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The Impact of Social Capital on the Development of Transactive Memories in Multilevel Group Knowledge Systems

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Abstract

A multilevel, multi-theoretical model of transactive memory theory was developed by integrating the emergence model with social capital theories. The revised theory explains how individual and collective social capital influences the development of transactive memories for group knowledge sharing. Data showed that individual social capital significantly impacted development of the micro-level component of transactive memories, but collective social capital did not impact development of macro-level transactive memories.

Keywords: social capital, transactive memory, multilevel

The Impact of Social Capital on the Development of Transactive Memories in Multilevel Group Knowledge Systems

Managing organizational knowledge is a challenging task because knowledge and expertise, unlike many other organizational resources, are distributed at multiple places, including people, tasks, tools and connections among them (Argote & Ophir, 2002). The burgeoning research interest in studying how organizations pool these distributed resources together has brought about fundamental changes in how we conceptualize organizational cognition. One major change is recognition of the importance of communication for organizational learning (Weick & Ashford, 2000). Communication provides not only information exchange, but also mechanisms to generate, transfer and retain knowledge (Wegner, 1987). Conscious efforts have been made to incorporate communication in organizational learning theory.

One prominent example is Wegner's transactive memory theory (1987; 1995). He proposes that a transactive memory system is "a group information-processing system" (1987, p 191) made up of individual memory systems, as well as communication processes linking them together. In the past two decades, the theory has attracted considerable attention in the research community. Extensive laboratory research has been conducted to study how the existence of a transactive memory system between familiar couples enables them to outperform strangers when performing different tasks (1998a; Hollingshead, 1998b; Wegner, 1987; Wegner, Erber, & Raymond, 1991). Collective training has been shown to produce more reliable transactive memories than individual training (Liang, Moreland, & Argote, 1995; Moreland, Argote, & Krishnan, 1998). Face-to-face communication generally yielded more comprehensive memories than computer-mediated communication (1998a; Hollingshead, 1998b) and different incentive mechanisms created different motivations for learning about each other's expertise (Hollingshead, Fulk, & Monge, 2002).

Although transactive memory theory has shown great promise for understanding the challenges and opportunities for managing distributed knowledge and expertise resources, the theory needs further development in two critical areas: cross-level linkages and network properties. First, the theory falls short of spelling out the multilevel nature of group cognition. Wegner (1995) argues that individual directory updating, information allocation and information retrieval are vital for the development of shared transactive memory systems (p. 320). In essence, transactive memory is a macro-level concept describing collective cognition. But the actual actions of encoding, storage, and retrieval of knowledge are all taken by individual persons at the micro level. How do the three individual-level actions produce results at the collective level? What are the cross level mechanisms that link micro-level activities and collective outcomes? In the original articulation of transactive memory theory, the multilevel nature of the concept and the cross-level linkages between individual and collective cognition were implied, but were not made explicit enough to draw the attention of subsequent researchers. Ensuing discussions of the development of transactive memory systems tend to shift between levels of analysis, without specific efforts to make cross-level connections. Such conceptual problems have also caused confusion in empirical research. In a review and critique of extant transactive memory research, Yuan (2004; 2004), and Yuan, Fulk and Monge (2005)found that most transactive memory studies actually did not provide a clear measure of the concept at all.

Second, although the theory asserts that transactive memory systems describe networks of individual minds (Wegner, 1987), this property has never been fully explored in either his original articulation of the theory (1987), further theoretical developments (1995), or empirical research. Yet network relationships are crucial for the development of transactive memories because they provide connections among disparate individual memory systems as well as validate and correct false judgments of expertise based on stereotypes (Hollingshead & Fraidin, 2003).

The current research explores solutions to these two problems. First, it develops transactive memory theory from a multilevel perspective using the emergence framework developed by Kozloswski and Klein (2000). Second, it formulates a network theory of transactive memory by developing a series of propositions from social capital theories about how individual and collective social capital shape the development of knowledge directories at the individual level and transactive memory systems at the collective level. Finally, the research provides a multilevel structural equation test of the proposed multilevel, multi-theoretical model.

Transactive Memory Theory from a Multilevel Perspective

The concept of transactive memory was developed to represent group knowledge storage systems (Wegner, 1987). Group knowledge, however, is not just a macro-level concept that can be approached in isolation from micro-level cognitions; all cognitive activities happen within individuals' heads (Simon, 1991). A group has to rely on its members for knowledge creation, retention and transfer. Given this nature of group cognition, a transactive memory system can be approached as a multilevel emergent phenomenon. Kozlowski and Klein (2000) have provided a general framework for studying emergence. They argue that a phenomenon is emergent when properties of individual elements are manifest at the collective level via interactions. Elemental content describing individual cognition, affect, and behavior is "the raw material of emergence" (p. 55). Interaction is the communication process through which people share feelings and exchange resources. "The form of interaction process, in combination with the elemental content, comprises the emergent phenomenon" (p 56). Although it takes time for micro-level phenomena to manifest upward across levels, the emergent properties of the collective, once stabilized, can exert contextual influences downward on micro-level activities. The relationship between properties at different levels is bi-directional. Depending on the cycles of the system, the two forces alternate to drive the developmental processes of the system.

Reframed from a multi-level perspective, transactive memory refers to a macro-level cognitive representation of knowledge distribution of a group or organization that emerges from micro-level interactions. Individual mental maps of knowledge distribution form the elemental content[1] for emergent transactive memory systems at the macro-level. Information allocation and retrieval are the two major interactive processes through which people develop and update the elemental content for the emergent transactive memory. Through social interactions, congruent knowledge directories develop at the collective level from the bottom up. The extent to which this mental map is accurate, consensual, and convergent across individuals reflects the level of development of transactive memory at the macro level (Brandon & Hollingshead, 2004). Top-down influences can happen when individuals modify their respective knowledge directories and subsequent information allocation and retrieval activities in accordance with the shared knowledge directory. The whole transactive memory system evolves over time as a consequence of these two joint forces. In the early stages of the development of transactive memory systems, bottom-up emergence is more likely to dominate, while after the system

[1] The addition of the individual knowledge directories as elemental content for emergence to Wegner's original transactive memory model is important because they are the direct objects of interactive actions. Furthermore, although frequent information allocation and retrieval can definitely contribute to the development of individual knowledge directories, development of individual knowledge directories by itself may not contribute to the development of transactive memory at the collective level: transactive memory develops only when individual expertise directories are shared. If people choose to hoard their individual knowledge directories, transactive memory will remain under-developed despite growth in individual knowledge directories. It is overly simplistic to assume that information allocation and retrieval activities at the individual level will automatically lead to the development of transactive memory systems at the collective level. Without sharing, individual knowledge of knowledge distribution remains individual and cannot be transformed into collective knowledge.

achieves stability, top-down contextual influences may become more prominent (See Figure 1 for illustration).

