Communication Research
37(1) 20–47

DOI: 10.1177/0093650209351469
http://crx.sagepub.com
SAGE

Expertise Directory Development, Shared Task Interdependence, and Strength of Communication Network Ties as Multilevel Predictors of Expertise Exchange in Transactive Memory Work Groups

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Abstract

Building on Kozlwoski and Klein's emergence framework, this research developed and tested a set of multilevel hypotheses regarding individual and team transactive memory processes in work teams. Literature from social psychology suggested hypotheses on how shared task interdependence influences individual expertise exchange. Social network theory suggested hypotheses that individual expertise exchange is channeled according to communication tie strength. Using data collected from 218 individuals from 18 organizational teams, the proposed hypotheses were tested using hierarchical linear modeling techniques. The results showed that at the individual level the relationship between directory development and expertise exchange was mediated by communication tie strength and moderated by shared task interdependence. Team-level variables also were significantly related to individual-level outcomes such that individual expertise exchange happened more frequently in teams with well-developed team-level expertise directories, as well as with higher team communication tie strength and shared task interdependence.

Keywords

communication tie strength, transactive memory, task interdependence

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Managing organizational knowledge is a challenging task in part because knowledge and expertise, unlike many other organizational resources, are distributed in multiple places, including people, tasks, and tools, as well as in the connections between them (Argote & Ophir, 2002). The burgeoning research interest in studying how teams and organizations pool these distributed resources together has brought about fundamental changes in how we conceptualize team and organizational cognition. One major change is recognition of the importance of communication for team and organizational learning (Weick & Ashford, 2000). Communication provides not only conduits for expertise exchange but also mechanisms to generate, transfer, and retain knowledge (Hollingshead, 1998; Wegner, 1987).

Transactive memory theory has become an important foundation for understanding the role of communication in information sharing. A transactive memory system is "a group information-processing system" (Wegner, 1987, p. 191) made up of the memory systems possessed by individuals as well as the communication processes linking these individual memory systems together. The theory offers propositions to support two key issues: (1) how teams develop and sustain mechanisms for communication and expertise sharing among their members, and (2) how teams develop and assess individual members' expertise in relevant knowledge domains. The theory has been extended to include organizational knowledge systems as well as those at the team level (Anand, Manz, & Glick, 1998). Brandon and Hollingshead (2004) also offered an important extension by articulating in greater detail the theoretical mechanisms underlying the actual processes by which teams achieve well-developed transactive memory systems over time.

The research reported here follows in the tradition of recent work that has developed the theory extensively beyond its initial roots in dyadic interpersonal contexts. We explicate three contributions to transactive memory-related processes: (1) connections between individual and collective level cognitions, (2) shared task interdependence, and (3) social network properties. The original theory (Wegner, 1995) implies connections between individual and collective cognition by arguing that the development of shared transactive memory systems at the collective level relies on individual-level processes involving individuals' actions to (a) update their directories of who knows what, (b) allocate information to other team members, and (c) retrieve information from other team members. Collective-level cognitions have been studied extensively in transactive memory research, but much less is known about the connections between individual and collective cognition in regard to how the three individual-level actions (directory updating, information allocation, information retrieval) produce results at the collective level. This creates confusion in the research community in that some studies examine transactive memory at the individual level, whereas others do this at the collective level. We employ the emergence framework of Kozlwoski and Klein (2000) as a theoretical mechanism to explicate the nature of cross-level transactive processes. The framework has provided a valuable explanation for cross-level processes in a variety of theoretical realms (e.g., Burton-Jones & Gallivan, 2007; Meade & Eby, 2007; Seibert, 2001).

Task interdependence has been described as a prerequisite for transactive memory systems because it implicates cognitive interdependence across team members (Hollingshead, 2001). Task interdependence has been defined in a variety of quite different ways in the organizational management literature (Wageman, 1995). In this research, we examined interdependence that arises from working together on a specific task, focusing in particular on how variations in degree of shared task interdependence influence transactive memory system functioning at both individual and team level.

With regard to network properties, the theory asserts that transactive memory systems describe networks of individual minds (Wegner, 1987). Among the many explications of the theory for the work context, this property has yet to be fully explored (Palazzolo, Serb, She, Su, & Contractor, 2006). Network relationships are crucial for the development of transactive memories for two reasons. First, network ties provide connections between otherwise disparate individual memory systems. In the absence of network ties, retrieval of expertise can be more difficult. Second, network relations can help to validate perceptions of expertise distribution. Hollingshead and Fraidin (2003) found that people tend to make false judgments of expertise based on stereotypes. Direct communication among expertise seekers and providers can help to mitigate errors in perception.

The article is organized as follows. In the first section we begin by reviewing the basic ideas of transactive memory as a multilevel concept. Then, we review the emergence framework of Kozlwoski and Klein (2000) as a theoretical mechanism to explicate how transactive processes at the collective and individual levels emerge in relation to each other in teams. In the second section, we review alternative conceptualizations of task interdependence and propose how variations in degree of shared task interdependence are implicated in transactive memory system functioning at both individual and team levels. In the third section, we explore findings from social network research to propose how strength of communication ties can shape the development of knowledge directories at the individual level and transactive memory systems at the team level. Finally, we present the results of an empirical test of the hypotheses.

Emergence of Multilevel Transactive Memory

The concept of transactive memory was developed to represent team knowledge storage systems (Wegner, 1987). A team as a whole relies on its members for knowledge creation, retention, and transfer because cognition in reality takes place at the individual level (Simon, 1991). Given the multilevel nature of team cognition, Klimoski and Mohammed (1994) recommended that empirical research on team cognition be rooted in the individual level of analysis to avoid making the concept yet another elusive metaphor that has proven so difficult to link to specific actions. Following this logic, transactive memory should be perceived as *a multilevel phenomenon* that contains both individual- and team-level components.

Kozlowski and Klein (2000) have provided a framework for studying emergence of collective level phenomena from individual-level behaviors, cognitions, and affect. This framework, which has been widely accepted in organizational research (e.g., Gibson, Zellmer-Bruhn, & Schwab, 2003; Meade & Eby, 2007), addresses such questions as follows: How does individual performance of team members generate team-level performance? How does organizational climate emerge from the cognitions of individuals? How does a team affect develop from individual affective states? Kozlowski and Klein argued that such emergence can involve a range of alternatives from composition to compilation. Composition emergence occurs when emergent team properties are essentially the same as those at the individual level, involving "convergence of similar lower-level characteristics" (p. 9). At the opposite end of the continuum is compilational emergence, where lower-level properties combine to produce higher-level properties that may have different antecedents and processes. For example, if team performance is well captured by the sum or average of individual performances, as in, for example, a relay race, then emergence is relatively compositional. On the other hand, where team performance is a complex combination of individual performance elements, as in the Tour de France where teammates "draft one another…[and] muscle and block to protect teammates from passing moves by competitors" (Brown & Eisenhardt, 1998, p. 62), then emergence is relatively more compilational.

In the emergence framework, individual cognition, affect, and behavior are the "elemental content" of emergence. The elemental content is transformed into higher-level team cognition, affect, and behavior via interpersonal communication and exchange of information, affect, and other resources within the team. This communication and exchange is critical to the production of team-level outcomes. From the emergence perspective, transactive memory can be viewed as a macrolevel cognitive representation of knowledge distribution of a team or organization that emerges from microlevel interactions. The elemental content that becomes manifest at the team level through interaction is the individual mental maps of knowledge distribution (directories). The interactions include information allocation and retrieval processes through which people develop and update the elemental content for the emergent transactive memory. Through these interactions, compositional knowledge directories develop at the team level from the bottom up.

