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Coevolution of Communication and Knowledge Networks in Transactive Memory Systems: Using Computational Models for Theoretical Development

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This study focuses on the initial conditions of work teams and the impacts of these conditions on the development of teams' transactive memory (TM) systems through computational modeling. TM theory describes the conditions under which team members retrieve and allocate information to accomplish collective tasks. Previous research has shown evidence for teams developing TM systems over time, but field research does not allow for the extensive manipulation of initial conditions a team might face when working together; conversely, this experimental research allowed for such manipulations without negatively impacting the ongoing productivity of organizations. Initial knowledge, initial accuracy of expertise recognition, and network size are explored as predictor variables on the development of a TM system as mediated through communication. System development is measured by the degree to which team members accurately perceive other members' expertise and the extent to which the system has differentiated its stored knowledge. This study includes theoretically derived propositions tested through a path analysis of computationally generated data. The analysis validates the five propositions and is consistent with the developmental mechanisms of TM theory. Three additional paths proved to be significant and directly connect the initial conditions with the developmental indicators at the end state model.

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Researchers have investigated whether "information-age organizations" need to develop and transfer intellectual material to survive (Badaracco, 1991; Drucker, 1997; Peters, 1992). What has resulted is an overwhelming belief in the importance of using workers' knowledge in order for organizations to thrive in the present

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knowledge economy; in any work based on knowledge, expertise is the most important resource (Anand, Manz, & Glick, 1998; Argote & Ingram, 2000; Faraj & Sproull, 2000). Klein and Prusak (1994) illustrate the importance of using workers' knowledge, suggesting that organizations compete with one another based on their intellectual resources, and similar to financial, physical, or human capital, knowledge capital allows organizations to increase the value of their products and services.

The emphasis on transferring intellectual material among people creates a greater need to identify what individuals know, as well as what those individuals think others know. Perceptions of what others know is a strong indicator of information sharing within work teams (Borgatti & Cross, 2003; Palazzolo, 2005). Clearly, organizational knowledge sharing must be enhanced, but how this can be accomplished still remains a critical question. Part of the answer may include improving individuals' ability to accurately identify who knows what and working toward a differentiated knowledge structure. Developing an accurate and differentiated knowledge structure helps in sending and requesting information from appropriate individuals in an efficient and effective manner. However, as knowledge gets spread out among various people, who can be geographically dispersed, it becomes increasingly difficult to identify the location of needed knowledge.

To address the above concerns, this study describes how transactive memory (TM) theory (Wegner, 1987, 1995) provides a theoretical basis for understanding the development of organizational memory in work teams. TM theory is based on the premise that members of effective teams, working on interdependent tasks requiring multiple areas of expertise, seek to reduce individual workload and repetitive work by developing expertise in distinct areas and relying on others in the team to specialize in other areas where they lack expertise. A TM system is a collection (or network) of interdependent individuals, their memory systems, and the communication occurring among them (Wegner, 1987). Rulke and Galaskiewicz (2000) suggest that research on TM theory would greatly benefit from taking a network perspective when examining how expertise is divided among different individuals, and, perhaps more importantly, how information is retrieved and allocated in teams. A network perspective allows for the direct measure of connections between multiple people and, therefore, provides more rich information regarding the underlying processes of the system. In recent years, some researchers have begun to look at and describe TM systems as networks (Borgatti & Cross, 2003; Carley & Hill, 2001; Contractor & Monge, 2002; Cross, Rice, & Parker, 2001; Palazzolo, 2005). This network perspective is used here to examine TM systems.

The TM system is expressed as a collection of people in a network, encompassing both attributes of the individuals as well as the relations among them (Wasserman & Faust, 1994). A TM system allows members to gain access to a knowledge base larger and more complex than any one person possesses alone (Moreland, 1999; Wegner, 1987). Thus, a TM system is a property of the network and can be developed over time as people in the network allocate information to and retrieve information from one another (Wegner). Ideally, this access to a wider amount of information should improve team performance.

Given the heavy emphasis on work to be accomplished by teams in the present economy, this research is important because it seeks to understand the dynamics of team development, based on a variety of team member configurations, and how various initial conditions can affect the development and utilization of a team's TM system. Such an understanding is important not only for TM theorists but also for all who work in teams and manage teams. Further, this work is applicable to those who study interpersonal communication, group communication, and organizational communication in that TM systems encompass these levels and the findings have implications for researchers at each of these levels as well.

Last, this work demonstrates the role of computational modeling for theoretical development in communication. It shows the benefits and importance of understanding communication from a network perspective and illustrates how connections among people can be modeled and, thus, specified at an extremely detailed level. Further, the computational modeling allows for the generation of macrolevel systematic properties of group interaction stemming from the microlevel, individual, and dyadic properties specified. Although this research focuses on TM theory, the methodology is applicable to a wide range of communication theories.

TM theory offers three generative mechanisms to describe the development of a TM system: directory updating, communication to allocate information, and communication to retrieve information. This paper defines these mechanisms and their interrelations in greater detail through a network perspective and computational model. Based on these theoretical mechanisms and prior empirical research, five theoretically deduced propositions are presented to explain the emergence and development of a TM system. Next, an agent-based computational model formulated on the three generative mechanisms of TM theory is used to logically validate the theoretically derived propositions through a virtual experiment. Although the results of these simulations need to be validated with empirical data, they provide important theoretical contributions and directions for future research. The study concludes with a discussion of the findings with respect to TM theory for organizational communication.

Theoretical components as generative mechanisms and developmental measures

Consider a network that must accomplish a set of tasks for a large project. The tasks may require multiple areas of expertise that each individual may not possess alone. However, collectively the network may have the necessary knowledge to complete the tasks. Thus, members in the network are interdependent because they must exchange information to complete their tasks. To understand how a team could complete their project, TM theory identifies three interrelated processes or generative mechanisms by which network members develop their TM system: (a) directory updating, (b) communication to allocate information, and (c) communication to retrieve information. Following these processes yields two measures of the extent to which the TM system has developed or matured: (a) accuracy in expertise recognition and (b) knowledge differentiation.

Extensive research identifies accurate expertise recognition and knowledge differentiation as characteristics of a well-developed TM system. Accuracy of expertise recognition is the extent to which people in the network accurately perceive what knowledge other people possess (Rau, 2000) and is used as a TM system development measure because the three generative mechanisms should lead to accurate perceptions. Knowledge differentiation is the extent to which network members are experts in areas that other members are not (Wegner, 1987). Knowledge differentiation is used as a measure of the TM system development and occurs as individuals accept responsibility for different knowledge topics (Wegner).

Knowledge differentiation and accuracy of expertise recognition are essential for the development of a TM system (Faraj & Sproull, 2000). The mere presence of diverse expertise, or differentiation, is a necessary but insufficient precondition to a well-developed TM system (Faraj & Sproull). Equally important factors are knowing who possesses expertise, realizing where it is needed, and bringing the needed expertise to that context through interaction. Additionally, accurately recognizing expertise and having differentiated expertise facilitate the sharing of tasks and allow goals to be accomplished collectively (Faraj & Sproull). Finally, accurate expertise recognition and a differentiated knowledge base reduce the workload for team members because they can simply go to an expert for information, rather than duplicating existing knowledge (Faraj & Sproull; Hollingshead, 1998b; Moreland, 1999). The intention here is to explore how different initial conditions can influence the outcomes, or end states, of teams that strictly follow the generative mechanisms of TM theory.