>>>>> INSERT FIGURE1 ABOUT HERE<<<<<

Kozlowski and Klein (2000) make a distinction between two alternative types of emergence. *Composition emergence* is based on the isomorphic assumption that the elemental content and emergent higher-level property are essentially the same at different levels of analysis. *Compilation emergence* is based on the assumption of “discontinuity” (p. 16) that the elemental content and emergent higher-level properties are “functionally equivalent” (p. 16) but distinct as emergence takes place across levels. Based on this conceptual framework, it is assumed that transactive memory systems develop through composition emergence because the knowledge directories operating at both levels of the system are essentially the same (Brandon & Hollingshead, 2004; Moreland et al., 1998; Wegner, 1987; Wegner et al., 1991).

Social Capital and Transactive Memory Systems

Information allocation and retrieval are the two knowledge-sharing activities that connect the individual systems together. Jointly they form a social network for resource exchange. Building on social capital theories, the next section explores how different properties of this resource exchange network influence the level of development of individual knowledge directories and the emergent transactive memory systems. In this research we propose to measure the development of individual expertise directories from two dimensions. *Accuracy* reflects the deviation of individual perception from the group consensus. *Extensiveness* refers to the scope of individual expertise directories. Expertise directories are accurate but not extensive when people can correctly report the expertise of several group members, while remaining ignorant about the rest of the group. Expertise directories are extensive, but not accurate if people have a rough idea of everyone's expertise area even though the information is not completely correct. An individual expertise directory is considered well developed only when it is both accurate and extensive.

Defining Social Capital

Bourdieu (1985), generally considered to be the first scholar to provide a systematic analysis of social capital (Portes, 1998), defined it as "the aggregate of the actual or potential resources which are linked to possession of a durable network of more or less institutionalized relationships of mutual acquaintance and recognition" (Bourdieu, 1985, p. 248-9). That is, social capital refers to resources embedded in network relationships from which people can benefit. Subsequent social capital research, however, also included trust and norms as different forms of social capital (e.g., Putnam, 1995, p. 67). This expansion, however, has the potential danger of making the construct too "muddled" to have a distinct conceptual identity (Mondak, 1998, p. 434). Portes (1998), and Schuller, Baron and Field (2000) warn against such tendencies to turn the concept of social capital into a big umbrella term that is a mixture of too many different concepts. Following this suggestion, the current research adopts Bourdieu's original definition and studies social capital as properties of network structure only.

A central issue in the social capital literature is whether social capital is an individual or collective good (Putnam, 1998; Wellman, 1998[2]). One group of scholars, exemplified by Granovetter (1973) and Burt (1992), treats social capital as a private good (Borgatti, Jones, & Everett, 1998), arguing that the benefits accrued from the investment in social capital go to a particular person, not to the general public. In contrast, another group of scholars, exemplified by Coleman (1988) and Putnam (1996; 2000), treat social capital as a collective good (Putnam,

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[2] See Putnam and Wellman's posts on the origins of the term Social Capital in a 1998 SOCNET discussion edited by Stephen Borgatti (1998).

1998), arguing that the benefits of social capital extend to all members of the collective, regardless of individual differences in network positions. As discussed later, there are significant advantages to treating social capital as *both* an individual and a collective good.

Individual Social Capital and Development of Individual Knowledge Directories

Individual social capital refers to resources that people can obtain from their network relations to facilitate their individual actions, in this case to keep their knowledge directories updated. Two dominant theories on individual social capital include Granovetter's strength of weak ties theory and Burt's (1992) structural hole theory. Granovetter (1973) proposed that the strength of ties vary along four dimensions: "amount of time, emotional intensity, mutual confiding and reciprocal service" (p.1361). Networks ties are strong when resource exchanges are frequent, intense, reciprocal and personal. Contrary to conventional wisdom that argues for the strength of strong ties, Granovetter proposed that weak ties are an important resource to facilitate individual actions because weak ties are more likely than strong ones to provide unique information. Burt (1992) in his structural hole theory, however, criticizes Granovetter's approach, and argues that what really matters is not the strength of network ties, but rather the structural properties of a network – the existence of structural holes in a person's network. Burt defines a structural hole as the absence of direct ties between two network nodes. He proposes that people can fill or bridge or broker structural holes by linking to the two others while keeping them from linking to each other. Brokers thus enjoy greater information advantage because they are more likely to gain unique information from independent sources. In the development of individual knowledge directories, the capability to connect to diverse information sources is very important because it facilitates building an *extensive* expertise directory.

While Burt's structural hole theory stresses the importance of expanding non-redundancies of information sources, we argue that overlaps in network ties are also beneficial for the growth of well-developed individual knowledge directories. As discussed earlier, individual knowledge directories are considered well-developed only when they are both extensive and accurate. To achieve accuracy in expertise recognition, it is crucial that people have multiple sources to consolidate and cross-validate the information. Repetition of information in this situation is actually very beneficial.

Therefore, it seems to us that the most important factor influencing the development of individual expertise directories is neither tie strength, nor structural holes, but rather network "reachability": connections to many different people in the network through *both* strong and weak ties and *both* bridging and non-bridging links. Network reachability can facilitate the development of individual knowledge directories by (a) allowing people to have multiple sources to cross-validate the accuracy of the information, and (b) allowing people to reach the other actors in the network via a minimum number of steps. The network metric for reachability is closeness centrality. People of high closeness centrality will have a better knowledge of who knows what in the group A short distance to the other nodes in the network means easier access to information resources (Gulati, 1999). Based on these arguments, we hypothesize that

> Hypothesis 1: Closeness centrality at the individual level is positively associated with the development of individual knowledge directories.

Collective Social Capital and the Development of Transactive Memory Systems

Network density as collective social capital. In contrast to Burt and Granovetter who are mainly concerned about how social capital may benefit individuals, Coleman (1988) is concerned with how social capital benefits communities. Although the ultimate beneficiaries of social capital are still individual people, the key difference between the two approaches is that when social capital is treated as a collective property, all members of the community can enjoy the same benefits regardless of individual network positions. Coleman (1988) proposes that social capital can be measured through the study of closure of network structure. He defines closure as the existence of ties among network members that are sufficient to enforce group or community norms. He argues that collective social capital is richest in dense networks because group norms are more easily enforced. In his analysis of high-school dropouts, he found that students whose parents knew each other were much less likely to quit school because parental control, facilitated by network ties, could be more easily implemented. In this case, the benefit of social capital went to the entire population of the school district. No distinction was made between those individuals who had substantial individual social capital versus those who did not.

In the context of the current research, collective social capital should be positively associated with the development of transactive memory systems. The reason is that in densely connected groups people in general have more communicative opportunities to learn about each other's areas of expertise. Even those people who do not have much individual social capital may still have an accurate knowledge of group expertise distribution because they are embedded in a resource-rich community. In addition, network density implies extensive resource exchanges among group members. Such interactions among people are beneficial for the development of transactive memory systems because they provide linkages among otherwise disparate cognitive activities. Also, through these interactions individual perceptions of expertise distribution get shared and subsequently transformed into group knowledge. Because densely connected networks offer extensive opportunities for these activities to take place, transactive memory systems will become better developed in groups that have rich collective social capital. Hypothesis 2 is based on these arguments:

> Hypothesis 2: Network density will be positively related to development of group transactive memory systems.