This emergence view emphasizes that transactive memory develops at the team level only when individual expertise directories are shared through interactions. If people choose to hoard their individual knowledge directories, transactive memory will remain underdeveloped despite growth in individual knowledge directories. That is, information allocation and retrieval activities at the individual level do not automatically lead to the development of transactive memory systems at the team level. Without sharing, individuals' knowledge directories cannot be transformed into a robust collective knowledge directory. It is important to note that this position neither argues that collective knowledge directories are perfect repositories of individual knowledge nor that all communication automatically leads to effective information sharing (Pavitt, 2003). Indeed, decades of research have documented the limitations and pitfalls involved in pooling knowledge across team members (see Poole & DeSanctis, 1990, for some recent reviews). Rather, we argue that compositional emergence is facilitated when team members communicate and share information, even though such sharing may not be flawless and may be subject to its own biases. Transactive memory systems develop through compositional emergence because the knowledge directories operating at both levels of the system are based on the same antecedents and processes (Brandon & Hollingshead, 2004; Moreland, Argote, & Krishnan, 1998; Wegner, 1987; Wegner, Erber, & Raymond, 1991).

The emergence framework also suggests that the emergent properties of the collective, once stabilized, can exert contextual influences downward on individual-level behaviors, cognitions, and affect (Kozlowski & Klein, 2000). Thus, the relationship between properties at different levels is bidirectional. Depending on the cycles of the system, the two forces alternate to drive the developmental processes of the system. For transactive memory systems, this model means that as team expertise directories emerge and develop, they can also influence further development of individual directories as well as the interactive processes involved, including information allocation and retrieval. Research has supported this contention that the existence of a well-developed transactive memory system in a work team can greatly expand each individual person's capacity to encode, retrieve, and store information and thereby to help team members gain access to a wider range of expertise needed for the collaborative task (Moreland, 1999; Moreland & Myaskovsky, 2000; Morgeson & Hofmann, 1999; Wegner, 1987). This application of the emergence perspective, in combination with the extant literature, suggests that at the individual level where elemental content is made manifest through interactions:

Hypothesis 1: Individual directory development is positively related to individual expertise exchange.

And comparing across teams, team-level directory development, which represents the sum of individual directory development, can exert a cross-level contextual influence on individual expertise exchange. Hence,

Hypothesis 2: Team-level directory development is positively related to individual expertise exchange.

Shared Task Interdependence and Multilevel Transactive Processes

Given the importance of direct interactions between team members for the emergence of team transactive memory, a central question centers on what factors motivate and/or influence those interactions. Prior theorizing has suggested that task interdependence is a fundamental driving force. Hollingshead (2001) has argued that task interdependence is a prerequisite for development of transactive memory systems. In this section we explore how task interdependence can be incorporated into the emergence framework to offer a multilevel perspective.

In organizational research, scholars disagree (Wageman, 1995) on whether task interdependence is an intrinsic feature of work (Thompson, 1967) or whether it reflects how people actually perform the task that may or may not be faithful to the original task arrangement (Hansen, Podolny, & Pfeffer, 2001). Wageman argued for an alternative approach that considers task interdependence as interrelationships between tasks that are acted out by people per their understanding of intertask relationships. Such a position is consistent with Simon's (1991) general call for connecting collective-level concepts with their individual-level roots because individuals are those who act out the influence of interdependent task relationships. We label this type of task interdependence as "shared task interdependence."

Shared task interdependence creates cognitive interdependence among people when members rely on each other's expert knowledge to finish a joint task (Tindale & Anderson, 1998). Cognitive interdependence also provides motivation for collaboration and expertise exchange for several reasons (Brandon & Hollingshead, 2004; Hollingshead, 2001; Wegner et al., 1991). First, cognitive interdependence means that some of the expertise that an individual needs for task completion is stored with other team members. The knowledge must be acquired from other team members through exchange processes to effectively complete the task. Second, task interdependence heightens the sense of the collective (Wageman, 1995, p. 150), potentially reducing social dilemmas in sharing that arise when the knowledge provider incurs the costs but only the receiver gets the benefits. This imbalance in costs and benefits creates disincentives to share, thus impairing the development of transactive memory (Fulk, Monge, & Hollingshead, 2005). Such a dilemma can be alleviated, however, when people share a sense of belonging to a collective and value collective success (Kalman, Monge, Fulk, & Heino, 2002). Finally, task interdependence can reduce social loafing. Social loafing (similar to free riding) refers to the loss of motivation when in a crowd (Karau & Williams, 1993). The reason is that a crowd provides a shield of anonymity for the unmotivated (Geen, 1991). When working on interdependent tasks, however, contribution from each team member becomes more visible, and social loafing may become less likely. Based on the reasoning listed above, we propose that individual shared task interdependence of the type described by Wageman is related to individual expertise exchange. At the individual level,

> *Hypothesis 3:* Individual shared task interdependence is positively related to individual expertise exchange.

In addition to the direct effects proposed in Hypotheses 1 and 3 as outlined above, we propose that individual shared task interdependence interacts with individual directory development to influence individual expertise exchange with team members. Expertise exchange is most likely to happen among those who know what each other knows, and who also share high task interdependence. The reason for this phenomenon is that although employees in an organization may have a well-developed expertise directory of "who knows what" about many people, they exchange expertise and resources most frequently with only a portion of the team—those who share task interdependence with them. Whereas individuals' expertise directories can help locate needed expertise, task interdependence provides the actual reason that makes expertise exchange necessary. Thus, at the individual level,

> *Hypothesis 4:* The interaction of individual shared task interdependence and individual directory development is positively related to individual expertise exchange.

At the team level, it follows that the greater the overall interdependence among all the tasks in the team, the more each individual is dependent on the expertise of other team members. Team-level task interdependence, which emerges via compositional processes from individual task interdependencies, also encourages collaborative behavior by team members (Wageman & Baker, 1997). Teams need many resources for completing a task. For a highly interdependent task, when the key resource is information/knowledge and it is distributed among team members, the need for effective collaboration and expertise exchange grows (Wageman, 1995), and the more valuable will be a transactive memory system. Thus, we propose that individual-level expertise exchange among team members within a transactive memory system is motivated by the team-level task interdependence. Comparing across teams in regard to cross-level contextual influence,

Hypothesis 5: Team-level shared task interdependence is positively related to individual expertise exchange.