Directory updating

Directory updating is the process by which team members create and revise their perceptions of "who knows what" (Wegner, 1995). This process consists of two separate directories: a self-directory and an others-directory. The self-directory is used to keep a record of one's own knowledge levels for various knowledge domains and is based on three determinants: (a) what the person knew at a previous point in time, (b) what information was sent to the person from the environment outside of the team, and (c) what information other people in the network allocated to him or her. People learn about their own level of expertise through interactions as people assert their individual expertise, question others about their expertise, demonstrate expertise, reference common knowledge or interests, reference shared knowledge or interests, discuss previous experiences related to the topic, or discuss lack of knowledge about the topic (Hollingshead, 1998a).

In the others-directory, people maintain perceptions of what they think each other network member knows (Nickerson, 1999; Wegner, 1995). The others-directory is influenced directly by communicating with a second person, as well as indirectly by communicating with other team members who have their own perceptions of the second person's knowledge. For example, in a network with three people (*i*, *j*, and *k*), *i*'s perception of how knowledgeable *j* is regarding organizational policies might increase by directly asking *j* questions and finding *j* to be a good source of information on this topic. However, *i*'s perception of how knowledgeable *j* is on organizational policies might decrease after *i* talks with *k* who, based on past interactions, knows that *j*'s information is inaccurate and outdated. This process of learning what others know is not novel; it has been studied via networks in the social influence literature (Marsden & Friedkin, 1994; Rice, 1993; Robins, Pattison, & Elliott, 2001). TM theory incorporates social influence as one process of many that yield a TM system (see Palazzolo, 2003, for a discussion of social influence in TM systems).

Through directory updating, people are able to recognize where expertise resides within the network. Here, the expert is the person or people perceived to have the most knowledge on a given topic based on these two directories; thus, expertise is the knowledge of the perceived most knowledgeable member(s). Given its perception-based status, a team's expert (and, therefore, the team's expertise) can vary by each team member. This process of directory updating occurs in several ways, including default entries based on surface attributes (such as age or gender), negotiated entries based on the acceptance of responsibility for certain information, access entries based on the duration or recency of exposure to information, and expertise entries based on the identification of one person having more knowledge or interest in an area than another (Wegner, 1995).

Networks can comprise of people having varying levels of expertise. For example, some networks may exclusively comprise people with low levels of individual knowledge (e.g., novices working on a new project); alternatively, other networks may have members all with high levels of individual knowledge (e.g., expert teams for crisis management). Different initial levels of individual knowledge may affect the development of TM systems in different ways.

As demonstrated by Moreland (1999), if team members personally have all the knowledge needed to complete their tasks (i.e., higher initial knowledge across all topics for all members), then there is little incentive to identify the expertise of others in the network. Highlighting this point, Nickerson found that when people are highly knowledgeable across different topics, they assume others know the same information (Nickerson, 1999; Nickerson, Baddeley, & Freeman, 1987). Collectively, these results suggest that in situations where everyone in a network is highly knowledgeable on all topics, they will be self-sufficient for their tasks and have little need or incentive to communicate to get or send information within the network. In contrast, when everyone in a network has little knowledge across all topics, they will have a much greater need to communicate to get and send information. Thus, the first proposition relates initial individual knowledge levels and communication in the network.

P1: Networks with members who start with a lower individual knowledge base will have a higher rate of communication than networks where members have a higher initial individual knowledge base.

Communication

Communication is a vital mechanism in TM systems since it is the means by which team members share information. Communication is particularly necessary for directory updating when people do not know one another (Hollingshead, 2000; Lewis, 2000; Nickerson, 1999). In line with network theory and terminology, the extent to which people communicate is referred to as communication density and is defined as the percentage of the actual communication ties between pairs of team members compared to the total amount of communication possible between all pairs of team members. In TM theory, there are two types of communicative acts that are essential to the TM system: communication to allocate information and communication to retrieve information.

Communication to allocate information refers to the process by which members forward information to those whom they believe to be most qualified to encode the information for future access (i.e., the perceived experts in the network for a specific topic). Within a TM system, individual knowledge, perceptions of others' knowledge, and expertise recognition play important roles in determining how to manage incoming information. The allocation of information is important not only to signal identification of experts but also to provide informational support to the experts as well (Faraj & Sproull, 2000). Information allocation is triggered by new information entering from the environment from sources such as e-mail messages, Listserv messages, conversations, or newspaper articles, among many others. When people receive new information, rather than isolating it in their personal memory, the information may be allocated to others in the network who have a more "relevant and most well-developed directory structure for items of that kind" (Wegner, 1995, p. 329).

Communication to retrieve information is the process by which team members access information from knowledgeable others in the network. Retrieval coordination is used to accomplish or assist in assigned tasks for which they do not possess all the necessary expertise (Rice, Collins-Jarvis, & Zydney-Walker, 1999), and it allows members to systematically leverage knowledge from within the TM system (Palazzolo, 2005). There is evidence that seeking information outside of the immediate network increases the flow of information into the network (Austin, 2000; Teigland & Wasko, 2003). This process then leads to an increase in awareness of others' knowledge resources and expands the possibilities for finding new sources of expertise, thus resulting in greater accuracy of expertise recognition. Research by Stasser, Stewart, and Wittenbaum (1995) demonstrates the importance of explicit expertise recognition when retrieving information stored by others in the network. Their results suggest that although expert roles facilitated the dissemination of unshared information and the discovery of a hidden profile, awareness of expertise based solely on forewarning or gained through interaction apparently did not promote the sampling of unshared information.

Several studies show how communication can positively impact accuracy of expertise recognition. For example, Liang, Moreland, and Argote (1995) found teams that were trained together and worked together had greater accuracy in determining expertise as communication allowed them to share information about their abilities, skills, and knowledge. However, other empirical evidence suggests not all communication may lead to higher accuracy in identifying expertise. Littlepage, Schmidt, Whisler, and Frost (1995) had 34 teams of university students participate in a noneureka intellective task. They found that individual perception of others' expertise is closely related to the rate of others' participation in the discussion rather than their actual expertise. They argued that the teams' inability to accurately recognize expertise might be the result of the noneureka nature of the task, task difficulty, and participation patterns. Therefore, people may use communication to identify expertise but may not be very proficient at doing so. Further, Austin (2000) found that a high amount of communication is not inherently related to accurate expertise recognition or team performance. Austin proposed that it is not the interaction patterns themselves that lead to improved accuracy of expertise recognition but the frequency of specific types of interactions, such as communication for problem solving with fewer redundant ties.

Clearly, there are inconsistencies in empirical evidence examining the impact of communication density on expertise recognition. However, it is argued here that the level of communication density will positively affect accuracy of expertise recognition such that experts in the network become obvious to others through communication that leads to increased accuracy of expertise recognition. Thus, given the need for communication in a network to support and utilize its experts, as well as to update team members' directories of others' knowledge, the following proposition relating communication density and accuracy of expertise recognition is presented.