Task Interdependence in the Group

Cognitive interdependence exists in work groups when members rely on each other's expert knowledge to achieve a common goal (Tindale & Anderson, 1998). Transactive memories rest on cognitive interdependence (Hollingshead, 2001; Wegner et al., 1991). Cognitive interdependence arises from the reward system and from interdependence among group members' tasks. Although not directly measured in laboratory research on the topic, task and reward interdependence are assumed to be important factors influencing the development of transactive memory systems. Typical tasks in such research involve working together to assemble radio sets (Liang, Moreland and Argote's, 1995), or learning collectively as many special terms as possible to win a knowledge recall contest (Hollingshead 1998a, 1998b and 2001). Success and concomitant rewards in such tasks depend on group performance. Because knowledge is distributed across group members, no individual can assure success without the participation of other group members.

Reward independence, in itself, can also arise from task interdependence. Task interdependence refers to the extent that different components of a work process are interconnected with each other so that changes in the state of one element dynamically affect the state of another (Scott, 1998). When tasks are interdependent, individuals must coordinate their actions with interdependent others. Some scholars (Brandon & Hollingshead, 2004; Hollingshead, 2001; Xu, Fulk, Hollingshead, & Levitt, 2004) propose that task interdependence is a precondition for the development of transactive memory systems because it creates cognitive interdependence among people. Others argue that task interdependence can have a significant positive impact on the development of group transactive memories (Brandon & Hollingshead, 2004; Wegner et al., 1991).

Interdependent tasks vary in the degree to which the individuals are interdependent in completing them (Thompson, 1967). The simplest form occurs when people's efforts are simply pooled, generating the minimum reward interdependence. Sequential task interdependence means that a group member relies on one or more group members to complete a preceding or succeeding stage of a task. In the highest level of interdependence, the whole team must work together, share knowledge, and coordinate efforts on a continuing basis in order to complete the task. Higher levels of interdependence are heavily reliant on well-developed and quickly accessible knowledge directories. Cognitive interdependence is likely to be quite high in such situations (Brandon & Hollingshead, 2004). Thus, we argue that the degree of interdependence across the tasks of group members will shape cognitive interdependencies among people. It is therefore hypothesized that

> Hypothesis 3: Task interdependence in a group is positively related to the development of group transactive memory systems.

Individual and Collective Access to Task-Related Information

Transactive memory theory (Wegner, 1987) predicts a positive relationship between the development of transactive memory systems and accessibility to task-related information. At the micro level of analysis, individuals can more easily find needed information when they themselves have well-developed individual knowledge directories. Knowing where the information is located facilitates access to it. At the collective level of analysis, when consensus knowledge of expertise distribution is available, all members of the group benefit. As a result, collective access to information will increase. Based on these arguments, the following two hypotheses are proposed:

> Hypothesis 4(a): Development of individual knowledge directories is positively associated with individual accessibility to task-related information.
>
> Hypothesis 4(b): Development of group transactive memory systems is positively associated with collective accessibility to task-related information.

Contextual Downward Influence

In addition to the hypotheses proposed above, collective level variables can also exert top-down contextual influences on lower-level relationships.

Collective social capital. Collective social capital can mitigate the impact of individual social capital on the development of individual knowledge directories for two reasons. First, in densely connected networks, differences between people in terms of structural holes, closeness centrality and eigenvector centrality will be low due to the ceiling effects intrinsic to the measurements (Wasserman & Faust, 1994). Second, as discussed earlier, collective social capital complements deficiencies in individual social capital. People in densely connected networks generally have more chances to learn about each other's expertise than in sparse networks. Therefore, the impact of differences in strong ties and brokerage opportunities through structural holes on the development of individual knowledge directories will be comparatively weaker in dense networks than in sparse ones. These arguments lead to the following hypothesis:

> Hypothesis 5: Collective social capital, as indicated by network density at the group level, has a negative moderating effect on the impact of individual social capital

dimensions on the development of individual knowledge directories such that the relationships are weaker in dense networks than in sparse ones.

Task interdependence in the group. In addition, group level task interdependence can moderate the relationship between individual social capital and development of individual knowledge directories. Variation in levels of individual task interdependence will create different levels of motivation among group members to learn about each other's expertise (Brandon & Hollingshead, 2004; Hollingshead, 2001). When task interdependence is pooled, others' expertise does not directly affect a focal individual's personal performance, although it will influence the performance of the group as a whole. When task interdependence is sequential, people may be highly motivated to learn about the expertise of those who hold preceding or succeeding tasks, but not necessarily others. When task interdependence is reciprocal, people may be more motivated to learn about all of the group members' areas of expertise and task competencies because they know that the outputs of the different tasks will mutually influence each other. Thus, the higher the level of task interdependence in a group, the more extensive will be the motivation to learn about others' expertise (Hirst, 1988). Under high task interdependence conditions, the impact of individual social capital on the development of individual knowledge directories will be mitigated. The reason this should occur is that motivation can drive people to learn about each other's expertise through avenues other than direct social interactions or resource exchanges. As a result, differences in possession of individual social capital will matter less in learning about who knows what in the group. Therefore in high task interdependence conditions, the impact of individual social capital on the development of individual knowledge directories will be weaker. It is hypothesized that

> Hypothesis 6: Task interdependence has a negative moderating effect on the relationship between closeness centrality and the development of individual knowledge directories so that the relationship is weaker in high task interdependence groups than in low task interdependence groups.

Transactive memory. A well-developed group transactive memory system at the collective level implies easier access to task-related information for members of the group. The existence of such a system can complement deficiencies in individual knowledge directories (Hollingshead, 2000; Moreland, 1999; Wegner, 1987). Some individual knowledge directories may be under-developed. However, members of a group that has a well-connected transactive memory system have better chances to find the needed information by relying on the group knowledge directory. By facilitating access to information for all members of the group, the transactive memory system renders the development of individual knowledge directories less important for information access. Transactive memory moderates the micro-level relationship between the two variables so that people's reliance on their individual knowledge directories for information access is weaker when the group transactive memory system is well developed. It is therefore hypothesized that

> Hypothesis 7: Development of group transactive memory has a negative moderating effect on the impact of the development of individual knowledge directories on access to information so that the relationship in groups with well-developed transactive memory systems is weaker than in groups with less well-developed systems.

Figure 2 provides a summary of the combined set of hypotheses.

>>>>> INSERT FIGURE2 ABOUT HERE<<<<<

Method

Design and Procedure

The proposed model was tested on data collected from 179 people in 15 project groups in several industries. Interview protocols were sent out to group managers prior to collecting individual data. Managers served as informants with regard to the names of group members, individual tasks for the group, descriptions of the knowledge areas required to finish each task, and some other non-confidential contextual information about the group and their work. Information obtained from manager interviews was used to tailor the final on-line data collection instrument. The response rate was 100% because extensive follow-ups were made to remind participants. Overall, the median group size was 13 with the largest group consisting of 20 members and the smallest with 5 members. On average, they had worked together for 2.5 years (*SD* = 3.90). Sixty-eight percent of the respondents were male and their average age was 37.8 years (*SD* = 9.82).

