>Coefficient</th>
<th>SE</th>
<th>t</th>
<th>p</th>
</tr>
</thead>
<tbody>
<tr>
<td>Random intercept as outcome model, π₀</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Base, β₀₀</td>
<td>2.577</td>
<td>0.077</td>
<td>33.560</td>
<td>0.000</td>
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<td>Tenure, β₀₁</td>
<td>−0.122</td>
<td>0.071</td>
<td>−1.721</td>
<td>0.097</td>
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<td>Individual awareness, β₀₂</td>
<td>0.284*</td>
<td>0.134</td>
<td>2.115</td>
<td>0.044</td>
</tr>
<tr>
<td>Individual accessibility, β₀₃</td>
<td>0.375*</td>
<td>0.133</td>
<td>2.809</td>
<td>0.010</td>
</tr>
<tr>
<td>Individual media multiplexity, β₀₄</td>
<td>0.165*</td>
<td>0.062</td>
<td>2.638</td>
<td>0.015</td>
</tr>
<tr>
<td>Dyadic proximity → retrieval slope, π₁</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Base, β₁₀</td>
<td>0.019</td>
<td>0.033</td>
<td>0.588</td>
<td>0.561</td>
</tr>
<tr>
<td>Dyadic awareness slope, π₂</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Base, β₂₀</td>
<td>0.491*</td>
<td>0.076</td>
<td>6.443</td>
<td>0.000</td>
</tr>
<tr>
<td>Individual awareness β₂₁</td>
<td>0.562*</td>
<td>0.106</td>
<td>5.324</td>
<td>0.000</td>
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<td>Dyadic accessibility slope, π₃</td>
<td></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Base, β₃₀</td>
<td>0.491*</td>
<td>0.076</td>
<td>6.443</td>
<td>0.000</td>
</tr>
<tr>
<td>Dyadic media multiplexity, π₄</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Base, β₄₀</td>
<td>0.138*</td>
<td>0.041</td>
<td>3.373</td>
<td>0.002</td>
</tr>
<tr>
<td>Dyadic awareness × Dyadic accessibility, π₅</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Base, β₅₀</td>
<td>0.183*</td>
<td>0.057</td>
<td>3.198</td>
<td>0.004</td>
</tr>
<tr>
<td>Dyadic awareness × Dyadic media multiplexity, π₆</td>
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</tr>
<tr>
<td>Base, β₆₀</td>
<td>−0.002</td>
<td>0.037</td>
<td>−0.057</td>
<td>0.956</td>
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<td>Dyadic accessibility × Dyadic media multiplexity, π₇</td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Base, β₇₀</td>
<td>−0.013</td>
<td>0.026</td>
<td>−0.480</td>
<td>0.536</td>
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</table>

<table>
<thead>
<tr>
<th>Random effect</th>
<th>Variance component</th>
<th>df</th>
<th>χ²</th>
<th>p</th>
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</thead>
<tbody>
<tr>
<td>Intercept, r₀</td>
<td>0.161</td>
<td>9</td>
<td>48.889</td>
<td>0.000</td>
</tr>
<tr>
<td>Dyadic proximity slope, r₁</td>
<td>0.078*</td>
<td>13</td>
<td>24.658</td>
<td>0.025</td>
</tr>
<tr>
<td>Dyadic awareness slope, r₂</td>
<td>0.189*</td>
<td>12</td>
<td>23.754</td>
<td>0.022</td>
</tr>
<tr>
<td>Dyadic accessibility slope, r₃</td>
<td>0.248</td>
<td>13</td>
<td>10.716</td>
<td>&gt;0.500</td>
</tr>
<tr>
<td>Dyadic media multiplexity slope, r₄</td>
<td>0.176</td>
<td>13</td>
<td>14.926</td>
<td>0.312</td>
</tr>
<tr>
<td>Dyadic awareness × accessibility slope, r₅</td>
<td>0.113</td>
<td>13</td>
<td>16.024</td>
<td>0.247</td>
</tr>
<tr>
<td>Dyadic awareness × Dyadic media multiplexity, r₆</td>
<td>0.094</td>
<td>13</td>
<td>13.860</td>
<td>0.384</td>
</tr>
<tr>
<td>Dyadic accessibility × Dyadic media multiplexity, r₇</td>
<td>0.080</td>
<td>13</td>
<td>11.125</td>
<td>&gt;0.500</td>
</tr>
<tr>
<td>Level-1 effect, e</td>
<td>0.335</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

*Significant at the 0.05 level (two-tailed).
Awareness of Expertise Distribution

Our study supported a significant relationship between awareness of expertise distribution and expertise retrieval. Our multilevel model identified unique contributions of both individual-level awareness and dyadic-level awareness on dyadic expertise retrieval. As predicted by TM theory and suggested by recent research on the impact of social relationships on knowledge transfer (Argote, McEvily, & Reagans, 2003; Borgatti & Cross, 2003; Cross & Sproull, 2004), dyadic-level awareness of a specific person’s expertise was significantly related to a higher likelihood of expertise retrieval from that person. Similarly, individuals who have high general levels of awareness of expertise distribution also tended to retrieve more expertise than did other individuals. These findings confirm the need to sharpen the definition of awareness of expertise distribution to clarify whether the awareness is held by an individual or by the pair of people engaged in expertise retrieval.

