MIS Quarterly

RESEARCH ARTICLE

THE IMPACT OF KNOWLEDGE COORDINATION ON VIRTUAL TEAM PERFORMANCE OVER TIME[1]

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Abstract

As the role of virtual teams in organizations becomes increasingly important, it is crucial that companies identify and leverage team members' knowledge. Yet, little is known of how virtual team members come to recognize one another's knowledge, trust one another's expertise, and coordinate their knowledge effectively. In this study, we develop a model of how three behavioral dimensions associated with transactive memory systems (TMS) in virtual teams—expertise location, task–knowledge coordination, and cognition-based trust—and their impacts on team performance change over time. Drawing on the data from a study that involves 38 virtual teams of MBA students performing a complex web-based business simulation game over an 8-week period, we found that in the early stage of the project, the frequency and volume of task-oriented communications among team members played an important role in forming expertise location and cognition-based trust. Once TMS were established, however, task-oriented communication became less important. Instead, toward the end of the project, task–knowledge coordination emerges as a key construct that influences team performance, mediating the impact of all other constructs. Our study demonstrates that TMS can be formed even in virtual team environments where interactions take place solely through electronic media, although they take a relatively long time to develop. Furthermore, our findings show that, once developed, TMS become essential to performing tasks effectively in virtual teams.

Keywords: Virtual team, transactive memory, trust, repeated measures, temporality

Introduction

In today's rapidly changing business environment, an organization's ability to create and share knowledge is important for establishing and sustaining competitive advantage (Teece et al. 1997). Teams are the key building blocks of today's knowledge-based organization (Leonard and Sensiper 1998), and are increasingly becoming "virtual," in that they are often geographically dispersed and communicate via computer-mediated tools (Jarvenpaa and Leidner 1999). It is not un-

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[1]Ritu Agarwal was the accepting senior editor for this paper. Alberto Espinosa and Susan Gasson served as reviewers. The associate editor and a third reviewer chose to remain anonymous.

Authors are listed alphabetically. Each contributed equally to the paper.

common to find that organizations rely heavily on virtual teams for key operations, such as product development, strategic analysis, and customer service (Majchrzak et al. 2000; Maznevski and Chudoba 2000). However, such teams pose a particular challenge for knowledge coordination, as knowledge is distributed across team members (Cannon-Bowers et al. 1993; Faraj and Sproull 2000; Moreland 1999).

Recent studies suggest that knowledge coordination in virtual teams is problematic due to temporal and spatial separation among team members and the use of computers as the primary means of communication (Cramton 2001; Griffith and Neale 2001; Hollingshead 1998b). Organizations rely on mobilizing more diverse sets of unevenly distributed knowledge resources through virtual teams, and effective knowledge sharing between members is more difficult in virtual teams than in traditional forms of organization. Furthermore, virtual teams are often short-lived and consist of members who are not familiar with one another, factors that exacerbate the problem of distributed knowledge. In fact, Cramton (2001) notes that the problem of mutual knowledge is a central issue in understanding how virtual teams perform and develop. Yet little is known about how knowledge is coordinated in virtual teams and how the impact of knowledge coordination on team performance evolves over time.

To address this gap in the literature, we draw on the notion of *transactive memory systems* (TMS) to examine the impact of knowledge coordination on virtual team performance over time. TMS refer to a specialized division of labor that develops within a team with respect to the encoding, storage, and retrieval of knowledge from different domains (Wegner 1987). Past research on TMS in face-to-face environments has shown that teams with effective TMS exhibit three dimensions of behavioral abilities—*recognizing*, *trusting*, and *coordinating* specialized knowledge among team members—and such dimensions have a positive impact on team performance (Hollingshead 2000; Liang et al. 1995; Moreland 1999; Moreland and Myaskovsky 2000). Although some prior studies have suggested that TMS continue to be important in virtual environments (Griffith and Neale 2001), it is not clear if virtual teams are able to develop effective TMS. For example, Lewis (2004) found that early face-to-face communications, along with prior familiarity among team members, were critical in the development of TMS. She went on to argue that TMS might not be effective if teams could not communicate face-to-face, particularly in the early stages of the project. Such an observation raises a serious question regarding the efficacy of virtual teams as a means of coordinating and sharing knowledge for task performance. Yet, to our knowledge, there has been no empirical research that studied the virtual development of TMS and its impact on the performance of virtual teams over time. In this study, we examine the impact of TMS on the performance of 38 virtual teams of MBA students over an 8-week period.