Strength of Communication Ties and Multilevel Transactive Processes

Transactive memory describes a network of individual minds (Wegner, 1987). Strength of communication ties reflects a property of the linkages in the network, indicating a degree of connectedness among the individual minds. Granovetter (1973) proposed that communication ties are strong when interactions are frequent, intense, reciprocal, and personal. Strong ties are very important for expertise exchange for the following reasons. First, trust and familiarity are more likely to develop in the presence of strong communication ties (Krackhardt, 1992). Research shows that people in trusting relationships are more motivated to share resources (Gulati, 1995; Nahapiet & Ghoshal, 1998; Uzzi, 1996; Zaheer, McEvily, & Perrone, 1998), which in turn increases exchangers' chances of obtaining accurate, complete, in-depth information (Uzzi, 1997). Second, strong communication ties provide access to tacit knowledge that can neither be easily articulated (Polanyi, 1967; Uzzi, 1997) nor readily transferred across persons (Cohen & Levinthal, 1990; Hansen, 1999). Firsthand experience through close contacts supported by strong communication ties is crucial for learning this type of knowledge (Lave & Wenger, 1991; Nonaka & Takeuchi, 1995; Polanyi, 1967; Uzzi, 1996). Whereas the original formulation of transactive memory theory focuses more on exchanging codified expertise residing in external storage places, gaining tacit knowledge through apprenticeship supported by strong ties provides an additional explanation for the importance of communication ties to transactive memory, a direction that has not been well developed in the theoretical formulations to date. The original theory emphasized the importance of having common labels for expertise sharing (Wegner, 1987). Yet because tacit knowledge is difficult to articulate and presents important challenges to arriving at common labels, learning this type of knowledge through strong ties becomes especially valuable (Palazzolo et al., 2006). Given the benefits of strong ties for expertise exchange, we first predict a direct effect of strength of network ties on expertise exchange. At the individual level,

Hypothesis 6: Individual communication tie strength is positively related to individual expertise exchange.

In addition, we propose that individual communication tie strength interacts with individual directory development to influence individual expertise exchange with team members. That is, people who not only know where to find resources (Hypothesis 1) but also have the ability to obtain them when needed (Hypothesis 6) will exchange expertise more. At the individual level,

Hypothesis 7: The interaction between individual communication tie strength and individual directory development is positively related to individual expertise exchange.

At the collective level, we propose that teams that have, on average, strong communication ties will motivate more expertise exchange among team members at the individual level. The reasoning behind this prediction is that strong communication ties among a vast majority of a team breed team cohesion and collaboration (Coleman, 1988). Influenced by a cohesive team culture emergent from the composition of individual communication ties, people are more likely to trust and support each other and to share expertise (Lawler, Thye, & Yoon, 2000; Reagans & McEvily, 2003). Comparing across teams in regard to cross-level contextual influence,

Hypothesis 8: Team level communication tie strength is positively related to individual expertise exchange.

In summary, we have argued that the basic transactive memory process described in Hypothesis 1 (individual directory development is positively related to individual expertise exchange) is more likely to occur under two situations: high shared task interdependence and strong communication ties. These refinements suggest that the strength of the direct effect of individual directory development on direct exchange among team members may vary substantially across individuals on the same team. In addition, we have argued that these individual-level effects cumulate at the collective level such that teams whose members have greater team-level shared task interdependence and team-level communication tie strength will report greater individual levels of expertise exchange. This refinement incorporates cross-level contextual influences from the team to the individual. Figure 1 provides a visual summary of all the research hypotheses.

Method

Design and Procedure

The hypotheses were tested using field data collected from 218 people in 18 organizational teams from five industries: aerospace, hospitality, legal, military, and consulting. The first step in data collection involved interviews with team managers to determine the names of team members, the knowledge areas required to finish each task, and some other nonconfidential contextual information about the teams and their work. Information obtained

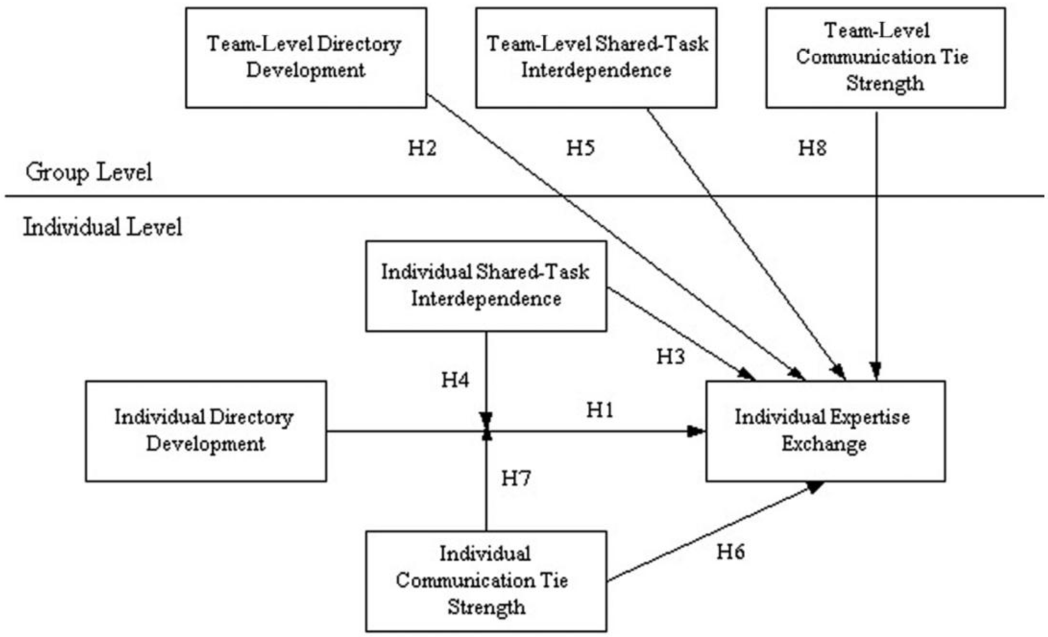

Figure 1. Summary of research hypotheses

from these interviews was used to tailor an online data collection instrument for each team. The second step was to administer an online assessment to all team members. Participants were brought to a computer lab or conference room in each of their home organizations to finish the assessment during the day when one of the members of the research team was on site to address questions. Researchers explained the goals of the project as understanding, explaining, and improving knowledge networks in project teams. Respondents were directed to the URL on a university server that contained the customized survey for their team. The respondents were informed that all their responses would be kept confidential to the research team and that they had the option to opt out of the study without penalty and could also refuse to answer any question on the assessment.

The response rate was 100% (no one opted out entirely), although some persons elected not to answer some of the questions, creating some missing values. The median team size was 13, with the largest team consisting of 20 members and the smallest with 5, and a third of them having identical team size (n = 13). Among those who provided valid responses, tenure with current project team averaged 41 months, although there was substantial variation across teams; 69% of the respondents were men and 76% had at least a BA degree.

Measurement

Research variables. *Individual expertise exchange* was computed from data arrayed in two sets of matrices, one for allocation and one for retrieval of expert information. Participants were asked to record whether they had allocated information to or retrieved information from each team member for each knowledge area required for the team to accomplish its tasks. For each matrix (allocation and retrieval) the data were aggregated through several steps. In Step 1, the responses were coded as 0 for "no allocation (retrieval)" and 1 for "some allocation (retrieval)" for each knowledge area. In Step 2, these binary responses were averaged across knowledge areas for each person to create a single average knowledge sharing score from each person to each other person within each team. This averaging across knowledge areas by person was necessary to create comparability across teams because teams differed in the number of knowledge areas needed for their tasks (ranging from a low of 5 to a high of 7). In Step 3, the average allocation and retrieval matrices for each team were summed to build a composite indicator of the expertise exchange network for each team. This composition was justified by a high correlation between the allocation and retrieval matrices (quadratic assignment procedure [QAP] correlation = .526). In Step 4, a composite score was created for each person to represent that person's individual expertise exchange with team members by averaging each person's scores across all team members, excluding the focal person's self-report on individual allocation and retrieval. This final score measures each person's general tendency, as perceived by other team members and across different knowledge areas, to exchange information directly with other team members.