Measures

Development of individual knowledge directories was measured along two dimensions: accuracy and extensiveness. *Accuracy* of expertise recognition evaluated whether a group member's knowledge about expertise distribution in the group was congruent with that of the group. Subjects were asked to rate the level of expertise of each team member in each of the knowledge areas required to finish the group project. The response categories included (a) don't know, (b) none, (c) beginner, (d) intermediate, and (e) expert. A group map about expertise distribution was derived by averaging across each individual team member's report. Accuracy of expertise recognition for each respondent was then calculated by totaling the absolute differences between the respondent's individual cognitive map of expertise distribution across team members and the group map. A large deviation score from the group map would indicate the lack of accurate knowledge about group expertise distribution. To facilitate cross-group analysis, the composite score was then normalized. Finally, the normalized deviation score was multiplied by –1 so that a high score would imply a high level of accuracy.

Extensiveness of knowledge directory was derived from the same matrix. The “Don’t Know” response was coded as 0, and all the other values were coded as 1. The proportion of non-zero values in the matrix was then calculated to represent extensiveness of individual cognitive mental map. Measures of accuracy and extensiveness were transformed so that they were similarly scaled to permit summation. Correlation between the two dimensions was .77 ($p < .05$, $N = 179$). They were then summed together to represent the level of development of individual knowledge directories.

Individual access to information was measured using a four-item scale asking about both the quality and quantity of information obtained to perform tasks. Responses were on a five-point scale, with one representing “strongly disagree” and five “strongly agree.” A composite scale measuring access to information was created by summing up the four items. Cronbach’s alpha for the scale was .81.

Collective access to information was measured by averaging individual scores on access to information across group members. *Task interdependence* was derived from each respondent’s report on who was responsible for what tasks. Based on each individual member’s response, a consensus matrix of task responsibility was created using the average CSS function available in UCINET 6. The resulting matrix had rows representing different tasks and columns representing people. An affiliation people-by-people matrix was then derived from this consensus matrix to measure inter-relations among people performing different tasks. The density of this matrix was used to measure task interdependence for each group.

Network indicators of individual and collective social capital were computed from data arrayed in two sets of matrices, one for information allocation and one for information retrieval. Subjects were asked to record whether they had allocated information to or retrieved information from each team member for each knowledge area needed for the group tasks. The responses were binary where 0 represented "no allocation (retrieval)" and 1 represented "some allocation (retrieval)." Because groups differed in the number of areas of expertise needed for their tasks, the knowledge allocation and retrieval matrices were averaged across tasks to facilitate aggregation. Finally, the average information allocation and retrieval matrices were summed to build the resource exchange network for each group. Network indicators of social capital that were computed based on this matrix include *closeness centrality* at the individual level, and *network density* at the collective level. These measures were calculated using standard network methods via UCINET 6.0 (Borgatti, Everett, & Freeman, 2002)

Data aggregation was used to measure the *development of group transactive memory systems* because it follows a compositional emergence model (Bliese, 2000). Two dimensions were assessed: development of knowledge directories and sharedness of expertise perceptions. Measures of development of individual knowledge directories were averaged across group members to gauge the level of development of knowledge directories at the group level. To evaluate the level of sharedness of transactive memory among group members, standard deviations of the development of individual knowledge directories were also calculated. To facilitate across-group comparisons, coefficients of variation were calculated by dividing standard deviations by means. The correlation between the mean and the coefficient of variation was r = -.84 (p < .05, N = 15). To build a composite scale measuring the sharedness of knowledge directories memories, the resulting coefficient of variation variable was multiplied by –1 so that a high coefficient of variation would imply high variability in people's expertise perception and therefore a low level of sharedness. Because the mean and the coefficient of variation dimensions for development of transactive memory systems were on different scales, z-transformations were conducted on both variables to permit summation. The final scale for development of group transactive memories was the sum of scores on these two dimensions. Descriptive statistics are reported in Table 1.

>>>>> INSERT TABLE 1 ABOUT HERE<<<<<

Tests of Within-Group Versus Between-Group Variability

Snijder and Bosker (1999) suggest that standard analysis of variance (ANOVA) tests be conducted prior to multilevel tests to provide justification for these tests. Significant between-group differences necessitate the use of multilevel modeling techniques to handle the grouping effects in measurement. ANOVA analysis results showed significant differences between groups for all the variables involved in the model.

Another purpose for testing within versus between group variability is to check for the validity of data aggregation (Bliese, 2000; Klein et al., 2000). Of all the group level measures, collective access to information was the only one that was derived from aggregation of individual level measures. Within-group agreement analyses, the r_{wg} tests developed by James, Demaree and Wolf (1984), were conducted in advance to provide justifications for this procedure. Both the median and mean r_{wg}s were larger than the cutoff point of .70. Therefore data aggregation was appropriate.

Analysis

The model presented in Figure 2 was analyzed via multilevel structural equation modeling (SEM) for three reasons. First, the model contains multiple levels. Second, the data were clustered by groups, which rendered the use of OLS regression inadequate (Klein et al., 2000). Third, multilevel SEM can provide tests of overall model fit, in addition to the evaluation of each individual path. The tests were conducted using Mplus 3.0 (Muthen & Muthen, 2003).

Results

Tests of Theoretical Model

In the SEM analysis at the individual level of analysis, the unstandardized regression coefficient[3] for development of individual expertise directories on closeness centrality was $\beta_{\text{closeness centrality}} = .51$ ($t = 3.34$, $p < .05$). Hypothesis 1 was supported. The regression coefficient of individual access to information on development of individual knowledge directories was $\beta_{\text{development of individual knowledge directory}} = .004$ ($t = .10$, $p > .05$). Hypothesis 4(a) was not supported.

At the group level of analysis, the unstandardized regression coefficient of development of transactive memory systems on network density was -.46 ($t = -.31$, $p > .05$). This means that collective social capital did not impact the development of transactive memory systems at the group level. Hypothesis 2 was not supported. The unstandardized regression development of transactive memory systems on coefficient of task interdependence was – .02 ($t = -.01$, $p > .05$). Hypothesis 3, which predicted that task interdependence would be positively related to development of transactive memory systems, was also rejected. The unstandardized regression coefficient of collective access to information on development of transactive memory systems

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[3] Mplus 3.0 does not provide standardized solutions for this type of analysis. In addition, E. Rigdon (post to SEM discussion list on March 30,2004) recommended the use of unstandardized solutions over standardized solutions in all cases because “(s)tandardizing based only on sample data is especially risky, as each given sample is subject to random sampling error.”

was .01 ($t = 1.30$, $p > .05$). Hypothesis 4(b) was also rejected. These regression coefficients of the baseline model without the moderation effects are reported in Figure 3.

>>>>> INSERT FIGURE 3 ABOUT HERE<<<<<

The overall model fit indices gave mixed results. The Standardized Root Mean Residuals (SRMR) is a standardized summary of the average covariance residuals that describes "the differences between the observed and model-implied covariances" (Kline, 1998). Among them, SRMR(W), the standardized summary of the average covariance residuals for the within-group part of the model at the individual level of analysis was .03. Since it was smaller than the conventional value of .10, it indicated good model fit. However, a significant $\chi^2 = 10.57$ ($df = 3$, $p = .01$) indicated relatively poor model fit. The Comparative Fit Index (CFI) was .58. Since it was smaller than the conventional cutoff point of .90, it showed that the model did not fit the data well. The Root Mean Square Error of Approximation (RMSEA), which compares the fit of the proposed model and the saturated model, was .12. As it was larger than the conventional value of .05, it showed that the model did not fit the data. Finally, SRMR(B) for the between-group collective part of the model was .14. Because it was larger than .10, it also showed poor fit. A summary of the overall model fit indices, together with their respective conventional cutoff values, is reported in Table 2.