In what follows, we briefly discuss recent developments in the virtual team and TMS literature and develop the research framework and our hypotheses. We then describe the research methodology and key results. We conclude the paper by discussing the implications of our findings for future research and practice.

Theoretical Framework and Model Development

Following Jarvenpaa and Leidner (1999), we define a virtual team as a temporary, geographically dispersed, and electronically communicating work group.[2] The temporary nature of the virtual team implies that the members do not share a past history and may not work together in the future. Geographical dispersion implies that team members are situated across geographical, and often organizational, boundaries, and rarely meet face-to-face. Finally, collaboration across time and space is enabled by a heavy reliance on computer-mediated communications.

Over the last decade, a large body of literature on virtual teams has emerged (Powell et al. 2004; Wiesenfeld et al. 1999). Trust (Jarvenpaa, Knoll, and Leidner 1998; Jarvenpaa and Leidner 1999), leadership (Kristof et al. 1995), group composition (Jarvenpaa, Knoll, and Leidner 1998), culture (Jarvenpaa, Knoll, and Leidner 1998; Massey et al. 2001), conflict (Massey et al. 2001), and the appropriation of communication technology (Majchrzak et al. 2000) are among a few of the factors that have been identified as drivers of the success and failure of virtual teams. In addition to these previously studied factors, Cramton (2001) found that the sharing and coordination of knowledge in virtual teams are problematic due to the geographically distributed nature of knowledge and the consequent lack of mutual knowledge. Building upon her work, we study knowledge coordination in virtual teams by examining the changes in TMS, a cooperative system of coordinating specialized knowledge, over time. We approach TMS through the lens of three behavioral dimensions: recognizing, trusting, and coordinating specialized knowledge among team members. We develop our model and hypotheses in two stages. First, we discuss the

[2]In their original definition, Jarvenpaa and Leidner also included cultural diversity as a part of definition of a *global* virtual team. We did not include cultural diversity because virtual teams could be both global and domestic.

structural aspect of TMS in virtual teams. We establish the salience of three key behavioral dimensions of TMS in virtual teams and develop hypotheses about the structural relationships among them. We then develop hypotheses about the temporal aspect of TMS in virtual teams, emphasizing the changing dynamics among the three behavioral dimensions over time.

The Structure of TMS in Virtual Teams

Wegner (1987; see also Wegner et al. 1991) found that couples in close relationships develop TMS and treat their partners as external memory aids, relying on each other to remember details about specific domains of expertise. Extending this idea to teams, Liang et al. (1995) conducted an experiment to examine the impact of TMS on team performance in a controlled laboratory setting. They found that TMS had a larger impact on team performance than did other variables, including cohesion, motivation, and social identity, which were previously studied for group performance. Subsequent studies by Moreland and his colleagues further confirmed that the presence of TMS improved team performance (Moreland et al. 1996; Moreland and Myaskovsky 2000).

Prior studies have consistently suggested that the development of TMS is associated with three distinct, yet closely interrelated, dimensions of group behaviors (Brandon and Holllingshead 2004; Lewis 2003; Liang et al. 1995; Moreland 1999). First, a central aspect of TMS is the awareness of knowledge specialization among team members. TMS develop and exist among team members as they actively use their own individual meta-knowledge of others' knowledge in order to leverage other members' knowledge in jointly performing a given task. For example, John does not know how to calculate net present value using a spreadsheet, but he knows his teammate Jane does (individual knowledge possessed by John). On the other hand, Jane does not know how to do market forecasting, but she knows John does (individual knowledge of Jane). As they work on a joint task that requires both forecasting and the calculation of net present value, John and Jane can access and use necessary knowledge that is unevenly distributed between the two of them. It is their awareness of the location of necessary specialized knowledge in the team that enables the performance of the task. Past research has repeatedly shown that awareness of the location of knowledge improves team performance (Faraj and Sproull 2000; Henry 1995; Henry et al. 1993; Littlepage et al. 1997; Littlepage and Silbiger 1992). Drawing on these studies, we define *expertise location* as the extent to which team members know who on the team knows what.