> P2: Networks with a higher average communication density will have greater accuracy of expertise recognition over time than networks with a lower average communication density.

Communication density should also affect the distribution of knowledge in a network. Although a team may initially have a relatively uniform distribution of knowledge across all topics, through information allocation, small differences in the amount of knowledge possessed by each person may be amplified over time, leading to a progressively differentiated knowledge network (Wegner, 1995). Empirical research by Moreland (1999) found that communication fosters the development of a differentiated TM system—as networks that communicated during training were able to collectively recall more unique and specific information from the training than networks whose members were not allowed to communicate. Thus, the following proposition is proposed relating communication density and knowledge differentiation.

> P3: Networks with a higher average communication density will have greater knowledge differentiation over time than networks with a lower average communication density.

Accuracy of expertise recognition

Given that team members' knowledge levels can vary and their perceptions of others' knowledge levels can vary, it becomes evident that members will also vary in the extent to which they accurately perceive their teammates' knowledge levels. Initial levels of accuracy in expertise recognition will impact the emergent communication within the network. Littlepage, Robison, and Reddington (1997) found that experience working with others in a network facilitates recognition of expertise and utilization of expertise. They suggest that working together in the network provides an opportunity to further develop accurate perceptions of others' expertise. In other words, inaccurate initial perceptions may become more accurate through increased interaction. Likewise, Austin (2000) found that the greater the mean of network tenure (i.e., the length of network membership), the greater the accuracy of expertise recognition. Hollingshead (2000) demonstrated the importance of having accurate perceptions of who knows what by observing people learning new information on a variety of topics. People focused on their core competencies and left other areas to be learned by those whom they perceived to be more knowledgeable. Finally, Lewis (2000) found that familiarity increases the ability of team members to recognize expertise.

This familiarity and experience identified above is developed, over time, through communication between the team members. That is, communication serves as a mediating variable between the initial state of accuracy of expertise recognition and the final state of accuracy of expertise recognition. Maintaining an accurate directory of who knows what within a team should facilitate future communicative interactions. In a functional system, an accurate directory should facilitate communication; however, it is possible that individuals widely believed to have little knowledge could be marginalized in such a system. Therefore, the next proposition argues for a positive connection between initial accuracy of expertise recognition and communication.

> P4: Networks with a higher initial level of accuracy of expertise recognition will have a higher average communication density than networks with a lower initial level of accuracy of expertise recognition.

Network size

Network size refers to the number of people in the TM system. Most of the early empirical work on TM systems focused on dyads and found support for the differentiation of knowledge and shared agreement regarding who possesses what knowledge in romantic couples (Hollingshead, 1998a, 1998c; Wegner, Erber, & Raymond, 1991). In addition to dyads, several empirical studies have examined artificial work teams in laboratories (Liang et al., 1995; Moreland, 1999) and intact work teams (Palazzolo, 2005). Liang et al. (1995) found that teams of three people who trained together on a task had more accurate beliefs about the distribution of skills among team members than those who were trained separately. Moreland (1999) also showed teams of three people, when training and working together, developed a more accurate TM system than teams of three who were either trained individually or trained as teams but then worked with different people. Although these prior studies have found strong support for TM theory between two and three people, Palazzolo argues that larger teams (8–17 members) have difficulty developing their TM systems and do not structure their communication patterns consistently with TM theory.

A follow-up study by Moreland and Myaskovsky (2000) showed an alternative to training together: by providing teams with lists of information on who knows what, the teams performed as well as those who were trained together. Having such an outside reference may be a means by which larger teams can still develop as TM systems without the additional costs of training everyone together.

Although the development of TM systems has been examined extensively in dyads and to some extent in small teams, there remains a need for additional theoretical and empirical investigation in teams with more than three people, particularly in regard to the impact of team size on communication, knowledge differentiation, and accuracy of expertise recognition. Moreland (1999) indirectly addresses the potential impact of team size on accuracy, suggesting people in large teams are more likely to have trouble identifying who knows what because there are simply too many directories of others to keep updated. In contrast, Austin (2000) examined cross-functional networks consisting of between 8 and 11 people in an organizational setting and found that network density was not related to the ability to identify expertise. Austin's results may hold for teams up to 11 people, but it does not address 15- or 20-person teams.

Further, people who feel more familiar or connected with others in a network may be more flexible in coordinating their recall strategies (Weldon, Blair, & Huebsch, 2000). Peterson and Thompson (1997) assert that people who are highly acquainted should view situations in similar ways as a function of their transitive memory network. However, larger networks may have greater difficulty in feeling connected, maintaining team familiarity, and becoming highly acquainted. Thus, people in large networks may have an opportunity to talk with more people, but few will actually connect with all their teammates. Based on people's cognitive limitations and the increased difficulty of becoming familiar and well acquainted with all members of a larger network, the following proposition relating network size and communication density is proposed.

P5: Smaller networks will have a higher average communication density than larger networks.

The five propositions proposed above, and represented schematically in Figure 1, were derived from the theoretical descriptions of TM systems. We take a systems perspective and use computational modeling as a tool to address these propositions. As scholars who advocate a systems perspective have noted, though interpretive research has great merit, it does not offer the full-range panorama of a well-developed systems theory. That is, a systems theory that promises to deal with complex structures, such as nonlinear relationships, should require "specification of the relationships among the elements and levels," "take a holistic view," and explain the emergence of indirect consequences (Poole, 1997, p. 49). The computational model

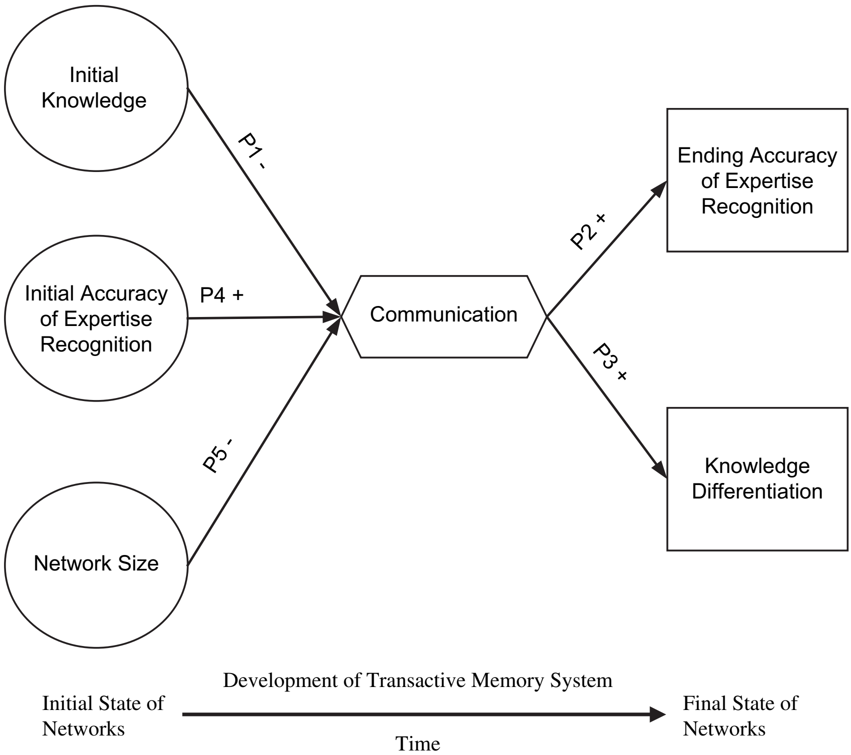

Figure 1 Theoretical model of transactive memory system development with propositions to be validated.

implemented here, and described below, incorporates these important aspects of a systems theory perspective and applies them to TM theory.