>>>>> INSERT TABLE 2 ABOUT HERE<<<<<

Model Revisions

To improve the overall model fit, the baseline model was revised. Because the model fit index showed that the individual-level part of the model fit the data better than the group-level part of the model (SRMR for within group met the standard, while SRMR for between group did not), model revision started from group level relationships. In Model 2, a direct path from task interdependence to collective access to information was added because zero-order correlations of group level variables showed that the two constructs were significantly correlated with each other. Conceptually, it is also reasonable to connect the two constructs because collective access to information is vital for people working on interdependent tasks. After adding this link, the model fit improved significantly. All the fit indices now met conventionally values: $\chi^2 = 2.52$ (df = 2, p = .25, not significant), CFI= .97 (> .90), RMSEA= .04 (<.05), SRMR(B) = .04 (<.10), SRMR(W) = .03(<.10). Although dropping insignificant links in the model can further improve model fit, these links are of theoretical importance. Therefore, no further model modifications were made to avoid removing hypotheses that are of conceptual importance. The unstandardized regression coefficient of collective access to information on task interdependence $\beta_{\text{task interdependence}}$ was .12 ($t = 2.47$, $p < .05$), indicating that the added link was statistically significant. Coefficients at the individual and collective levels of analysis remained unchanged.

Moderating Effects

The moderating effects of group-level contextual variables on lower level relationships were tested via identification of significant random slopes in multilevel regression analysis (Klein et al., 2000). Hypothesis 5 predicted that network density would negatively moderate the relationship between closeness centrality and individual access to information. Hypothesis 6 predicted that task interdependence would negatively moderate the relationship between closeness centrality and individual access to information. The tests showed that across the 15 groups included in the study, the average slope of the regression line of individual social capital on the development of individual knowledge directories was 1.08 ($t = 6.83$, $p < .05$). The unstandardized regression coefficient for the moderating effect of network density on this slope was -.14 ($t = -3.86$, $p < .05$). Therefore, Hypothesis 5 was supported. The unstandardized regression coefficient for the moderating effect of task interdependence on this slope was –.02 ($t = -.27$, $p > .05$). Therefore Hypothesis 6 was not supported. Hypothesis 7 was tested in a similar fashion. The results showed that across the 15 groups that participated in the study, the average slope of the regression line of development of individual knowledge directories on individual access to information was .002 ($t = .04$, $p > .05$). The unstandardized regression coefficient for the moderating effect of transactive memory systems on this slope was .003 ($t = 1.24$, $p > .05$). Therefore, Hypothesis 7 was rejected. Figure 4 provides a result summary.

>>>>> INSERT FIGURE4 ABOUT HERE<<<<<

Discussion

Contributions

The current research examined antecedents to individual and collective access to organizational knowledge from a network perspective at the team level. The research was based on a new multilevel, multi-theoretical model of how individual and collective social capital influences the development of individual and collective knowledge directories in transactive memory systems and how these subsequently affect access to knowledge.

A multilevel model. Although the multilevel nature of group cognition is not unrecognized, it has not been given the level of attention it deserves in transactive memory research. In both the original and subsequent developments of the theory, discussion of transactive memory tends to travel between different levels of analysis in an unsystematic fashion. Building on Kozlowski and Klein’s (2000) conceptual framework, this study proposed that transactive memory represents a shared knowledge directory at the collective level, which emerges from bottom-up interactions. The benefits of having such a theoretical framework are twofold. First, it paves the road for future multilevel research on the topic. Aided by a clearer articulation of the basic components and the action process of emergent transactive memory systems, scholars can more easily identify and investigate factors that influence the process at different levels. Second, the emergent typology provides a clearer guide to empirical tests. As observed by Yuan, Fulk and Monge (2005), hampered by an evasive discussion of level of analysis, empirical measurements of the concept have been problematic. It is confusing to researchers as to which level is appropriate for measuring the concept. This research offered a solution to the problem through better multilevel theory-development.

A multi-theoretical framework from a network perspective. The second major contribution of the current research is the development of a multi-theoretical framework by which transactive memory systems can be studied from a network perspective. Building on the proposed multilevel model of transactive memory systems, this research utilizes multiple theories to investigate how properties of resource exchange networks shape the development of transactive memory at both individual and collective levels of analysis. Networks are central to transactive memory systems because they provide connections among otherwise disconnected cognitive activities. However, this issue has never been fully explored in either Wegner's original articulation of the theory (1987) or in any subsequent theoretical developments (1995). The current study represents an effort to place networks as the central focus for transactive memory research.

Monge and Contractor (2003) advocate the use of multiple theories to study the formation and evolution of networks. In the current research, Burt's (1992) structural hole theory, Granovettor's (1973) strength of weak ties theory, and Coleman's (1988) network closure theory of social capital were used to develop the multilevel network model. Conceptually, these theories enable a comprehensive framework to study how properties of communication networks for resource exchange could shape the development of transactive memory. Empirically, they provide theoretical foundations for determining which indicators of network properties should be used to measure individual social capital.

Model Results

At both the individual and collective levels of analysis, development of knowledge directories (referred to as transactive memory at the collective level) was found not to significantly relate to access to information. Empirically, this may be caused by the differences in the reference framework for data collection. The data used to derive measures of development of knowledge directories were collected using network matrices, with each knowledge area occupying one column in the matrices. In contrast, access to information was measured in a more general sense without a clear reference to these different knowledge areas. This difference in reference points may have created some noise in data analysis.

Conceptually, the broken link between the two sets of variables is indicative of knowledge management pitfalls. It sometimes happens in organizations that experts are isolates in the communication networks through which group members attempt to access others' knowledge. As a result, their expert knowledge is not easily accessible to the rest of the group, in spite of wide recognition of their expert knowledge. If no conscious efforts are made to facilitate access to knowledge expertise, organizations cannot make full use of their available competence.

Network density and task interdependence at the collective level of analysis were not found to have any significant impact on the development of transactive memory systems. Small group-level sample sizes may be one of the major causes. A post hoc analysis found that task interdependence had direct relationships with collective access to information. One possible reason for this is that task interdependence has localized expertise recognition. When task interdependence was high, group members' primary concerns were accessibility to information from their task partners, but not necessarily accessibility to information from the absolute experts in the larger collective. One issue worth mentioning here is that after the post hoc link from task interdependence to collective access to information was added, the insignificant link between the development of transactive memory systems and collective access to information in a prior model became significant. Inflation of results may have occurred because task interdependence and the development of transactive memory systems were negatively correlated with each other. However, the t-value of this path before adding the post hoc link was not too far away from the critical t-value for one-tailed directional hypothesis testing. Were a larger sample available, the results could have been different.