Second, in addition to expertise location, past studies also suggest that teams with well-developed TMS show a high degree of trust of other team members' knowledge and their ability to carry out the task on their behalf (Griffith and Neale 2001; Lewis 2003). Liang et al. (1995) found that the members of teams with highly developed TMS did not have to make explicit claims to justify their own knowledge as the members trust one another. Zand (1972) found that team members share information more freely when they trust each others' capabilities and competencies. Lewis (2003) also showed that the credibility of task performance and the possession of task-relevant knowledge was an important element of TMS. Past studies on trust suggest that trust is a multidimensional construct that has both cognitive (e.g., competence, reliability, and professionalism) and affective (e.g., caring, benevolence, and emotional connection to each other) elements (Lewis and Weigert 1985; McAllister 1995).[3] Past studies on TMS have focused primarily on the competence and reliability aspect of trust as it relates to the development of TMS. As such, we define *cognition-based trust* as team members' beliefs about one another's ability and reliability to carry out the task.

Finally, past research suggests that teams with highly developed TMS demonstrate an ability to effectively coordinate tasks and knowledge among team members (Liang et al. 1995; Wegner 1987). Within the context of software development teams, Faraj and Sproull (2000) found that team members' willingness and ability to share hard-to-find specialized knowledge with other team members (bringing expertise to bear) were as important as their ability to recognize the location of expertise. However, research on team mental models suggests that it is not enough to know and be willing to share specialized knowledge. These studies found that for effective knowledge coordination, team members need to develop effective representations of how tasks can be divided, how subtasks are interrelated with each other, and how subtasks are assigned to team members (Cannon-Bowers and Eduardo 2001; Cannon-Bowers et al. 1993; Klimoski and Mohammed 1994; Weick and Roberts 1993). Returning to the earlier example of John and Jane, in order for them to effectively use TMS, they not only need to be aware of the location of knowledge, but also understand that the given task

[3] Although most scholars agree that trust is a multidimensional construct, they disagree on exactly how many different dimensions exist. For example, Mayer et al. (1995) suggest three dimensions (benevolence, ability, and integrity), McKnight et al. (1998) suggest four dimensions (benevolence, honesty, competence, and predictability), and Lewis and Weigert (1985) and McAllister (1995) suggest two dimensions (cognition-based and affect-based). We chose to draw on a two-dimension model as it characterizes cognition-based trust as including both competence and predictability, which are included in the TMS literature.

can be broken into subtasks of market forecasting and net present value (task representation). They then need to agree, either implicitly or explicitly, on the assignments of subtasks between the two, followed by individual action on their respective subtask to maximize the performance of the overall task. Elaborating on the notion of coordination in TMS, Brandon and Hollingshead (2004) argue that team members need to attend not only to who knows what, but also to who *does* what in order to perform a complex task effectively. Therefore, a team with well-developed TMS will develop task representations that include how the task can be decomposed and who should perform a subtask in order to achieve the overall goal (Lewis 2003). Drawing on these studies, we define *task–knowledge coordination* as the team's ability to develop overlapping mental representations of how the task can be divided and the relationships between subtasks and team members.

Taken together, these three dimensions—expertise location, cognition-based trust, and task–knowledge coordination—are the key behavioral abilities that are often found in teams with highly developed TMS. Past studies, however, have not examined the structural relationships among these behavior dimensions (Lewis 2004; Liang et al. 1995). In this paper, we argue that not all dimensions have the same immediate impact on team performance. More specifically, we posit that the impact of expertise location and cognition-based trust on team performance will be mediated by task–knowledge coordination. For example, although the players on an all-star basketball team may know the skills of their team members, the team as a whole requires the experience of practicing together in order to perform effectively. Players need to learn how to understand and anticipate one another's abilities and behaviors in order to coordinate their game play on the court (Berman et al. 2002). Therefore, a high degree of expertise location is a necessary condition for effective task–knowledge coordination. Similarly, Weick and Roberts (1993) argued that to coordinate knowledge among team members, they need to trust each others' capabilities. Zand (1972) posited that when team members experience the low-trust behaviors of other members, they are hesitant and unlikely to share information for fear that the other party will use the information for its own gain. He further found that high-trust teams exchanged ideas more openly, had clearer goals, sought out more alternative actions, were more motivated and satisfied, were better at locating and utilizing other members' skills, and demonstrated more of a willingness to be part of the group than low-trust teams. Huemer et al. (1998) also argue that team members with higher trust are more likely to work together cooperatively and conscientiously. Therefore, it is likely that a high degree of cognition-based trust reduces the complexity among social actors (Luhmann 1979), thus potentially enhancing the team's task–knowledge coordination ability. Taken together, we hypothesize

H1a: Expertise location will positively influence task–knowledge coordination.

H1b: Cognition-based trust will positively influence task–knowledge coordination.

H1c: Task–knowledge coordination will positively influence team performance, mediating the impact of expertise location and cognition-based trust.