Computational models for theory development and specification

In this study, simulations based on a computational model of TM theory help examine how different initial conditions influence the dynamic development of the TM system. The goal here is to examine the results obtained by systematically conducting simulations of a large number of computationally created teams that vary on three initial conditions and whether or not these systematic differences support the five propositions. Confirmation will serve to logically validate the deduced propositions. Thus, computational models can highlight which aspects of the theory can benefit from further theoretical development and empirical exploration.

"Creating a formal model forces the researcher to be precise about the relationship among entities, to make implicit assumptions explicit, and to describe in detail the mechanisms by which entities and relationships change" (Carley & Prietula, 1994, p. xiv). For theoretical development, computational modeling forces the explicit or precise identification of theoretical mechanisms where verbal theories lack such detail (Monge & Contractor, 2003). Specifically, theorists must provide detailed descriptions of people, tasks, and the interrelations within the network (Carley & Prietula). Since the creation of a formal model requires precise mathematical definitions of theoretical mechanisms, multiple interpretations of the verbally described theoretical statements are possible. Thus, this paper proposes an interpretation of the theory of TM as a computational model based on a strict interpretation of the heretofore verbally described theory.

Most theories, including TM, offer a core set of generative mechanisms explaining how people's attributes (e.g., individual level of knowledge on a particular topic) and relations with one another (e.g., communication to retrieve information from others) change over time. Since the generative mechanisms explaining these changes are typically nonlinear, it is extremely difficult to mentally construe their interdependent implications over time—for a large number of entities or at multiple levels of analyses (e.g., individuals, teams, organizations). Thus, computational models are an appropriate technique to specify, with considerable precision, the generative mechanisms proposed by TM theory.

Blanche, an agent-based computational modeling environment (Hyatt, Contractor, & Jones, 1997), was used to test these propositions. It was used to specify and execute the simulations based on a network formulation of the generative mechanisms proposed by TM theory. Other systems dynamics simulation programs such as Dynamo, STELLA, iThink, Vensim, and Powersim have been used to study the often nonlinear interrelationships among variables or concepts such as net labor, schedule pressure, fatigue, and productivity. However, Blanche's object-oriented (or agent-based) modeling environment makes it the most appropriate environment to study TM systems as networks.

Agent-based modeling environments are a more recent entry to the field of simulation. As Sterman notes, "In an agent-based model, the individual members of a population such as firms in an economy or people in a social team are represented explicitly rather than as a single aggregate entity. Important heterogeneities in agent attributes and decision rules can then be represented," (2000, p. 896). The building blocks in these environments are agents, and there has been considerable recent interest in the development of agent-based computational models and multi-agent simulation environments (Bond & Gasser, 1988; Drogoul & Ferber, 1994; Epstein & Axtell, 1996; Gilbert & Troizch, 1999; Langton, Burkhart, Lee, Daniels, & Lancaster, 1998; Latane, 2000; Page, 1997; Prietula, Carley, & Gasser, 1998). With respect to this work, agents are used as representations of people on work teams.

In Blanche, each agent has a set of attributes and one or more relations connecting the agents to one another. Further, each agent has associated with it a set of rules that specify how the value of the attributes and relations can change over time. Core issues in any network model of agents are (a) the articulation of the attributes in the network, (b) the relations among the agents, and (c) the coevolution of the attributes and relations over time based on a set of generative mechanisms or "rules." These core issues are addressed in our proposed TM computational model (the model and supporting information is available at http://curious.comm.ohio-state.edu/pub/TM/).

A discrete set of generative mechanisms provides flexibility and expressiveness such that dependencies among agents' attributes and relations over time are modeled as a stochastic (i.e., probabilistic) function of values at contemporaneous, prior, or both points in time. That is, rather than specifying deterministic changes in the values of agents' attributes and the values of the relations among agents, they simply alter the likelihood for that change. For example, one can think of a person's individual knowledge (an attribute), at a point in time, t, as a function of the person's knowledge at prior points in time, $t - 1$, as well as a function of the person's communication to allocate and retrieve information (two relations) with other members in the network contemporaneously at time t. Other people allocating information to the focal person only alters the likelihood for a change in individual knowledge; it does not guarantee learning. Under the assumption that attributes and relations take on real values, Blanche employs nonlinear difference equations as a natural and efficient computational approach to represent the evolution of a person's attributes and relations over time.

Computational method

Sample

To logically validate the five propositions examining the mechanisms that may influence the development of TM systems and the role of communication in TM systems, artificial networks were created within the Blanche computational modeling environment. These networks contain a set number of agents or nodes representing the people on work teams, three attributes for each agent (individual knowledge, new information, and task assignment), and four relations between the agents (perception of others' knowledge, communication to allocate information, communication to retrieve information, and overall communication). The initial values for one attribute of the agents and two relations among the agents were systematically manipulated with high and low values (as described in the research design section below), allowing for the examination of how networks with different initial conditions develop over time. Since properties of the TM system, such as knowledge differentiation, are defined as properties of the network, the unit of analysis for this study is the network of agents, rather than individual agents. The propositions were tested on a set of 3,200 networks as described under the research design.

Theoretical variables

The process of directory updating is represented by Equation 1 for the self-directory and Equation 2 for the directory of others (the full equations are available online at http://curious.comm.ohio-state.edu/pub/TM/). In network terminology, the self-directory is defined as the attribute KIx_i, which indicates i's level of expertise on a particular topic, X. Here, X, Y, and Z are used to represent knowledge topics important to the team (e.g., marketing, market trends, or thermal dynamics). This attribute expresses the knowledge level of the agent and can change or be updated over time.

$$\mathrm{KIx}_{it} = \text{function}\ [\mathrm{KIx}_{i(t-1)},\ \mathrm{INFx}_i,\ \mathrm{CAIx}_{ji}] \tag{1}$$

The self-directory, KIx_i, is a function influenced by the agent's actual knowledge (KIx_i) at the previous point in time, incoming information on topic X to *i* (INFx_i) at the current point in time, and new information allocated from *j* to *i* on topic X (CAIx_{ji}) at the current point in time. The perception of knowledge possessed by others is defined as the relation KOx_{ij}, which indicates *i*'s perception of *j*'s level of expertise on topic X. Likewise, a second relation, KOy_{ij}, would indicate *i*'s perception of *j*'s actual level of expertise on topic Y (KIy_j).

$$\mathrm{KOx}_{ij} = \text{function}\ [\mathrm{KIx}_i,\ \mathrm{COM}_{ij}, \textstyle\sum((\mathrm{COM}_{ik})(\mathrm{KOx}_{kj}))] \tag{2}$$

The directory of others' knowledge, KOx_{ij}, is a function of *i*'s knowledge (KIx_i), communication from *i* to *j* (COM_{ij}), and the sum of communication to others weighted by the others' perceptions of *j*'s knowledge on topic X ($\sum((\mathrm{COM}_{ik})(\mathrm{KOx}_{kj})))$. For example, *i* might upgrade (or downgrade) her perception of *j*'s knowledge level in a specific domain after communicating with *j*. Additionally, *i* may revise her perception of *j*'s expertise in a certain area after communicating with other agents, *k*, about *j*'s expertise.