The results for tests of moderating effects showed that network density had a significant moderating effect on the relationship between individual social capital and the development of individual knowledge directories, as predicted. When collective social capital was high, people's reliance on individual social capital to develop accurate and extensive knowledge directories became weaker. However, counter to our prediction, task interdependence was not found to have a significant mitigating influence on the impact of individual social capital on the development of individual knowledge directories. This means that the strength of the relationship between the development of individual social capital and the development of individual expertise directories does not vary significantly between high versus low task interdependence groups.

The research also examined the moderating influence of transactive memory systems on the relationship between development of individual knowledge directories and access to information. The hypothesis stated that with well-developed transactive memory systems, the relationship between the two lower-level variables should be weaker. The assumption for the hypothesis was that given well-developed transactive memory systems, people could rely more on the collective wisdom. No significant moderating effect was found. This is not surprising, given that, contrary to hypothesis 4(a), there was no significant direct relationship of development of knowledge directories to individual access to information. One other possible explanation is that the results are spurious because in the current research, following the composition model of emergence, the average of individual knowledge directories was a component of the measure for development of transactive memory systems. The interdependent relationship between the two variables at different levels of analysis may have caused this result. This rationale would not provide a complete explanation, however, because the two variables correlated only .17, and the within- versus between groups analysis showed substantial within-group variability across individuals in relation to the group average. Nevertheless, a more objective measure of transactive memory, separate from the measure derived from individual level variables, is desirable.

Limitations and Directions for Future Research

The major limitation of the current research was the small sample size, particularly at the group level. There is no consensus about the minimum number of 2nd level units required for doing multilevel analysis. While Snijders and Bosker (1999) propose that 10 groups is the bottom line, others (Mass & Hox, in press) tend to use 30 as the cutoff point. Caution is warranted in interpreting the results, particularly at the group level effects, because the total number of groups examined in this research was only 15. A simulation study of Muthen’s Mplus multilevel model (Hox & Mass, 2001; Mass & Hox, in press) found that estimates of regression coefficients and significance tests of within-groups part of the model are generally accurate in multilevel structural equation modeling of small samples (less than 50 groups). The coefficients for the among-group part of the model are accurate if model convergence is achieved. However, standard errors of those estimates tend to be too small, which results in an increased likelihood of rejecting the null hypothesis when it is true. Given these results from the simulation studies, caution should be exercised when interpreting results about group level effects. However, because true relationships are more likely to be rejected as non-significant in small samples in comparison to large ones, it is reasonable to assume that the significant results from the within-group parts of the model would be true in larger research samples as well.

Conceptually, the current research was limited because no distinction was made between different types of knowledge. Hansen (1999) found an interaction effect between knowledge type (codified vs. non-codified knowledge) and network tie strength (strong vs. weak ties) in organizational knowledge transfer processes. When the information being transferred was codified, weak ties were more preferable than strong ties. However, when the knowledge transferred was not well codified, strong ties became more useful. Future research needs to address whether interaction effects between types of knowledge and network properties also exist within the dynamics of knowledge retention.

A second conceptual limitation was that this research mainly focused on connective transactive memories that rely on person-to-person information allocation and retrieval. Xu et al. (2004) proposed that in communal transactive memory systems, such direct connections are not required for knowledge sharing activities. Knowledge directories may be updated by consulting expertise databases. Future research should also investigate what factors influence the development and utilization of communal transactive memory systems for expertise location (Hollingshead, Fulk & Monge, 2002).

The third limitation of the current research is that it mainly focused on one type of social network, i.e., resource exchange networks about task related information. Although one type of network can be used for other purposes, recent research shows that there is a limit to network appropriability (Podolny & Baron, 1997). Future research should also investigate whether non-task related network ties would have the same impact on development of transactive memory systems.

Conclusion

In a knowledge economy, how organizations successfully retain knowledge that they have created can have a significant impact on their performance (Argote, McEvily, & Reagans, 2003). As organizational knowledge is distributed among its members, effective storage and retrieval become key challenges for knowledge management. Transactive memory theory provides a useful framework about how distributed knowledge is organized and utilized. This research examined how individual and collective social capital influenced the development of transactive memory systems in work groups as well as individual and collective access to knowledge. It is one of the first studies to examine transactive memory as a network of individual minds (Wegner, 1987) from a network perspective. The research shows that in order to develop individual knowledge directories, people need to make conscious efforts to reach a large number of well-connected people. These better-developed individual knowledge directories, through sharing, will transform into better-developed transactive memory systems at higher levels that enable organizations to better retain and utilize their collective knowledge.

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Table 1

Descriptive Statistics and Zero-Order Correlations

		1	2	3	4	5	6	7	8	9
1	Task Interdependence	-	.16*	-.08	.56*	.51*	.05	.16*	.11	.27*
2	Network Density		-	.11	.12	.28*	.08	.09	.10	.08
3	Development of Transactive Memory Systems			-	.32*	.42*	.11	.21*	.17*	.54*
4	Collective access to information				-	.30*	.42*	.37*	.40*	.15*
5	Closeness centrality					-	.27*	.38*	.35*	.22*
6	Accuracy of Individual knowledge directories						-	.77*	.90*	.06
7	Extensiveness of Individual Knowledge directories							-	.97*	.01
8	Development of Individual Knowledge directories								-	.02
9	Individual Access to Information									-
	Mean	2.5	.50	.00	13.81	91.36	2.93	3.03	5.98	13.92
	Standard deviation	.97	.19	1.9	1.78	1.57	.70	1.27	1.85	3.14

Sample Size = 179; * Significant at the .05 level (One-tailed test)

Table 2

Summary of Results for Overall Model Fit Indicators

		Chi^2	df	*p*	CFI	RMSEA	SRMR	
							Between	Within
Convention				> .05	>.90	< .05	< .10	< .10
Model 1	Baseline Model	10.57	3	.01	.58	.12	.14	.03
Model 2	Added a path from task interdependence to collective access to information	2.52	2	.28	.97	.04	.04	.03

RMSR = root mean squared residuals; GFI = goodness of fit index; SRMR = standardized root mean square residual; SRMR(Between) = SRMR for between-group relationships at the collective level; SRMR(Within) = SRMR for within-group relationships at the individual level.