Individual directory development was calculated from respondent reports of "who knows what" in the team. Each respondent assessed the level of expertise in each of the team's knowledge areas for each other team member. For each team member in each knowledge area, respondents reported either an assessed level of expertise or "don't know." Any report of expertise was scored as "1" to indicate some sense of others' expertise, and "don't know" was coded as zero. The total number of reports by each respondent was equal to the number of team members multiplied by the number of knowledge areas. The proportion of this total that was nonzero was calculated to represent to what extent the focal person knows "who knows what" in the team. This measure reflects the level of development of the expertise directory at the individual level. Consistent with the compositional emergence model of transactive memory, the group mean of this variable was calculated to measure *team-level directory development*.[1]

Individual shared task interdependence with other team members was measured by asking individuals to provide information about who was responsible for what tasks. The responses were on a 3-point scale (0 = *not responsible*, 1 = *secondary responsibility*, and 2 = *primary responsibility*). Based on each individual member's response, a consensus matrix of task responsibility was computed by using the average cognitive social structures (CSS) function available in UCINET 6.0 (Borgatti, Carley, & Krackhardt, 2006; Borgatti, Everett, & Freeman, 2002). The resulting incidence matrix had rows representing different tasks and columns representing people and represented team consensus about task assignments. An affiliation people-by-people matrix was then derived from this incidence task assignment matrix using the affiliation function in UCINET 6.0 (Borgatti et al., 2002). The resulting matrix measured the extent to which pairs of individuals were interdependent with each other across all of the assigned tasks. The average of each row of the matrix (each person), excluding the diagonal (shared task interdependence with oneself), then represented the level of shared task interdependence one person had with other members of the team. Team-level shared task interdependence was calculated as the group mean of individual level task interdependence.

Individual communication tie strength was measured by asking respondents to report how frequently they had communicated with each member of the team. The responses were on a 7-point scale (0 = *never* to 6 = *once per day*). To avoid possible biases in self-report data, the mean of the responses reported by two parties in a relationship was used to represent the level of frequency of communication between them. For instance, if Person A selected 4 as the frequency of communication with Person B, whereas Person B reported 6, the mean of the two values, 5, was used in the final matrix to capture frequency of communication between these two people. To facilitate comparisons across teams of different sizes, the average of each row of the matrix (each person's ties with others) was calculated to represent how individuals were tied to their team members. *Team-level communication tie strength* was calculated as the team means of communication tie strength.

Control variables. *Education* was measured by a 4-item scale with 0 representing less than a BA degree and 3 representing having a PhD or equivalent. Education was included as a control variable because it is possible that well-educated people were consulted more frequently for expertise exchange. *Tenure with current project team* was measured by an open-ended question asking the respondents to report how long they had been working on the current project team. The variable was included in the model as a control variable because we anticipated senior team members may have had more connections with other team members and, therefore, would have been more likely to exchange information with others. Because the distribution of this control variable was skewed with only a few people having more than 10 years of tenure with their team, the data were right censored; that is, all those values larger than 10 were coded as 10, to reduce skewness of the data.

Descriptive statistics and zero-order correlations of research and control variables are reported in Table 1. The individual-level correlation coefficients are reported in the lower triangle of the table. They were calculated based on the whole sample, with no partitioning of grouping effect. Correlations among team-level variables are reported in the upper triangle of the table.[2]

Analysis

Because the data were clustered by teams and, therefore, violated the assumption of independence of observation in ordinary least squares (OLS) regression, hierarchical linear modeling (HLM) analysis was needed to obtain unbiased estimates of standard errors for hypothesis testing[3] (Raudenbush & Bryk, 2002). Essentially, HLM analysis takes a two-step procedure in which the intercepts and slopes of individual-level/Level 1 predictors are first estimated for each team, and then used as outcome variables for team-level/Level 2 predictors. Conceptually, random intercept models evaluate whether the intercepts of team regression lines varied significantly across teams, and the random slope models evaluate whether the slopes of the regression lines varied significantly across teams. The above

Table 1. Descriptive Statistics and Zero-Order Correlations

Variables	1	2	3	4	5	6	*M*	*SD*
1. Education	—	−.248	−.349	−.172	−.558*	−.367	1.075	.595
2. Tenure with current project team	−.151*	—	.198	.422*	.233	.500*	42.989	28.887
3. Individual expertise exchange	−.286*	.072	—	.359	.501*	.608*	3.126	1.696
4. Directory development	−.049	.160*	.245*	—	.507*	.248	.750	.134
5. Shared task interdependence	−.221*	.267*	.499*	.212*	—	.456*	2.794	1.019
6. Communication tie strength	−.394*	.179*	.542*	.361*	.438*	—	4.531	.854
M	1.091	36.149	3.017	.743	2.661	4.442	—	—
SD	.847	37.267	1.904	.315	1.081	1.008	—	—

Note: 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 team-level variables.
*Correlation is significant at the .05 level (two tailed).

mentioned mixed-effect models were tested using HLM 6.04 (Raudenbush & Bryk, 2002). HLM 6.04 was used because in addition to parameter estimates, HLM 6.04 also provides a reliability test of the coefficients generated, given distributional characteristics of the intercepts and slopes of the regression lines across different teams. The reliability estimates for the final random intercept models conducted were above .951 for all models.

Results

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 in the dependent variable, individual expertise exchange. The results provided evidence of significant between-team variance in individual expertise exchange (u_o = 2.772, df =17, χ^2 = 596.471, $p < .01$). The intraclass correlation (ICC), which measures the amount of variance in the outcome variable that can be accounted for by between-team differences, was .73, indicating that 73% of the total variance in individual expertise exchange could be explained by between-team differences, showing strong grouping effects of the data, and therefore, the need for using HLM data analysis techniques. The coefficient for the fixed effect (γ_{00}) in this null model was 3.119, representing the grand mean of expertise exchange among team members across all the teams, the range of which was 7.753.

In the second step of hypothesis testing, individual expertise exchange was regressed on the two control variables: education and tenure with the current project team. Following

Raudenbush and Bryk's (2002) suggestion, both variables were group mean centered. Theoretically, group mean centering is preferred when the focus is on generating reliable estimates of Level 1 coefficients, independent of the grouping effect (Hofmann & Gavin, 1998). Moreover, according to Enders and Tofighi (2007), group mean centering is the only appropriate method to examine interaction effects between a pair 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 predictor variables, including the control variables and the research variables, were group-mean 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).

All hypotheses are directional, so one-tailed tests were applied. First, when only two control variables were included in the model, the results showed a significant positive relationship between project tenure and individual expertise exchange, $\beta_{\text{project tenure}} = .005$, $t(201) = 2.172$, $p < .05$. The relationship between education and individual expertise exchange was nonsignificant. The Level 1 within-team variance remained roughly unchanged with the addition of the two control variables to the null model. This result suggests that a significant proportion of variance in individual expertise exchange remained explained. The regression coefficients examining fixed effects are reported under Model 1 in Table 2. The random effect component of Model 1, as well as those of subsequent models, are reported in the second half of the table. In all of the subsequent analyses, education and tenure with current project team were included as control variables. The deviance score (−2 log likelihood) of Model 1 was 646.830, which was used as a baseline to evaluate significance in model improvement. As described by Raudenbush and Bryke (2002) and Hayes (2006), differences in deviance scores between a pair of nested models follow a χ^2 distribution, and can be used to conduct likelihood ratio tests to evaluate significant improvement in model specifications.