Communication to allocate information is defined as the relation CAIx_{ij} and is represented by Equation 3.

$$\mathrm{CAIx}_{ij} = \text{function}\ [\mathrm{INFx}_i,\ \mathrm{KIx}_i,\ \mathrm{KOx}_{ij}] \tag{3}$$

The relation CAIx_{ij} is activated when *i* gets new information from the environment on topic X (INFx_i), on which *i* is not an expert (KIx_i) and *i* perceives *j* to be an expert on topic X (KOx_{ij}).

Communication to retrieve information is defined as the relation CRIx_{ij} and is represented by Equation 4.

$$\mathrm{CRIx}_{ij} = \text{function}\ [\mathrm{TASKx}_i,\ \mathrm{KIx}_i,\ \mathrm{KOx}_{ij}] \tag{4}$$

In network parlance, CRIx_{ij} indicates *i*'s communication to retrieve information about topic X from *j*. The relation CRIx_{ij} is activated when *i* receives a task requiring expertise in topic X (TASKx_i) on which *i* is not an expert (KIx_i), but perceives *j* to be an expert (KOx_{ij}).

Communication is defined as the relation COM_{ij} and is a collection of all interactions between *i* and *j* for information allocation and retrieval on all knowledge topics. COM_{ij} is represented by Equation 5 for the three knowledge areas modeled here.

$$\mathrm{COM}_{ij} = \text{function}\ [\mathrm{CRIx}_{ij},\ \mathrm{CRIy}_{ij},\ \mathrm{CRIz}_{ij},\ \mathrm{CAIx}_{ji},\ \mathrm{CAIy}_{ji},\ \mathrm{CAIz}_{ji}] \tag{5}$$

That is, communication, as a whole, comprises the work-related communicative exchanges across all the knowledge topics.

Next, the two developmental measures of TM systems are expressed in networks terms. First, accuracy of expertise recognition (AERx), as shown in Equation 6, is defined.

$$\mathrm{AERx}_{ij} = \text{function}\,[\mathrm{KIx}_j,\ \mathrm{KOx}_{ij}] \tag{6}$$

Accuracy of expertise recognition is a relation identifying the difference between what *i* thinks *j* knows on topic X (KOx_{ij}) and what *j* actually knows on topic X (KIx_j). The same is computed for topics Y and Z. Further, an overall measure of accuracy (AER) is calculated as the mean of AERx, AERy, and AERz.

The second developmental measure of TM systems, knowledge differentiation (KDFR), is represented by Equation 7.

$$\mathrm{KDFR} = \text{function}\,[\mathrm{KIx}_i,\ \mathrm{KIy}_i,\ \mathrm{KIz}_i] \tag{7}$$

Again, KIx_i represents agent *i*'s knowledge on topic X. Likewise, KIy_i and KIz_i represent *i*'s knowledge on topics Y and Z, respectively. Knowledge differentiation is an attribute that expresses the extent to which *i* is knowledgeable in one area and not knowledgeable in others.

Research design

Just as experimental design strategies are used in the study of real teams, an experimental design is required to logically validate the propositions put forth in this study as well. By manipulating the initial conditions in the computationally created networks, the specific impacts of each component can be systematically identified. As summarized in Figure 1, the five research propositions involve three predictor variables: (a) level of individual knowledge, (b) accuracy of expertise recognition, and (c) network size. Each of these three predictor variables was manipulated into a high and a low condition resulting in a $2 \times 2 \times 2$ complete factorial experimental design. Table 1 represents the computationally created networks for each of the eight experimental conditions.

Each condition contained 400 computationally created networks. For example, Cell 1 in Table 1 indicates that 400 computationally created networks were created with stochastically generated distributions where (a) the average initial individual knowledge (KI) among the members was high (on a scale of 0–1, the network mean was 0.75, with a standard deviation of 0.2), (b) the initial accuracy of expertise recognition (AER) among the network members was high (on a scale of 0–1, the network's mean KI was high and the agents' mean perception of others' expertise was also high with a mean of 0.75 and a standard deviation of 0.2; alternatively, the network's mean KI was low with a mean of 0.25 and a standard deviation of 0.2, and the agents' KO was also low with a mean of 0.25 and a standard deviation of 0.2), and (c) the network size was low (the network contained four agents with no variance).

Table 1 Experimental Design for Initial State of the Network

Accuracy of Expertise Recognition	Starting Knowledge	Team Size	
		4	20
High	High	1	5
	Low	2	6
Low	High	3	7
	Low	4	8

Note: The numbers in the cells correspond to the eight conditions in the experimental design.

In contrast, Cell 8 in Table 1 indicates that 400 computationally created networks were computed where (a) the average KI among the members was low (on a scale of 0–1, the network mean was 0.25, with a standard deviation of 0.2), (b) the initial AER among the network members was low (on a scale of 0–1, the network's mean KI was high with a mean of 0.75 and a standard deviation of 0.2 and the mean KO was low with a mean of 0.25 and a standard deviation of 0.2; alternatively, the network's mean KI was low with a mean of 0.25 and a standard deviation of 0.2, and the mean KO was high with a mean of 0.75 and a standard deviation of 0.2), and (c) the network size was high (the network contained 20 agents with no variance). In creating the 400 networks in each of the eight cells, the constrained normal distribution function in Blanche was used with the specified means and standard deviations listed above to ensure the values of the attributes and relations were confined within the range of 0–1.

Simulation

After creating networks with different initial conditions, the next step was to simulate the development of the TM systems in each of the 3,200 networks. As part of the simulations, each of the agents in these networks operated according to the rules specified in the computational model described above. Since these generative mechanisms were specified as nonlinear difference equations, the three attributes and four relations had the potential to change at each time step, or iteration. The simulation was carried out for 99 iterations for each network in each condition. The 99 iterations used in the simulation were deemed sufficient for the development of the TM system to "stabilize." That is, no dramatic changes in the values of the attributes and relations were discernible after the 75th iteration. For each network, the values of each agent's attributes and relations were stored for statistical analysis.

Analysis of computational data

Conducting a statistical analysis on the data generated by the simulations was the final step in logically validating the theoretically derived propositions. The five propositions in this study were designed to test the effects of various initial conditions on the development of the TM system as it is mediated through communication. The three predictors of communication were initial level of individual knowledge (P1), initial accuracy of expertise recognition (P4), and network size (P5). TM system development is characterized by the ending level of the network's accuracy of expertise recognition and knowledge differentiation and was proposed to be positively influenced by communication (P2 and P3). Although the networks were assigned to the eight cells (see Table 1) based on high and low conditions, the actual values of these initial variables were normally distributed around the specified means and standard deviations. Hence, there was variability within each of the conditions, although there was considerably greater variability between the eight conditions.