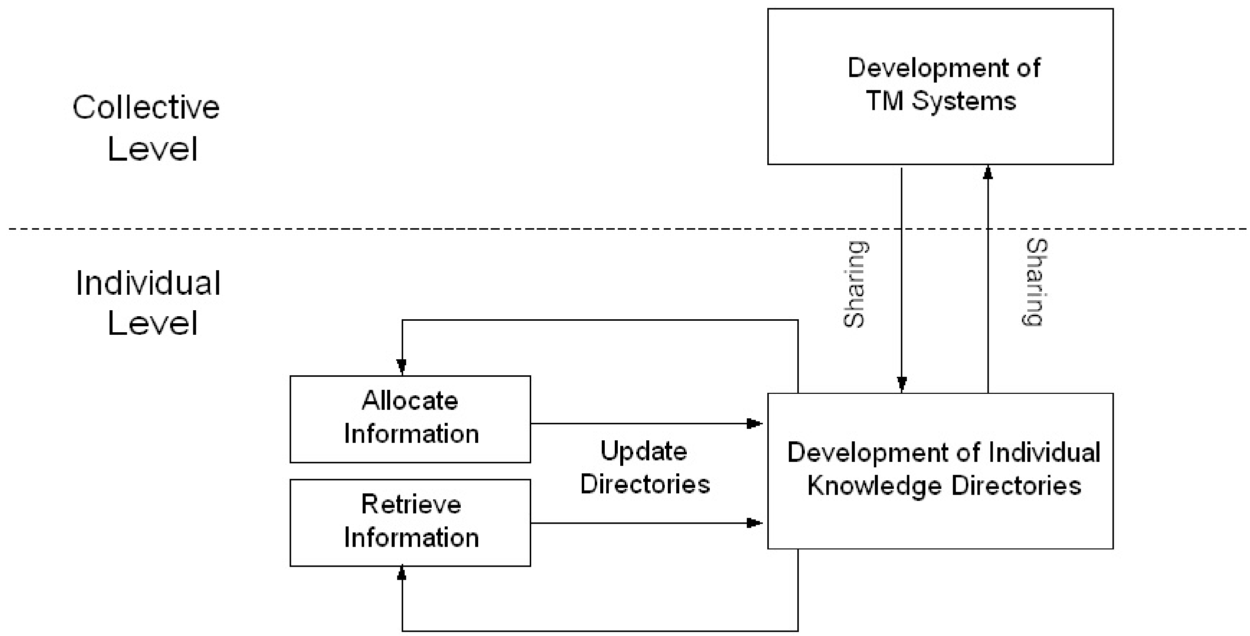
Figure Captions

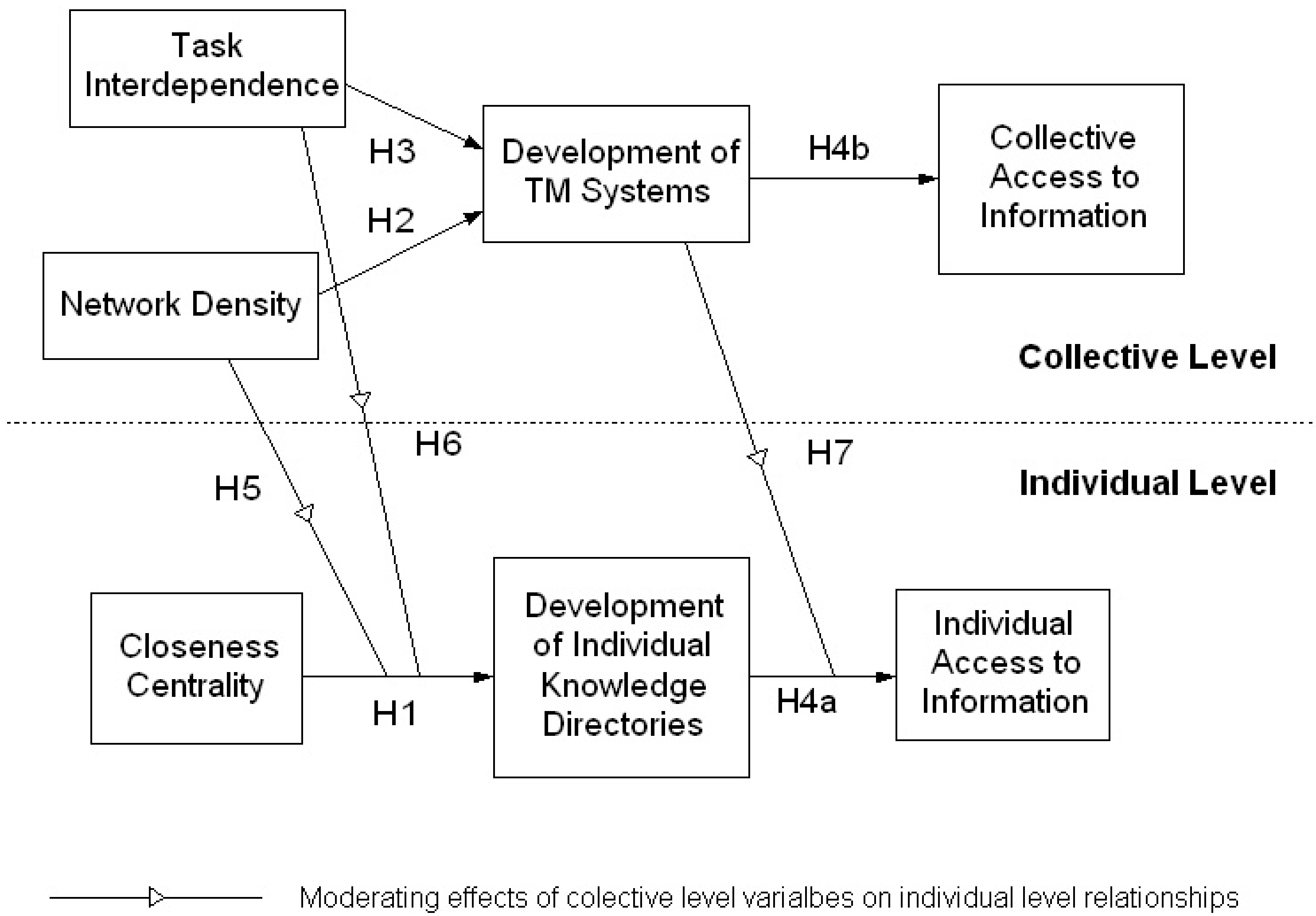
Figure 1: The emergence model of the development of transactive memory systems