According to past studies on TMS in face-to-face environments, teams build TMS using whatever relevant information is available, including surface characteristics, official assignments of the task, past experiences, and formal and informal communications among the team members (Brandon and Hollingshead 2004; Lewis 2004; Wegner 1987). In particular, Hollingshead (1998b) found that nonverbal, paralinguistic cues play an important role in forming the initial perception of others' knowledge. However, due to the lack of such visual cues, opportunities for informal and on-going interactions and shared history at the onset of a project, virtual environments make it particularly challenging for team members to form TMS. The only viable way to overcome these challenges is frequent and effective communication among team members. Past research in small group decision-making and computer-mediated communication suggests that the content of communications can influence the team process (Hirokawa and Pace 1983; Jarvenpaa and Leidner 1999; Sambamurthy and Poole 1991; Short et al. 1976). Researchers have suggested that computer-mediated communications filter out rich social and relational cues among team members (Sproull and Kiesler 1986) and, therefore, if not appropriately facilitated, communications in virtual teams will be overly task-oriented. Subsequent work argues that teams that experience more social communication can perform better by compensating for the lack of social cues (Chidambaram 1996; Hinds and Bailey 2003; Jarvenpaa and Leidner 1999; Maznevski and Chudoba 2000). It has thus been observed that it is beneficial for virtual teams to have socio-emotional communications (Maznevski and Chudoba 2000; Robey et al. 2000). However, most of these studies relied on socio-emotional factors such as satisfaction and cohesion as outcome variables and did not examine the impact of communication content on factors that are related to cognitive aspects such as transactive memory systems and task performance itself (Powell et al. 2004).

Challenging the prevailing view in the literature, Carte and Chidambaram (2004) drew on a large body of research on diversity in small groups to argue that social communication in virtual teams, particularly in the early stage, may in fact be harmful for team task performance. Building on the notion of surface-level and deep-level diversity (Kilduff et al. 2000; Pelled 1996), they suggested that socio-emotional communications that focus primarily on surface-level diversity (such as gender, age, and nationality) will hinder the ability of team members to take advantage of deep-level diversity in expertise, task background, and mental models. Surface-level diversity often leads to stereotypes, which in turn lead to inaccurate perceptions of others' knowledge (Brandon and Hollingshead 2004; Wegner 1987). Consistent with this, Hollingshead and Fraidin (2003) and Thomas-Hunt and Phillips (2004) found that gender stereotypes hinder the formation of an accurate perception of the knowledge of other team members. In contrast, task-oriented communications will provide more opportunities for team members to learn about others' knowledge more directly and accurately. Thus, we hypothesize

H2a: Task-oriented communications will positively influence expertise location in virtual teams.

As excessive socio-emotional communications among virtual team members may obstruct an accurate assessment of team members' knowledge and skills, virtual teams with too much socio-emotional communication may experience difficulty in developing cognition-based trust. This form of trust is fundamentally calculative and rational, and is based on reliability and competence in performing a task, rather than positive affect and emotional reactions to other team members (Lewis and Weigert 1985). Past research on trust shows that regular communication regarding one's approach to the task, beliefs, and the problem, as well as job-related information, lead to the formation of cognition-based trust (Butler and Cantrell 1994; Lewicki and Bunker 1996). Given that tasks are primarily carried out through task-oriented communications via communication media in virtual teams, it is expected that frequent task-oriented communication is likely to positively affect the formation of cognition-based trust. Thus, we hypothesize

H2b: Task-oriented communications will positively influence cognition-based trust in virtual teams.

Finally, task-oriented communication in virtual teams will not only influence expertise location and cognition-based trust, it will also directly influence a team's task performance. This is because frequent and effective task-oriented communication affects not only the development of TMS, but also promotes team activities that are directly related to task execution without requiring the coordination of knowledge and expertise among team members. This is particularly true in virtual team environments where task-communication is the only way of performing the task. Past studies showed that frequent communication is critical to team performance for both virtual teams (Iacono and Weisband 1997) and face-to-face teams (Hirokawa 1990). In particular, Steinfield (1986) found that task-oriented communication is effective in computer-mediated communications when task interdependency and uncertainty are high, factors that are typical in virtual team contexts. Therefore, we hypothesize

H2c: Task-oriented communications will positively influence virtual team performance.

Figure 1 summarizes our conceptualization of the structural aspect of TMS in virtual teams.