Hypothesis 1 proposed that individual directory development is positively related to individual expertise exchange. Hypothesis 2 predicted that team-level directory development is positively related to individual expertise exchange. Both hypotheses focused on the basic premises of transactive memory albeit at different (individual and team) levels of analysis. The two hypotheses were tested simultaneously.[4] Specifically, the individual directory development was added in addition to the two control variables as a Level 1 predictor and team-level directory development as a Level 2 predictor. The initial model contained both random intercept and random slope components. However, the random slope analysis yielded insignificant variance in $\beta_{\text{individual directory development}}$ ($u_\beta = .008$, $df = 17$, $\chi^2 = 17.301$, $p = .434$), indicating there was no significant across-team variability in the regression slopes. Therefore, the final analysis contained the random intercept analysis only. The results showed the predicted positive relationship between individual directory development and individual expertise exchange, $\beta_{\text{individual directory development}} = .078$, $t(199) = 1.746$, $p < .05$, and a significant influence of team-level directory development on individual expertise exchange, $\gamma_{\text{team-level directory development}} = .878$, $t(16) = 1.847$, $p < .05$. Therefore, both Hypotheses 1 and 2 were supported. The reliability of estimate remained high at .958. The Level 1 residual variance r_{ij}, which measures within-team unexplained variance

Table 2. Summary of Hierarchical Linear Modeling (HLM) Analysis Results

Fixed Effect: Predictors	Model 1	Model 2	Model 3	Model 4
Education	.054	.055	−.042	.042
Tenure with project team	.005*	.004*	.005*	.004*
Individual directory development	—	.078*	.053	−.003
Team-level directory development	—	.878*	.649	.308
Individual shared task interdependence	—	—	.830*	—
Individual directory development × Individual shared task interdependence	—	—	.234*	—
Team-level shared task interdependence	—	—	.838*	—
Individual communication tie strength	—	—	—	.802*
Individual directory development × Individual communication tie strength	—	—	—	.083
Team-level communication tie strength	—	—	—	.865*
Level 1 variance explained in addition to Model 1	—	1%	17.6%	18%

Random Effect	Deviance	Variance Component	*df*	χ^2	*p* Value
Model 1: Intercept, u_o	646.839	2.572	17	506.948	.000
Level 1 effect, r_{ij}		.999	—	—	—
Model 2: Intercept, u_o	644.772	2.272	16	404.887	.000
Level 1 effect, r_{ij}		.989	—	—	—
Model 3: Intercept, u_o	610.211	1.610	15	390.659	.000
Level 1 effect, r_{ij}		.823	—	—	—
Model 4: Intercept, u_o	612.996	2.030	15	395.639	.000
Level 1 effect, r_{ij}		.821	—	—	—

in the outcome variable, dropped to .989 from .999 for the controls-only model, meaning that development of individual- and team-level directories explained 1% additional variance in individual expertise exchange. The results are reported under Model 2 in Table 2. Comparing the deviance scores of Models 1 and 2, a $\chi^2(2) = 646.830 - 644.772 = 2.058$, $p > .05$, indicates that the improvement in model fit was not significant.

Hypotheses 3 and 5 proposed that shared task interdependence at the individual and team level, respectively, would be positively related to individual expertise exchange. Hypothesis 4 predicted that the interaction between individual shared task interdependence and individual directory development would be positively related to individual expertise exchange. The three hypotheses were tested simultaneously. Similar to previous model testing, random slope analyses were excluded from the final model because the results showed insignificant variance of the slope estimates. The results of the random intercept–only model showed a significant positive relationship between the predictors and the outcome variable at both the individual level, $\beta_{\text{individual shared task interdependence}} = .830$, $t(196) = 5.785$, $p < .05$, and the team level, $\gamma_{\text{team-level shared task interdependence}} = .838$, $t(16) = 2.649$, $p < .05$, supporting both Hypothesis 3 and Hypothesis 5. In addition, the results showed a significant positive interaction effect, $\beta_{\text{individual directory development} \times \text{individual shared task interdependence}} = .234$, $t(196) = 2.804$, $p < .05$. Therefore, Hypothesis 4 was supported. The Level 1 within team residual variance r_{ij} dropped to .834 from .999 for the controls-only model, meaning that shared task interdependence at both levels and the interaction effect together explained 17.6% additional variance in individual expertise exchange. Comparing the deviance scores of Models 1 and 3, a $\chi^2(5) = 646.830 - 610.221 = 36.609$, $p < .05$, indicates significant improvement in model fit. The results are reported under Model 3 in Table 2.

The interaction effect is plotted in Figure 2, in which the slopes of regression lines showed clear variations in the relationship between individual directory development and individual expertise exchange across different levels of shared task interdependence. For those in the lower 25th percentile of individual shared task interdependence, the relationship between development of expertise directories and expertise exchange was negative; the slope turned slightly positive for the 50th percentile and steeply positive for the 75th percentile.

Hypotheses 6 and 8 proposed that communication tie strength at the individual and team level, respectively, would be positively related to individual expertise exchange. Hypothesis 7 predicted that the interaction of individual communication tie strength and the individual directory development would be positively related to individual expertise exchange. To test Hypothesis 7, a product term between the two variables was created after group centering and scaling to make them comparable in measurement scales. The three hypotheses were tested simultaneously. Similar to previous model testing, random slope analyses were excluded from the final model because the results showed insignificant variance of the slope estimates. The results of random intercept–only model showed a direct positive relationship between the predictor and the outcome variables at both the individual level, $\beta_{\text{individual communication tie strength}} = .809$, $t(196) = 6.262$, $p < .05$, and the team level, $\gamma_{\text{team-level communication tie strength}} = .865$, $t(16) = 1.717$, $p = .06$,[5] supporting strongly Hypothesis 6 and, marginally, Hypothesis 8. However, counter to our prediction, the interaction term was not significant: $\beta_{\text{individual directory development} \times \text{individual communication tie strength}} = .083$, $t(196) = 1.214$, $p > .05$. Therefore, Hypothesis 7 was not supported. The Level 1 variance dropped to .821 from .999 for the controls-only model, meaning that strength of communication ties at both levels explained 18% of additional variance in expertise exchange. The results are reported under Model 4 in Table 2.[6] Comparing the deviance scores of Model 1 and 4, $\chi^2(5) = 646.830 - 612.996 = 33.894$, $p < .05$, indicates significant improvement in model fit.

Post Hoc Analysis

Hypothesis 7 predicted an interaction effect between individual communication tie strength and individual directory development on individual expertise exchange in teams. As reported in Model 4, the interaction term was not significant, indicating that individual communication tie strength failed to moderate the extent to which individual directory development influenced individual expertise exchange. Moreover, the direct effect of