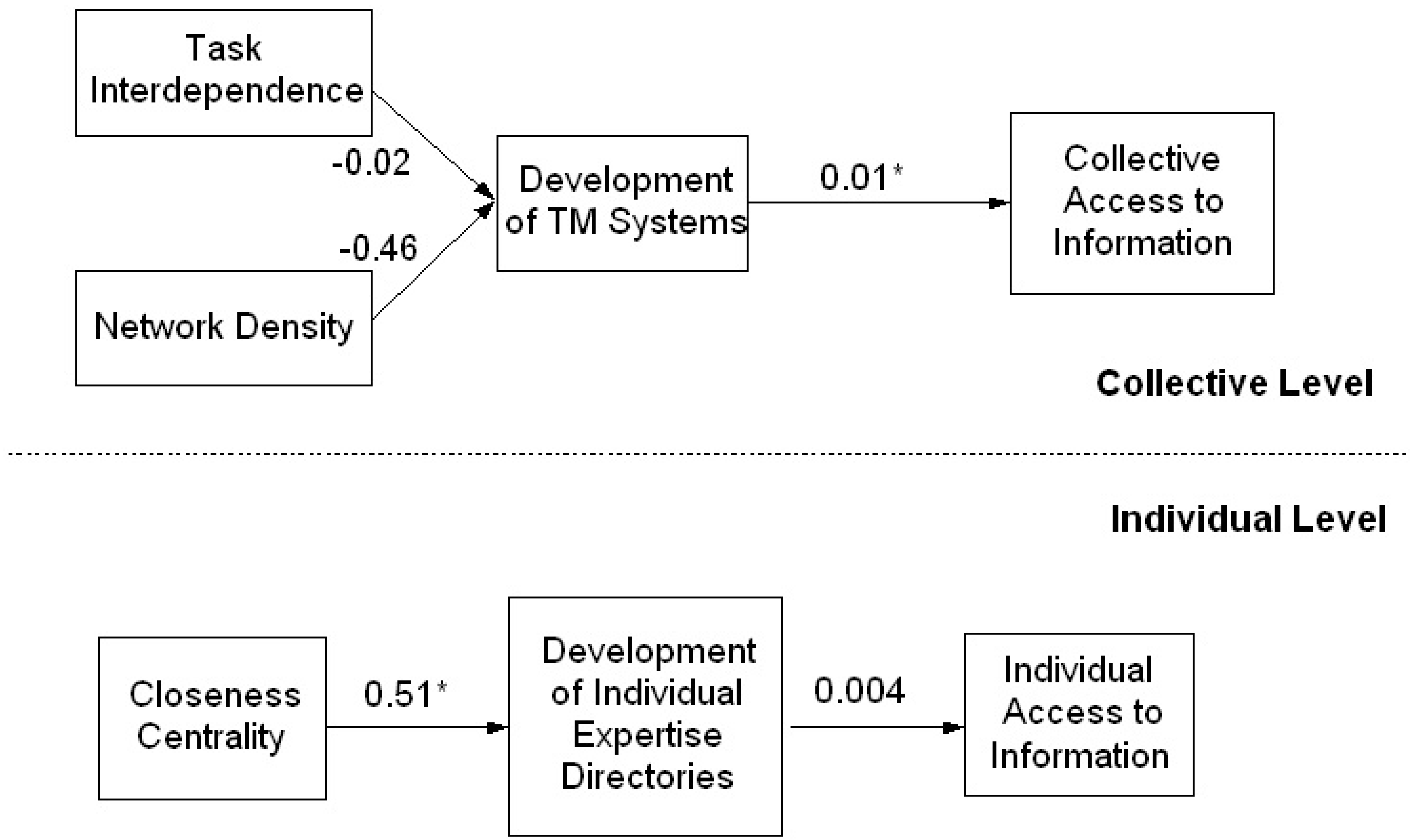
Figure 2: Multilevel, multi-theoretical model of the impact of social capital on the development of transactive memory systems

Figure 3: Results of the baseline model

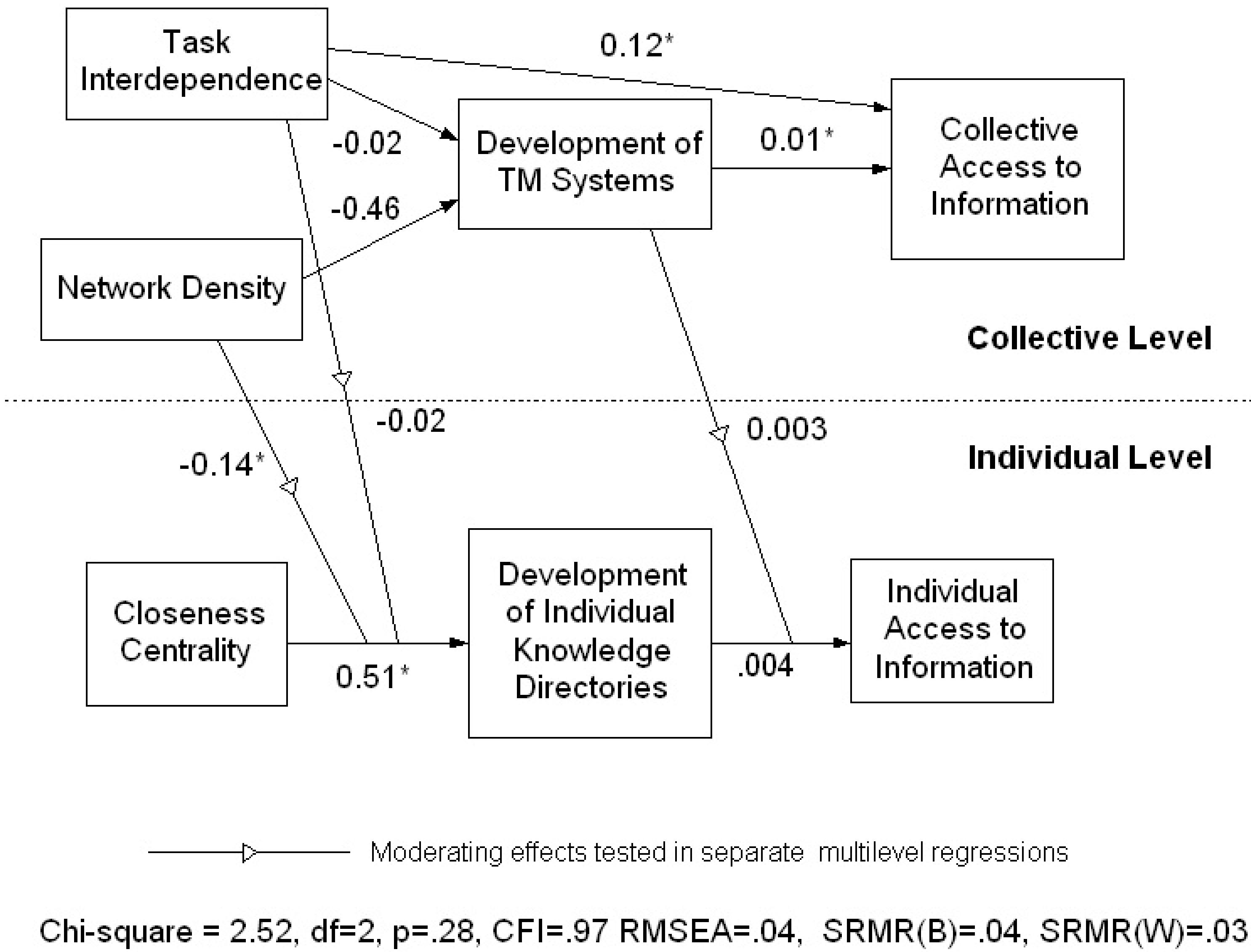
Figure 4: Results of the final model that added a link from task interdependence to collective access to information, and the moderating effects of collective level variables on individual level relationships


Collective Level
Development of TM Systems
Individual Level
Sharing
Sharing
Allocate Information
Retrieve Information
Update Directories
Development of Individual Knowledge Directories


Task Interdependence
Development of TM Systems
Collective Access to Information
Network Density
H3
H2
H4b
Collective Level
Individual Level
H5
H6
H7
Closeness Centrality
Development of Individual Knowledge Directories
Individual Access to Information
H1
H4a
Moderating effects of colective level varialbes on individual level relationships



Chi-square = 10.57, df=3, p=.01, CFI=.58, RMSEA=.12, SRMR(B)=.14, SRMR(W)=.03


Task Interdependence
0.12*
-0.02
Development of TM Systems
0.01*
Collective Access to Information
-0.46
Network Density
Collective Level
-0.02
0.003
-0.14*
Individual Level
Closeness Centrality
Development of Individual Knowledge Directories
Individual Access to Information
0.51*
.004
Moderating effects tested in separate multilevel regressions
Chi-square = 2.52, df=2, p=.28, CFI=.97 RMSEA=.04, SRMR(B)=.04, SRMR(W)=.03