Brandon and Hollingshead (2004), in their new conceptual model of TM theory, proposed that a consensus across the whole team about who are the experts may enhance the effectiveness of the system. Implied in the consensus proposition is that each individual should develop high awareness of expertise distribution of the whole team as a starting point for the team to reach a common agreement. When a group is large in size, however, developing such a consensus can be very challenging and time consuming. The question then becomes: Is it worthwhile to ask each individual team member to develop awareness of expertise distribution across the whole team when their expertise exchange is mainly confined to a few dyads? While few empirical studies have explicitly tested the consensus proposition (Austin, 2003), results from our multilevel analysis clearly demonstrate the benefits of developing expertise awareness at both the dyadic and individual levels. Each level made significant, independent contributions to the dyadic expertise exchange even when they were simultaneously included in the regression analysis. While Brandon and Hollingshead’s conceptual model mainly focuses on the collective properties of TM, the results from our study showed the importance of contextual influence of individual-level concepts on dyadic-level dynamics, where the actual expertise retrieval takes place. Future multilevel development of TM theory should integrate these existing collective-level propositions and examine how collective properties of TM exert contextual influence on both the individual- and dyadic-level development of awareness of expertise distribution and expertise retrieval.

Social Accessibility

Similarly, our multilevel model identified unique contributions of both individual-level and dyadic-level social accessibility on dyadic expertise retrieval, in addition to the influence of awareness of expertise distribution. Actualizing accessibility is central to diffusing knowledge-sharing dilemmas (Cabrera & Cabrera, 2002). Consistent with findings from earlier studies (e.g., Carlson & Davis, 1998), we found that perceiving someone to be socially accessible made expertise retrieval from that person more likely. Similarly, individuals who generally tended to perceive people as socially accessible also were more likely to successfully retrieve expertise than were other individuals. These findings suggest a reevaluation of one of TM theory’s implicit assumptions that awareness alone is sufficient for information retrieval.

As described earlier, the original TM theory is mute on the issue of social accessibility. Implied in this silence is the assumption that individuals are always willing and able to respond to expertise retrieval requests. To date, both the original theory and subsequent TM theory development (Brandon & Hollingshead, 2004; Yuan, 2009; Yuan et al., 2005) have focused almost exclusively on the issue of increasing awareness, based on the assumption that awareness of expertise distribution is the largest barrier to expertise retrieval. However, as demonstrated in our study, awareness of expertise distribution is not the only factor influencing success in expertise retrieval. Perceived social accessibility of experts also had significant influence on expertise retrieval at both the dyadic and individual levels. Further, the finding of a significant interaction effect between dyadic awareness and social accessibility suggests that a comprehensive TM theory needs to question the assumption of cooperatively motivated experts. While parsimony is an important standard with which to evaluate the elegance of a theory, the purpose of theory development is to understand more precisely the conditions under which the theory holds. Our study underscores the importance of considering the role of social accessibility in expertise retrieval.

Technological Accessibility as Supported by Media Multiplexity

In addition to social accessibility, we also evaluated the influence of technological accessibility on expertise retrieval. Instead of approaching technology use from the perspective of either the trait theories or the social influence models, and focusing on the use of one particular technology at a time, this study examined how different technologies can be used in combination to serve team members’ communication needs. Our approach is more consistent with the reality facing most employees of contemporary organizations who typically have multiple choices about the different means of communication. As a result, they also have the opportunity to use different technologies in an integrated fashion to meet their communication needs.

Building on Haythornthwaite and Wellman’s (1998) work on communication technology, we argued that media multiplexity indicated technological accessibility since the more media someone uses, the more likely he or she is to communicate with the expert in the expert’s preferred medium. Greater technical flexibility broadens the range of available information-seeking (and expertise-retrieving) tools. On both
the individual and dyadic levels, media multiplexity predicted dyadic expertise retrieval such that greater multiplexity was associated with greater retrieval. The introduction of media multiplexity to this exploration of expertise retrieval revives discussion on the importance of communication technology on information exchange.

Counter to our predictions, we failed to find an interaction effect between dyadic media multiplexity and either dyadic awareness of expertise or dyadic perceived social accessibility of source. Controlling for the impact of awareness of expertise distribution and social accessibility, media multiplexity had a significant main effect on expertise retrieval, and the strength of this main effect remained stable regardless of levels of awareness of expertise distribution and social accessibility. This suggests that media multiplexity did not amplify the positive effects of awareness and social accessibility on expertise retrieval.