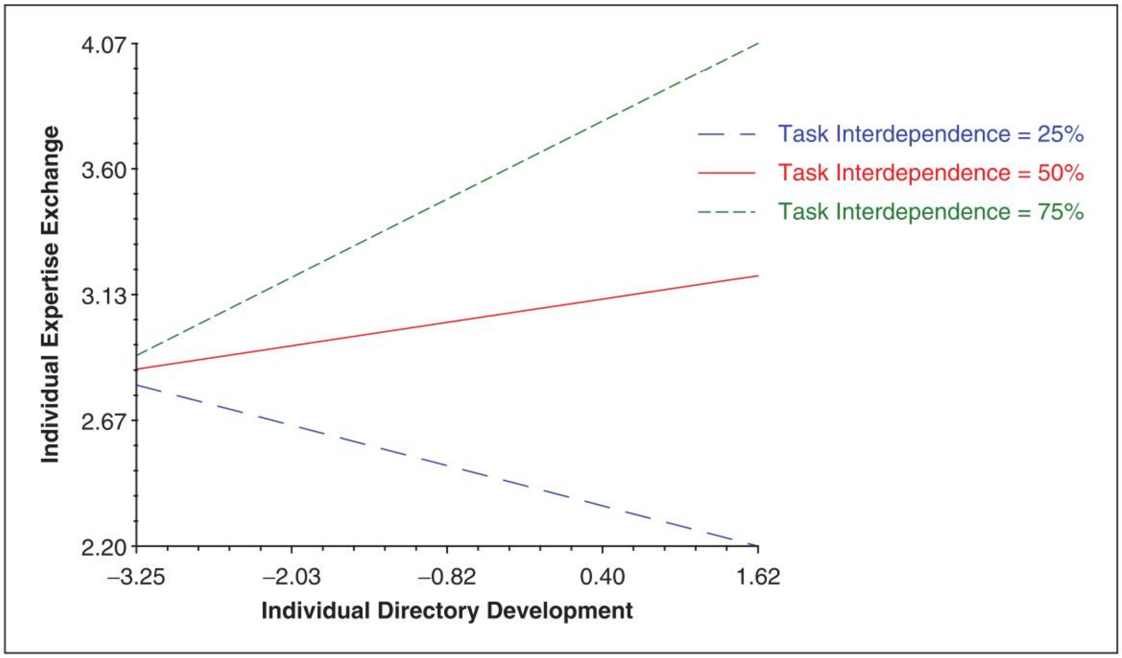

Figure 2. Interaction effect between individual directory development and individual shared task interdependence on expertise exchange

individual directory development, which was significant in Model 2, turned insignificant in Model 4. Taken together, these findings suggest that individual communication tie strength might mediate, rather than moderate, the influence of individuals' directory development on their expertise exchange. That is, individuals with well-developed expertise directories were more likely to build strong communication ties with potential experts and the strength of these communication ties would in turn explain their expertise exchange. This conjecture prompted exploration of possible mediation effects in post hoc analyses. Although the direct effect of individual directory development on direct expertise exchange also had turned insignificant in Model 3 when individual shared task interdependence was included, we decided not to pursue further the possible mediation effect of individual shared task interdependence on this relationship. The reason was that previous theoretical development has clearly stated that task interdependence should be treated as a prerequisite for the development of transactive memories (Hollingshead, 2001).

Mediation effect requires satisfaction of several preconditions (Baron & Kenny, 1986). First, individual directory development must be positively related to individual expertise exchange. Second, individual directory development must be positively related to individual communication tie strength. Third, individual communication tie strength must be positively related to expertise exchange. Assuming all these three preconditions are satisfied, individual communication tie strength would have a full mediating effect if, after controlling for individual communication tie strength, the relationship between individual directory development and individual expertise exchange was no longer significant. That is, the influence of the individual directory development on individual expertise exchange was completely mediated by individual communication tie strength. Precondition 1 was tested and confirmed in Hypothesis 1. Precondition 2 specified a positive relationship between individual directory development and individual communication tie strength. The precondition was supported even after controlling for the impact of education and project tenure: $\beta_{\text{individual directory development}} = .122$, $t(199) = 5.198$, $p < .05$. Precondition 3 required finding a significant relationship of individual communication tie strength to individual expertise exchange. It was confirmed even after controlling for the impact of education and tenure with project teams: $\beta_{\text{individual communication tie strength}} = .774$, $t(199) = 6.456$, $p < .05$. Finally, when both were included in the regression simultaneously, individual communication tie strength remained a significant predictor of individual expertise exchange, $\beta_{\text{individual communication tie strength}} = .793$, $t(198) = 6.164$, $p < .05$, whereas individual directory development became nonsignificant, $\beta_{\text{individual directory development}} = -.019$, $t(198) = -.423$, $p > .05$, supporting the mediation effect. The results of hypothesis testing, including the post hoc analysis, are summarized in Figure 3.[7]

Discussion

This research was designed to explicate and empirically test three contributors to transactive memory-related processes: connections between individual and team cognition, shared task interdependence, and communication tie strength as a network property. The emergence framework of Kozlwoski and Klein (2000) was employed as a theoretical mechanism to explicate the nature of cross-level transactive processes, focusing in particular on how team-level factors that emerge from individual interactions have corresponding effects back on individual cognitions and behaviors.

This study focused on these three factors because they have been central in prior theorizing about transactive memory systems. Task interdependence is a core condition for transactive memory (Hollingshead, 2001). Development of expertise directories and strength of communication network ties were prominently featured but not yet fully explored in Wegner's (1987) original articulation of transaction memory in which he describes that transactive memory is in essence a cognitive network about "who knows what" (Hollingshead & Contractor, 2002; Monge & Contractor, 2003).

We posited that influences on individual expertise exchange come from both the individual level and the team level. That is, individuals' expertise exchange is influenced not only by the development of their individual expertise directories (Hypothesis 1) but also by the development of the team-level expertise directory (Hypothesis 2). Likewise, individuals' expertise exchange is influenced not only by their individual shared task-interdependence with others (Hypothesis 3) but also by the overall extent of task interdependence within the team (Hypothesis 5). Finally, individuals' expertise exchange is influenced not only by the strength of their individual communication ties with others (Hypothesis 6) but also the overall strength of communication ties within the team (Hypothesis 8). In addition to these multilevel mechanisms, we posited that individual shared task interdependence (Hypothesis 4) and strength of communication (Hypothesis 7) would moderate the extent to which individual directory development influenced their expertise exchange.

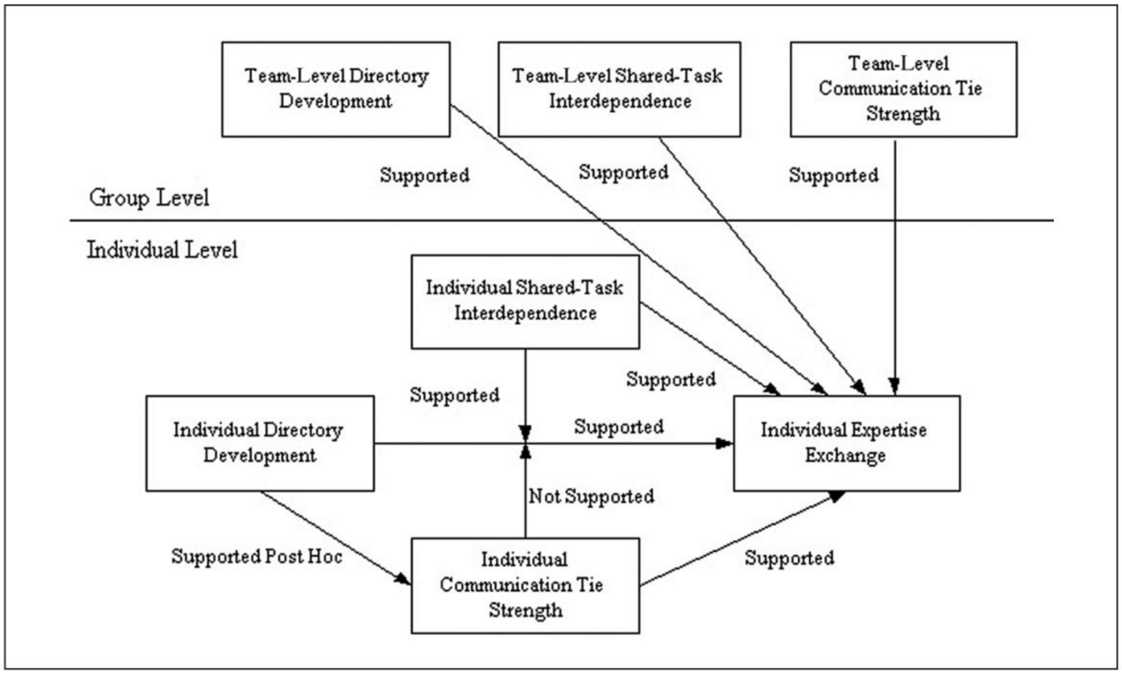

Figure 3. Summary of results

The empirical study was conducted in the field using data on expertise exchange collected from 218 employees of 18 organizational teams in different industries. Education and tenure at the individual level were included as control variables in all models. The results showed that at the individual level of analysis (Hypothesis 1), the relationship between individual directory development and individual expertise exchange was significant as predicted by transactive memory theory. For the contextual influence analysis (Hypothesis 2), our findings indicated that expertise exchange was more likely to occur in teams with better developed team-level directories. However, the amount of additional variance explained was quite small (1%) compared to a controls-only model.