Temporal Aspects of TMS in Virtual Teams

TMS are not static, but dynamic. When teams first meet, they build the initial TMS based on past experiences, if any, and other available cues including surface characteristics, official assignment of tasks, or other more explicit indications of capabilities, such as an academic degree (Wegner 1995). However, such initial TMS may not be accurate and team members will test and refine their initial perceptions of others' knowledge through on-going communication and performance feedback (Brandon and Hollingshead 2004). Furthermore, due to the unique characteristics of virtual teams—the lack of past history, the separation in time and space, and the use of computer-mediated communication—virtual team members will face even greater challenges in developing TMS than teams in face-to-face environments (Griffith and Neale 2001; Lewis 2004). Thus, it is likely that the initial TMS developed through early communications will undergo significant changes over time as team members learn more about one another.

Gersick's (1988, 1989) theory of punctuated equilibrium describes the evolutionary changes in teams and suggests that teams with clear milestones or deadlines often go through major transitions as they reach the midpoint of their progress toward key temporal landmarks. Before the transition point, a team has a weak structure (Gersick 1988; Jarvenpaa, Shaw, and Staples 2004). That is, team members often have different ideas about the goals and the ways in which they work together before the midpoint. During this period, virtual team members try to build and validate TMS. Following the midpoint transition, however, team members will likely have spent a significant amount of time together and gained experience with the task, the environment, and other team `members. Naturally, such changes in teams will be reflected in the development of the three dimensions of TMS.

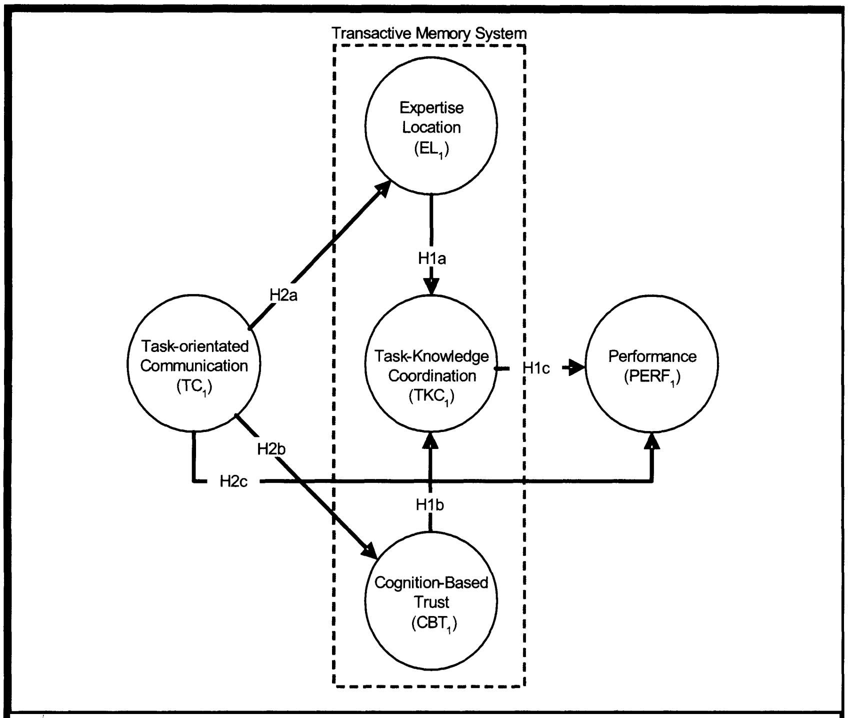

Figure 1. Structural Model of TMS in Virtual Teams

Finding out who is good at what, if others' claims of expertise are credible, and how to best match team members' expertise with the elements of the given task can often take time and effort. Brandon and Hollingshead (2004) argue that the development of TMS involves a cycle of construction and evaluation of hypotheses regarding other team members' knowledge, abilities, and credibility. They suggest that TMS in the early stage of group development can be "best viewed as hypotheses of varying strengths rather than certainty" (p. 637) of others' abilities and expertise that were formed based on early communications, initial impressions, and other social cues. As teams begin to perform and start receiving performance feedback, team members gain a better understanding of others' expertise and may adjust their initial impression. According to Gersick (1989), teams often make such adjustments during the midpoint of their life, if they operate with a definite deadline.