A path model in Amos 5.0 (Arbuckle, 2003) was used to simultaneously assess the significance of each of the three explanatory variables on communication and the influence of communication on the two dependent variables. Significant regression coefficients for each of the explanatory variables would indicate logical validation of the corresponding propositions. Further, comparing the standardized coefficients would provide insights into the relative contributions of each of the variables in explaining the two indexes used to measure the development of TM systems. In addition to the path analysis, individual regression analyses were used to test the individual contributions of the explanatory variables on the dependent variables. Although not reported here, the conclusions from those results were entirely consistent with the regression results reported here from the path analysis.

Figure 1 shows the theoretical model used to test the propositions. The fit of a path model, or structural equation model, is determined by a set of indicators. First, the χ^2 statistic is evaluated as a "badness-of-fit" measure. That is, a significant χ^2 value indicates a poor fit between the data and the model and a nonsignificant χ^2 value would indicate a good fit of the model to the data (Bollen, 1989). Additional indexes for assessing model fit are the goodness-of-fit index (GFI), the adjusted goodness-of-fit index (AGFI), and the comparative fit index (CFI) where values above 0.90 indicate a good fit (Byrne, 2001). Last, the root mean squared residual (RMSR) is evaluated, and values below 0.05 are indicative of a good fit (Byrne, 2001).

Figures 2 and 3 plot the changes in individual agents' knowledge in a network representing Cells 1 and 8. Figure 2 demonstrates that, over time, there was *higher* knowledge differentiation on topic X in the network representing Cell 1, a four-member network with high mean initial level of knowledge, and high initial accuracy of expertise recognition. Figure 3 demonstrates that over time, there was *lower* knowledge differentiation on topic X in the network representing Cell 8, a 20-member network with low mean initial level of individual knowledge, and low initial accuracy of expertise recognition. Since these are plots derived from single networks in two cells, they simply serve as a visual example to illustrate the influence of the explanatory variables on the execution of the computational model. As such, they should not be used to make generalizations or inferences.

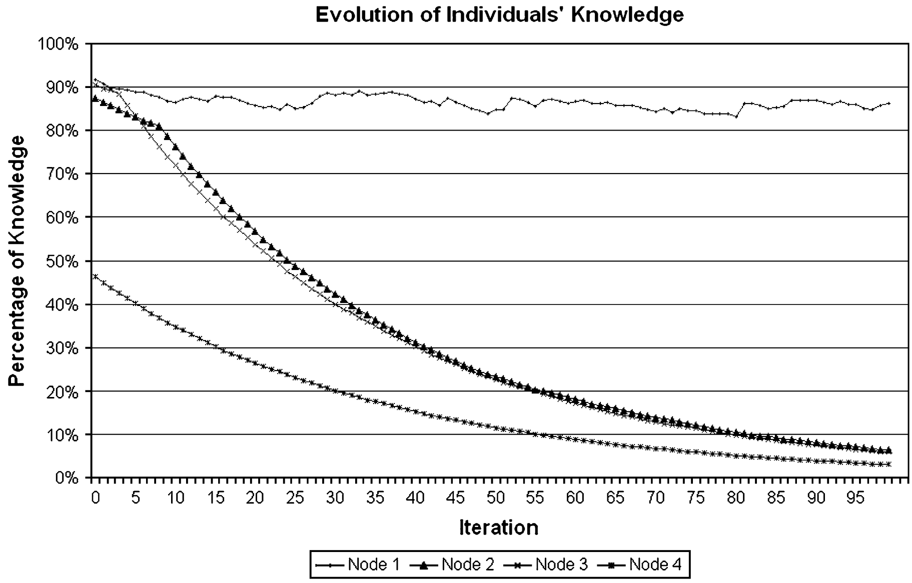

Figure 2 Evolution of individual level of knowledge in a four-person team where members have high initial level of knowledge and high initial accuracy of expertise recognition (Cell 1 from Table 1). Each line represents a specific agent's percentage of knowledge over time.

Note: Knowledge level is represented as the percentage of overall knowledge in one knowledge area as shown on the vertical axis; time iteration is shown on the horizontal axis.

Results

Initial analysis of the theoretical model yielded significant regression coefficients in the same direction as predicted in each proposition. However, the overall model fit statistics only indicate a modest fit between the data and the model. The significant chi-square value, $\chi^2(5) = 1052.60$, $p < .001$, indicates a poor fit between the data and the theoretical model. Similarly, the AGFI value is considerably below the conventional criterion of 0.90 for determining a well fit model (AGFI = 0.621). In contrast, two additional fit indexes, GFI and CFI, are both above the conventional fit criterion of 0.90 (0.91 and 0.92, respectively). Further, the RMSR is below the 0.05 conventional criterion (RMSR = 0.004). Each of these three indicators point to a good fit between the model and the data.

The results for this model are as follows. Proposition 1 argues that there will be a negative relationship between the team's starting knowledge level in the amount of communication between the members throughout their interaction. The regression coefficient between these two variables supports this proposition ($\beta = -0.55$, $p < .001$). The fourth proposition shows greater accuracy leading to more communication ($\beta = 0.05$, $p < .001$), but only to a small extent. The fifth proposition yielded a negative relationship between the size of the team and the amount of

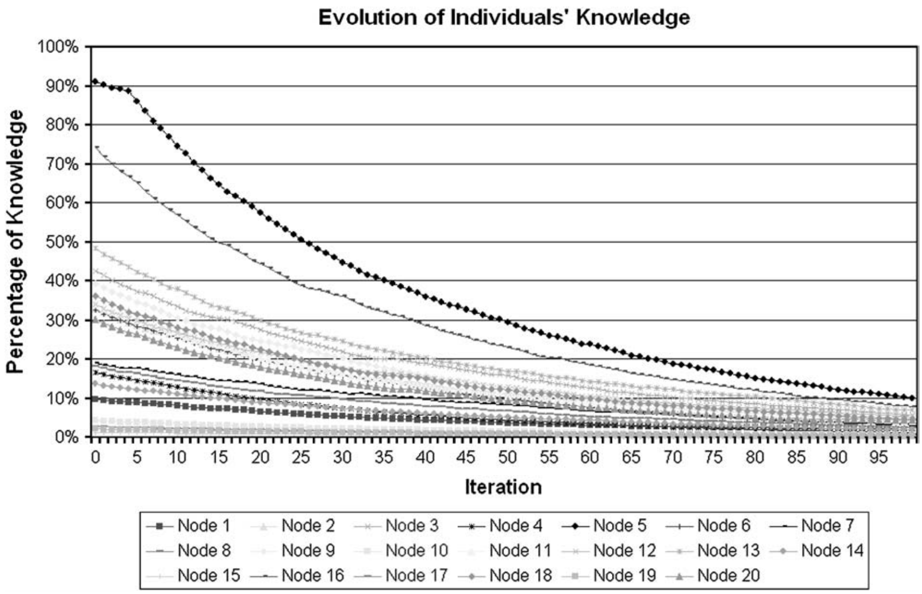

Figure 3 Evolution of individual level of knowledge in a 20-person team, where members have low initial level of knowledge and low initial accuracy of expertise recognition (Cell 16 from Table 1). Each line represents a specific agent's percentage of knowledge over time.