For shared task interdependence, the results showed that, as argued by Brandon and Hollingshead (2004) and Wegner et al. (1991), individuals' task-sharing interdependence influenced individual expertise exchange (Hypothesis 3). Furthermore, individuals were even more likely to exchange expertise if they belonged to a team that had a higher overall level of shared task interdependence (Hypothesis 5). Beyond this main premise, our results showed a strong interaction effect between individual directory development and individual shared task interdependence on individual expertise exchange (Hypothesis 4). As depicted in Figure 2, individuals with better developed expertise directories demonstrated higher levels of discretion in terms of expertise exchange based on the level of shared task interdependence. In situations that required high levels of shared task interdependence they were much more likely to exchange expertise than individuals with less well-developed expertise directories. By contrast, in situations of low shared task interdependence, individuals with better developed expertise directories were substantially less likely to exchange expertise as compared to those who had less well-developed expertise directories.

These results suggest that individuals with better developed levels of expertise directory had a better knowledge of "who knows what" and hence were able to calibrate their levels of expertise exchange more strategically than individuals who were less aware of "who knows what" and hence engaged in a relatively constant amount of expertise exchange irrespective of the level of shared task interdependence. These factors explained 18% more variance in individual expertise exchange compared to a controls-only model. Our finding that individuals' expertise directories led to different levels of expertise exchange based on the level of shared task interdependence suggests that shared task interdependence is an important contingency factor that should be theoretically developed from a transactive memory perspective.

The results also showed that communication tie strength at both the individual (Hypothesis 6) and team levels (Hypothesis 8) was an important predictor of expertise exchange. However, counter to our predictions in Hypothesis 7, we did not find an interaction effect between the individual directory development and individual communication tie strength on individual expertise exchange. That is, individuals with well-developed expertise directories (those who knew "who knows who") were not moderating their expertise exchange based on the strength of their communication ties. Instead, post hoc analyses revealed that individual communication tie strength had a strong mediating, rather than a moderating, effect. That is, individuals with well-developed expertise directories were more likely to have stronger communication ties, which in turn led to higher levels of expertise exchange. More important, individuals with well-developed expertise directories were not more likely to engage in expertise exchange without also having strong communication ties to the individuals who they recognized as the experts. The finding implies that although people can learn about each other's expertise via multiple avenues, such as conversations with others, reading journal publications, or attending conference presentations, it is through strong communication ties that people gain actual access to expertise. These direct ties may be particularly important when seeking to acquire tacit knowledge.

In summary, the results suggest that a multilevel network extension of transactive memory theory is beneficial. Although Wegner described transactive memory as a network of individual minds in his early conceptualization of the theory (Wegner, 1987), the communication network component of the theory has been relegated to the background until recently (Monge & Contractor, 2003; Palazzolo, 2005; Palazzolo, et al., 2006; Yuan, 2009). Most existing research focuses on understanding how people know "who knows what." As the findings in this study indicate, "knowing who knows what" does not by itself explain substantial variance in expertise exchange. Taking a networks perspective toward transactive memory provides a conceptual and empirical guide for understanding how distributed intelligence in organizations can be effectively pooled for collective benefits.

Limitations

The research reported here has the advantage of having been conducted in the field with functioning organizational teams using knowledge areas directly relevant to their work. This type of study is only recently becoming common in transactive memory research.

However, this research has three major limitations. First, the multilevel hypotheses were tested with cross-sectional data only. Although the HLM analysis showed that the pattern of relationships between the variables were indeed consistent with our theoretical reasoning, in the absence of longitudinal data, the individual-level causal relationships cannot be validated conclusively. Second, the matrix formulations of shared task interdependence used other team members' self-reports to calculate team and individual's scores. Though this aggregation is more reliable than a single individual's self-report, the study is limited by lack of objective measures.

Directions for Future Research

The results reported here point to a few issues worthy of further attention in future research. First, future research should investigate the extent to which team size influences the development of expertise directories and expertise exchange. For instance, in larger teams, it is more difficult for people to actually learn about each member's areas of expertise through direct interpersonal communication. In addition, although large teams offer more opportunities to interact and exchange expertise with a wider range of people, frequency of communication with others does not necessarily increase because people have limited amount of time and energy to maintain social relationships. Team size in our sample, however, did not have enough variability to adequately test its contextual influence on individual-level hypotheses because one third of the sample was the same team size. The research did have the benefit of examining larger teams that are found in the field compared to those typically studied in the laboratory.

Second, the current research focused on only one aspect of network properties: communication tie strength. This illustrates the potential of using network approaches to extend investigation of transactive memory systems. Future network-based research on transactive memory systems should parse out the differential influences on information retrieval and information allocation (which were combined in this study to constitute expertise exchange due to high levels of correlation between the two measures). Network approaches also can help us better understand transactive memory systems as multidimensional networks where, in addition to individuals, there are digital knowledge repositories that might serve as "nodes" for information allocation and retrieval. Finally, network approaches based on multitheoretical multilevel models (Contractor, 2009; Monge & Contractor, 2003) offer the possibility of integrating transactive memory's theoretical predictions for expertise exchange with additional theoretical mechanisms such as theories of self-interest, theories of collective action, and theories of homophily. These approaches will help elucidate a more contextual understanding of the various motivations that influence expertise exchange.

Third, when extending transactive memory theory using Kozlowski and Klein's (2000) emergence framework, we mainly focused on compositional emergence that emphasizes parallel processes at both individual and group levels of analysis. Though teams may not always be effective in pooling their collective intelligence together to outperform individuals (Pavitt, 2003; Stasser, 1992; Stasser & Titus, 2003), it is nevertheless interesting to explore situations in which compilational emergence can happen. Although the original transactive memory theory assumes that learning each other's expertise is not necessary, unintentional mutual learning between team members in close contact may still occur. It would be an interesting topic to explore whether such learning can contribute to compilational emergence and create a whole that is greater than the sum of its parts. Further theoretical development of compilational emergent process is a valuable future direction.