It is possible that in the sales team that we studied, the expertise shared among team members was more explicit or codified and therefore could be retrieved with any one of the communication media tested (Hansen, 1999; Polanyi, 1967). Consequently, there may have been a ceiling effect of the amount of additional benefit team members could obtain from using multiple media. Perhaps an amplifying effect is found only when the expertise shared is tacit and the success of retrieving such expertise really depends more on the magnitude of combinatory use of multiple media than it does on the level of flexibility in choosing any one medium to finish the expertise retrieval task. A more conclusive answer, however, can be reached only in future research by collecting more fine-grained data about the types of expertise being shared.

**Theoretical and Practical Implications**

Our multilevel model has important theoretical implications. Research based on the original TM theory has generally taken a collective, group-level approach to exploring factors relating to expertise retrieval. The interplay of levels has been ignored, creating confusions over concepts as well as making it difficult to integrate work on TM. Theoretically, focusing solely on the collective level ignores the fact that individual awareness of expertise distribution does not automatically translate into collective awareness when individual team members choose not to contribute their individual knowledge to the collective (Yuan et al., 2009; Yuan et al., 2005). Similarly, focusing just on the individual ignores the influence of variations at the dyadic level on expertise retrieval (cf. Borgatti & Cross, 2003).

To address these limitations of the original TM theory, Yuan et al. (2005; Yuan 2009; Yuan et al. 2009) proposed to root a group-level TM system in an individual level of analysis and to approach TM from a multilevel perspective. While this multilevel extension has opened up some new possibilities, their empirical testing of the multilevel extension mainly focused on individual and group levels of analysis, in negligence of the dyadic level in which actual expertise retrieval occurs. In this study, we demonstrated that dyadic-level interactive dynamics need to be included when investigating how awareness of expertise distribution influences expertise retrieval. Our study confirms the value of approaching TM from a multilevel perspective both conceptually and theoretically. It also paves the way for three-level theorization and empirical investigation on TM propositions that include propositions about cognitive activities at dyadic, individual, and group levels of analysis.

Our research also has practical implications. Our study was conducted in the context of one work group. Individuals in large, distributed organizations may face greater challenges to awareness and access. For this reason, companies have often invested in expertise-locator tools that can be used to search for people on the basis of knowledge or skills (Terence & McDonald, 2005). Yet, information science research has found that the implementation of such information systems does not necessarily deliver effective knowledge management because most of these tools represent the skills held by individuals, but do not also provide information that suggests their social accessibility (Alavi, Kayworth, & Leidner, 2006; Blair, 2002). Recently, a new class of expertise-locator tools have been introduced that includes information about each person’s social network in addition to their expertise to provide seekers with more and better information with which to make judgments about a potential target’s accessibility (Ehrlich, Lin, & Griffiths-Fisher, 2007; Lin, Griffiths-Fisher, Ehrlich, & Desforges, 2008). Our results further confirm the need to develop tools that go beyond simple profile information to recommend people based on both expertise and social accessibility (Kautz, Selman, & Shah, 1997; McDonald & Ackerman, 2000).

**Limitations and Directions for Future Research**

Our study has several limitations, each of which suggests a direction for future research. First, due to the time-intensive nature of social network data collection, we were unable to unpack the full complexity of some constructs. Accessibility, for example, may have as many as four different dimensions (Woudstra & van den Hooff, 2008), including availability, approachability, efficiency, and cognitive effort. In our study, we mainly focused on social and technological accessibility. When feasible, future research should try to measure all these dimensions of accessibility. Second, our hypothesis testing relied upon cross-sectional data, reducing our ability to make causal statements. For example, it may be that successful retrieval of expertise leads those who received the information to perceive those who gave the information as socially accessible. The difficulty of collecting longitudinal data has long been a concern in network research. Future research should investigate the questions we have raised in this study using panel data. Third, the current research did not test a three-level TM system, which may be more appropriate for studying the impact of awareness of expertise distribution on expertise retrieval. However, the size of the team from which we collected the network data was relatively large for
a work group which makes it difficult to find comparable groups to test a three-level TM model. As found repeatedly in small-group research (Arrow, McGrath, & Berdahl, 2000; Poole & Hollingshead, 2005), group size can have a major impact on group dynamics. Social network research also has emphasized the importance of comparing networks of similar sizes (Scott, 1991/2004) because many network measures (e.g., density) tend to be higher for smaller networks than they are for larger ones. Therefore, to empirically explore a TM system from three levels of analysis, future research should strive to collect data from multiple groups that are comparable in size.

Conclusion

The present research explored factors that may influence the success of expertise retrieval. Our primary objective was to expand the TM theory by proposing a novel model of expertise retrieval that considered the interplay between awareness of expertise distribution, social accessibility, and technological accessibility as supported by media multiplexity. Our study confirmed the value of approaching TM from a multilevel network perspective, both conceptually and theoretically. It also extended existing multilevel work on TM to a dyadic level of analysis, paving the road for three-level theorization and empirical investigation on TM propositions. On a practical level, our study also pointed to the importance of creating tools that provide not only a greater awareness of the expertise held by others but that also convey information that can help form judgments about a person’s accessibility.

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