Note: Knowledge level is represented as the percentage of overall knowledge in one knowledge area as shown on the vertical axis; time iteration is shown on the horizontal axis.

communication within the team ($\beta = -0.51$, $p < .001$). Propositions 2 and 3 argue that more communication interactions would lead to a better developed TM system as indicated by higher levels of accuracy of expertise recognition and knowledge differentiation at the end of the simulation. Both propositions are supported by this analysis ($\beta = 0.28$, $p < .001$; $\beta = 1.15$; $p < .001$, respectively). As the fit indexes only point to a modest fit between the model and the data, we explored alternative structural models as described in the next section.

Modified model

Given the less than adequate fit of the theoretical model, we pursue to improve the model based on the standard practice of referring to the modification indexes and only adding or removing a connection between variables when theoretically defensible. Toward that end, no connections were removed and three new connections were added: from starting knowledge level to ending accuracy level, from starting accuracy level to ending differentiation level, and from team size to ending differentiation level. The modified model is shown in Figure 4.

This modified model provides a much better overall fit to the data as evidenced by the nonsignificant chi-square, $\chi^2(2) = 1.98$, $p > .05$, the small RMSR

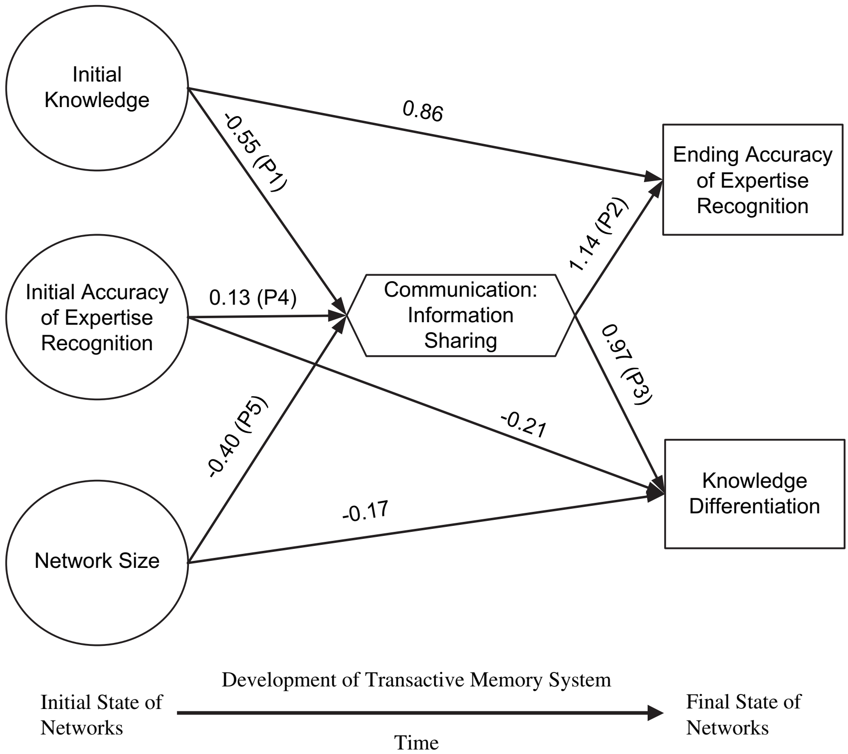

Figure 4 Modified model of transactive memory system development with standardized coefficients.

value (RMSR = 0.000), and fit indexes above 0.90 (AGFI = 0.998, GFI = 1.00, CFI = 1.00). Although the magnitudes of the regression coefficients are different than in the theoretical model, they are all significant in the same direction as initially proposed. Thus, this model bolsters support for the five proposed relationships and provides some insight into three relationships to consider when evaluating the evolution of TM systems. The model results and fit indexes for both the theoretical and the modified models are shown in Table 2 and Table 3, respectively.

From the modified model, we see in addition to the theoretically stated relationships that there is a positive relationship between the level of knowledge that the teams start with and their ending accuracy of expertise recognition ($\beta = 0.86$, $p <$ .001). Conversely, both the starting accuracy of expertise recognition and team size are negatively related to the extent to which the team differentiates its knowledge levels ($\beta = -0.21$, $p < .001$; $\beta = -0.17$, $p < .001$). That is, teams that start off accurate are less likely to end up differentiated. Similarly, larger teams are less likely to differentiate than smaller teams.

Table 2 Standardized Regression Coefficients of the Theoretical Model and Modified Model

Proposition		Theoretical Model		Modified Model	
		β	Significance	β	Significance
1	Initial level of knowledge	−0.55	***	−0.65	***
2	Communication on accuracy of expertise recognition	0.28	***	1.14	***
3	Communication on knowledge differentiation	1.15	***	0.97	***
4	Initial accuracy of expertise recognition	0.05	***	0.13	***
5	Size of the network	−0.51	***	−0.40	***

*** $p < .001$.

Discussion

This section discusses the effects of three distinct initial conditions on team members' ability to accurately perceive others' expertise and the team's ability to differentiate its knowledge system. Additionally, the mediating role of communication on TM development is discussed. The data generated by the computational model represent the multiple components of a TM system and show how such systems developed over time. These data support the proposed propositions and indicate three additional relationships between initial and developed systems. The findings of this study clearly show the impact of changes in initial conditions on TM system development and, therefore, highlight the importance of focusing on team composition when creating work teams. Further, this study highlights some of the benefits of computational modeling to advance verbally described theories using computational modeling to logically validate derived propositions from TM theory.

As a cautionary note, communication in this study was limited to information allocation and information retrieval—the two communication processes of TM theory. Further, the team context studied is information-based teams and not all work teams. Therefore, the claims and suggestions made below must be understood in this context. The relationship between each initial condition and the two

Table 3 Model Fit Statistics for the Theoretical Model and Modified Model

Model	Chi-Square	*df*	*p*	GFI	AGFI	CFI	RMSR
Theoretical	1052.60	5	***	0.910	0.621	0.922	0.004
Modified	1.98	2	.372	1.000	0.998	1.000	0.000

GFI = goodness-of-fit index; AGFI = adjusted goodness-of-fit index; CFI = comparative fit index; RMSR = root mean squared residual.
*** $p < .001$.

developmental measures is discussed next. We conclude with the discussion of the role of communication in TM theory.

Starting knowledge level

As predicted, team members' starting knowledge level was shown to be negatively related to the team's average communication. Following the path, initial knowledge level is negatively related to ending accuracy level and negatively related to the ending knowledge differentiation level. That is, teams starting with low knowledge levels (e.g., novices working together) are more likely to communicate, which results in a more differentiated and more accurate knowledge structure as the team develops over time. Conversely, teams with high initial knowledge levels (e.g., expert teams for problem solving) are less likely to communicate with each other for task-related issues. Although this finding is consistent with TM theory, reduced need to communicate is clearly shown to reduce the actual communication. Less communication may prove to be harmful to teams in the long run. Here, we see it reduces their differentiation and accuracy and, therefore, hinders the development of the TM system.