Practical Implications

Wegner (1987) maintained that a transactive memory system can function effectively so long as team members know (a) how the piece of knowledge is referred to in the team (*common label*), (b) who has the knowledge (*location*), and as long as they communicate to share the information as necessary. This argument seems to assume that the main challenge for effective expertise retrieval in teams is the lack of the knowledge of "who knows what." We believe that obtaining knowledge of the common labels and location of expertise within a team addresses only one of the challenges for effective expertise exchange. Our research demonstrates that having a well-developed expertise directory is a necessary but not sufficient condition for effective expertise. Developing strong communication ties and interdependent task relationships are crucial catalysts to actualize the potential benefit of knowing "who knows what." In addition, in the post hoc analysis, we found a significant mediation effect of communication tie strength on the relationship between the individual directory development and individual expertise exchange. It underscores the importance of communication as the principal mechanism that brings to bear the knowledge of "who knows what" on individual expertise exchange. Our findings indicate that although people in contemporary organizations can learn about each other's areas of expertise through direct interpersonal communications, expertise directories, and so on, it is through communication ties that employees can gain actual access to diverse expertise, particularly so when the expert knowledge is tacit and hard to codify into information databases. Our study reinforces recent experiences among organizations who have attempted to address the knowledge retrieval challenge by publishing expertise directories. Although these directories inform individuals about who in the organization has expertise, there is evidence that individuals are not necessarily seeking out these experts (Carlson & Davis, 1998; Casciaro, Carley, & Krackhardt, 1999; O'Reilly, 1982). Our results provide an important insight into this phenomenon. It suggests that unless individuals have a priori communication relationships with experts, they are not likely to approach them. Without communication ties, having the knowledge of "who knows what" cannot be translated easily into actual access to the expertise, especially from those derisively called "competent jerks" by Casciaro and Lobo (1999) because they are unwilling to share their high levels of expertise with others.

Finally, in studying the contextual influence of team-level variables on individual-level behavior, we found that expertise exchange happened more often in teams that on average had higher levels of development of team expertise directories (an indicator of the level of development of transactive memory), stronger communication ties, and higher levels of team-level shared task interdependence. These results indicate that, above and beyond individual differences in their capabilities to maintain up-to-date expertise directories and networks of strong ties with interdependent task partners, expertise exchange can happen more frequently as a result of belonging to a team that has a well-developed transactive memory system (reflected in having well-developed individual and team-level directories), strongly connected team members, and a high level of shared task interdependence. It underscores the importance of normative and cultural pressures that can promote or inhibit expertise exchange. Our findings suggest that incentives be applied not only at the individual level but also at the team level in an attempt to shape team norms toward facilitating expertise exchange among members.

Conclusion

More than at any other time in human history, advances in the 21st century will be based on systems and networks of human knowledge. What it is, how it is represented, how it is distributed, to whom, and with what success are all critical questions. Effective knowledge retention and sharing systems are crucial to teams and organizations in areas as diverse as law enforcement and criminal prosecution, hospital processes and patient safety, emergency crews and first responders to crises and disasters, and governmental and intergovernmental organizations. There is much to be gained from a better understanding of how to make knowledge systems work more effectively.

Appendix

Measurement Items

Directory development
At the bottom of the adjacent screen are icons that represent levels of knowledge in various knowledge areas that were identified by people in your team. We would like to know how much knowledge you think the members of your team (including yourself) have in each of these areas.

Individual expertise exchange
Please indicate whether you have provided unsolicited expertise to member XX about knowledge area YY in a typical week.
Please indicate whether you have retrieved expertise from member XX about knowledge area YY in a typical week.

Shared task interdependence
Here is a matrix containing the list of tasks that were identified by people in your group. We would like to know which tasks are interrelated. Please check the box for each pair of interrelated tasks. For example, Research is related to Project Admin. and Management, you would check the box in Row 3, Column 1. You may check more than one box in each row.

(continued)

Appendix (continued)

We would like to know how much responsibility you think each member of your group (including yourself) has in each of these tasks.

Communication tie strength
We would like to know how often you think the members of your group (including yourself) communicate (either via telephone, e-mail, or face to face) with one another.

0 = *never*, 1 = *less than once per year*, 2 = *less than once every 6 months*, 3 = *less than once every month*, 4 = *less than once a week*, 5 = *less than once per day*, and 6 = *once per day*.

Acknowledgements

The authors would like to thank J. Alison Bryant, Kathleen Carley, Andrea Hollingshead, Meikuan Huang, John Kunz, Ray Levitt, Edward Palazzolo, Michelle Shumate, Chunke Su, and Stanley Wasserman for their extensive work on the design and data collection in this project.

Declaration of Conflicting Interests

The authors declared no potential conflicts of interest with respect to the authorship and/or publication of this article.

Funding

The authors disclosed receipt of the following financial support for the research and/or authorship of this article: This research was supported in part by three grants from the National Science Foundation (NSF-IIS 9980109, NSF-SES 0822784, and NSF-SES 0822814).

Notes

1. Because there were no isolates in the teams we studied, group mean of individual directory development was used directly to represent collective directory development. If there were isolates in the communication network, they would be excluded from the calculation because, consistent with our proposed multilevel model of transactive memory, individual expertise directories of those who have no connections with other team members do not contribute to the collective directory.
2. Because individual and collective variables have a different number of cases, running correlations between them implies that all the members in one group would share the same value of one particular collective-level variable. Such a practice is not recommended in data analysis any more (Raudenbush & Bryk, 2002; Snijders & Bosker, 1999).
3. To the best of our knowledge, no existing network analysis software, including UCINET, MULTINET, or p* allow the type of multiple-level hypothesis testing discussed in this article. The multilevel network models discussed in Monge and Contractor (2003) mainly focus on dyadic, triadic, or clique properties of one network. These properties are multilevel, but they describe the network of one single group but do not consider the kinds of group differences as we want to explore in our article.

4. Using the averages of Level 1 variables as Level 2 contextual variables is quite common in multilevel analysis. For instance, Raudenbush and Bryk (2002) demonstrated such models in their very popular textbook on HLM models. In the example presented in chapter 4 of the book on pp. 72-86, both individual SES (socoioecnomic status) of a student and the average SES of a class are included in the same model as Level 1 and Level 2 predictors simultaneously to predict a student's performance.
5. In addition to common standard error estimates, hierarchical linear modeling (HLM; Raudenbush & Bryk, 2002) also produced robust standard errors for significance tests under the assumption that at the team level exist a larger number of units, which share distribution characteristics of the existing sample. According to this alternative test, if our study had been slightly larger, a strong significant result would have been found for the relationship between collective communication tie strength and individual expertise exchange: $\gamma_{\text{collective communication tie strength}} = .865$, $t(16) = 2.423$, $p < .025$.
6. In addition to the separate models (Models 2, 3, and 4), for each of the three predictor sets, we conducted a model analysis that included all three sets of variables simultaneously. This analysis is available from the authors. The results were highly similar to the separate models, except the significant coefficient for team-level tie strength in Hypothesis 5 became nonsignificant, as might be expected when the degrees of freedom dropped to 14, making it more difficult to detect significant results. Although it is important not to inflate the result, it is also important not to overlook at what level the sample can support stable findings.
7. The hypotheses were tested sequentially, with each step described from Model 1 to Model 4. Although the model depicted in Figures 1 and 3 resembles a multilevel structural equation model (SEM), we could not test the model using multilevel SEM because SEM is a large-sample data analysis technique (Bollen, 1989; Byrne, 1998; Kline, 1998). In this study, although the sample size at the individual level is more than sufficient (Kline, 1998) to produce stable coefficient estimates for path analysis, our sample size is not sufficient to test the whole model across both levels, particularly at the group level. Complex SEM models require much larger sample sizes, with at least 10 cases needed for each additional coefficient to be estimated (Kline, 1998).

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