Starting accuracy level

A starting level for accuracy of expertise recognition was predicted and shown to be positively associated with the communication level. The initial accuracy of expertise recognition proved to be the weakest predictor ($\beta = 0.13$) of communication. This finding is not surprising in that people tend to have perceptions of what they think others know, but they do not always have evidence of their accuracy. Therefore, although it would be ideal to have a stronger relationship here, such a connection may not be realistic for actual teams. In short, people act on their perceptions rather than the accuracy of those perceptions.

Team size

In this study, the teams were designed with 4 and 20 members. Although such a design does not provide much variance in team size, it does provide for the comparison between small and large teams. As evidenced in the results, size matters for TM systems. The change in team size from 4 to 20 members was shown to have an indirect effect on the systems development with respect to its accuracy in perceiving others' expertise as well as direct and indirect effects on differentiating its knowledge stores. Consistent with the anecdotal evidence most of us have, size is negatively related to the average amount of communication; in turn, the size of the team is negatively related to the ending level for accuracy of expertise recognition and negatively related to the ending level for knowledge differentiation. This finding goes against the claims of early theorists that TM theory would be directly transferable from the lab to the organizational setting (Hollingshead, 1998a, 1998b, 2000; Moreland, 1999; Wegner, 1987). However, this is not to say that TM theory should be discarded for organizational teams but that the theory may need to include other variables and better specify its boundary conditions, especially with respect to team size.

Again, the findings indicate a direct negative relationship with communication and a direct negative relationship with knowledge differentiation. It is worthwhile to note that there is a lot of variability between 4 and 20 members, and many functioning work teams show that team size varies considerably. That said, the relationship between size and these other variables may not be linear. In other words, four members may not be optimal team size for TM systems. Future research must explore a wide range of team sizes to identify the inflection point marking a decrease in communication, in knowledge differentiation, or both (i.e., there may be a positive relationship between size and communication up to a specific enrollment number). Further, the ideal team size may be a function of the number of knowledge areas needed by the team or the degree of complexity in the team's tasks. Likewise, future research needs to explore the relationship between size and number of knowledge areas as well as the relationship between signs and task complexity.

Communication

This research demonstrates the importance of communication for TM theory. As shown in these results, communication plays a clear role in the development of TM systems. Each of the initial conditions tested had a significant effect on communication, and communication significantly impacted the two developmental measures of TM systems. The strongest influence on communication is the initial knowledge level of the team members. As predicted, lower knowledge levels lead to higher communication levels, suggesting that team members will communicate with many people when they lack the requisite knowledge to perform their work. These higher communication levels aided team members in developing accurate directories of expertise recognition as well as differentiating their knowledge stores. That is, communication facilitates the development of the TM system. Thus, this work underscores the need to understand the role of communication for knowledge management. The rich history of communication theories can inform the important intersection between the knowledge that individuals, teams, and organizations possess and their ability to share it with each other—internally for product development and creativity or externally for profit.

The proposed model stated an indirect relationship, through communication, between accuracy of expertise recognition and knowledge differentiation with a positive net effect. However, beyond the proposed relationships, a direct relationship between these two variables was found to be negative. This finding suggests a potential paradox of TM systems worthy of further exploration. Namely, accuracy of expertise recognition and knowledge differentiation are the two indicators of a well-developed TM system and should be positively related. Independent of the time points observed, accurate directories should facilitate differentiated knowledge structures. We see the positive relationship that exists in a mediated path through communication, thus highlighting the importance of communication for TM development, but the negative direct relationship hints at a problem that could emerge in an unguided system where members are not actively working toward developing their TM system. Therefore, this direct relationship, the indirect relationship, and the interaction between the two need to be studied further.

As stated earlier, communication was limited in this model to task-related communication for information allocation and retrieval only. This constraint was imposed to most accurately model TM systems based on the generative mechanisms as described in the literature. Namely, people on TM systems are motivated to talk with one another when they need to transfer information. Future research in this area should expand this operationalization to include other dimensions of communication. Communication also serves an enabling and constraining role for team discussions (Poole, Seibold, & McPhee, 1996) in that it enables the sharing of information between members, but it also constrains their creativity by limiting the team members whom they can interact with, and moreover, in the context of TM theory, they are constrained to task-specific interactions. Additionally, other roles of communication in organizations include, but are not limited to, power and control, training, politics, and integration and assimilation.

Although this work does not point to a preferred communication density level for the TM system, it does show a strong positive relationship linking communication density with a well-developed TM system. Of course, it would be dangerous to conclude that, without exception, more overall communication in a team is good. As with many things in life, more communication can be helpful only up to a certain point. Identifying that specific point (or, more likely, range) is a topic for future research.

Last, TM systems, although important for coordinating and completing workloads, do not exist in isolation. That is, TM systems are often embedded within larger systems (e.g., organizational and societal) and the larger systems influence the TM systems. Therefore, the role of communication in TM systems goes beyond the communication density of the specific team and, therefore, needs to be incorporated into future research.

Future research directions

Expand concept of communication

In this research, the focus of communication on task-based exchanges points to the need for TM theory to include communication beyond task-based communication within the organization. An expanded view of communication should allow for directory updating outside of task-centric work. That is, the function of "water cooler" communication may still have its place in TM system development even though it is not directly task focused. Thus, future research on evaluating the development of an organization's TM system needs to account for other contributing factors besides work-related events to communication between team members.

For example, homophily, or similarity between people (McPherson & Smith-Lovin, 1987), and physical proximity (Conrath, 1973; Zahn, 1991) have been shown to promote communicative interactions.

Additional knowledge areas

This research was based on three knowledge areas, which is overly simplistic for any team. However, it does provide a good starting point for research in this area. Future research should include many more knowledge domains. Variations in the number of domains would be a good condition for future experimental research. In particular, future studies should explore situations where there are fewer knowledge topics than people (as is the case in this study), a one-to-one correspondence between the number of knowledge areas and the number of people, and more knowledge areas than there are people. Such a manipulation would show how teams balance various cognitive demands and the extent of redundancy.

Experimental and field research

Following the results of this model, teams starting with a small number of nonexperts who accurately perceive what others know have the best chances of emerging into well-developed TM systems. However, these results are modeled results and must be empirically validated. Additionally, the model implemented here was not designed to represent all types of work teams, but to represent work teams with an emphasis on knowledge management. Although the computational model appears to adequately represent the core mechanisms of TM theory, longitudinal research will allow for more detailed validation of the fit between the theory, the model, and the actual teams. That is not to say there is little value in modeling research, quite the contrary. The approach described in this study offers researchers the opportunity for a more precise exploration of the dynamics that emerge from the nonlinear mechanisms implied in the verbal descriptions of theories. As such, the approach proposed here extends recent interest in exploring more principled methods to use computational modeling as a tool for theory construction. However, data from experimental as well as intact teams are essential for model validation and prior to making recommendations to practitioners.

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