Here, we focus on two potential forces that jointly influence the evaluation and adjustment of TMS during the midpoint transition. First, drawing on the general theory of social structures (Giddens 1984) and the group development literature (Gersick and Hackman 1990; Poole et al. 1985), we expect that expertise location, task–knowledge coordination and cognition-based trust tend to reproduce themselves. Hutchins (1991), through a dynamic simulation model, showed that the initial condition of the social cognition of a team has an enduring impact on the way the team performs later. Past studies of work in computer-mediated teams also show that large portions of team interactions tend to reproduce existing routines and social structures (Orlikowski 1992; Zack 1993). In face-to-face environments, Lewis (2004) found that the TMS in the early phase of the project reliably predicted the TMS later in the project.

These prior studies, however, did not examine the potential moderating impact of performance feedback. Social learning theory (Bandura 1986) suggests that positive feedback achieved through learning by doing and vicarious learning acts as a powerful reinforcing mechanism of behaviors. Likewise, in virtual teams, observed behaviors that are successful are more likely to be emulated and continued. We therefore posit that team members are more likely to reassess the way they coordinate knowledge and readjust TMS if their initial assumptions about other members' knowledge, credibility, and the best way to coordinate knowledge and the task are not confirmed through positive performance feedback. We expect that expertise location, task–knowledge coordination and cognition-based trust formed before the midpoint are more likely to influence those factors after the midpoint transition when there is positive performance feedback. By contrast, if the team performs poorly, it will likely challenge the team members' initial hypotheses about other members' knowledge, credibility, and the way they coordinate their task and knowledge. As a consequence, the team will more likely show larger changes in three dimensions in TMS when there is negative performance feedback. Thus, we hypothesize

H3a: The impact of past expertise location on future expertise location is negatively moderated by performance feedback from the earlier stage of the project.

H3b: The impact of past task–knowledge coordination on future task–knowledge coordination is negatively moderated by performance feedback from the earlier stage of the project.

H3c: The impact of past cognition-based trust on future cognition-based trust is negatively moderated by performance feedback from the earlier stage of the project.

As TMS become more developed, the impact of task-oriented communication on expertise location and cognition-based trust is likely to become less important. Once TMS are well developed, unnecessary task-oriented communication can be nothing more than redundant and excessive and does not add additional value to the team's performance as long as the task environment remains stable. Hollingshead (1998a) found that the positive impact of communication on TMS is significantly reduced among people who know each other well and thus have more well-developed TMS, compared to its impact among strangers. Lewis (2004) found that for teams with highly developed TMS, frequent non-face-to-face communication in fact dampened their ability to refine the TMS later in the project. Thus, we hypothesize

H4a: After the midpoint, the impact of task-oriented communications on expertise location will significantly diminish compared to its impact before the midpoint.

Similarly, Jarvenpaa, Shaw, and Staples (2004) found that while communications in virtual teams are critical to establishing trust in the initial stage of team interaction, once trust is established, continuing a high level of communication is moderately detrimental to team performance. As such, we posit that the impact of task-oriented communications on expertise location and cognition-based trust will significantly diminish after the midpoint. Therefore, we hypothesize

H4b: After the midpoint, the impact of task-oriented communications on cognition-based trust will significantly diminish compared to its impact before the midpoint.

Finally, Moreland and Myaskovsky (2000) argue that members of a team cannot coordinate their knowledge and tasks without a thorough understanding of what other members know. Further, team members may be cognizant of each others' knowledge but still fail to effectively coordinate this knowledge to achieve a common goal (Moreland 1999, p. 25). Faraj and Xiao (2006) also note that effective coordination of knowledge is an emergent phenomenon highly dependent on the awareness of others' capabilities and skills. Therefore, since task–knowledge coordination can function effectively only after expertise location and cognition-based trust are developed, we expect that it will take longer for task–knowledge coordination to have a significant impact on team performance. Thus, it is likely that task–knowledge coordination will have a significantly stronger impact on team performance after the midpoint. At the same time, we expect that the direct impact of task-oriented communications on team performance will significantly diminish after the midpoint as TMS are more developed and adjusted based on team performance feedback. Therefore, we hypothesize

H5a: After the midpoint, the impact of task–knowledge coordination on team performance will significantly increase compared to its impact before the midpoint.

H5b: After the midpoint, the impact of task-oriented communication on team performance will significantly diminish compared to its impact before the midpoint.

Figure 2 depicts our conceptualization of the temporal aspects of TMS. The changes in the degree of impact of variables over time are denoted by differences in the thickness of the lines.

Method

We conducted a study with repeated measures to test the proposed model. Data were collected from the following three sources: (1) survey questionnaires; (2) archives of the electronic communications; and (3) objective team performance scores.

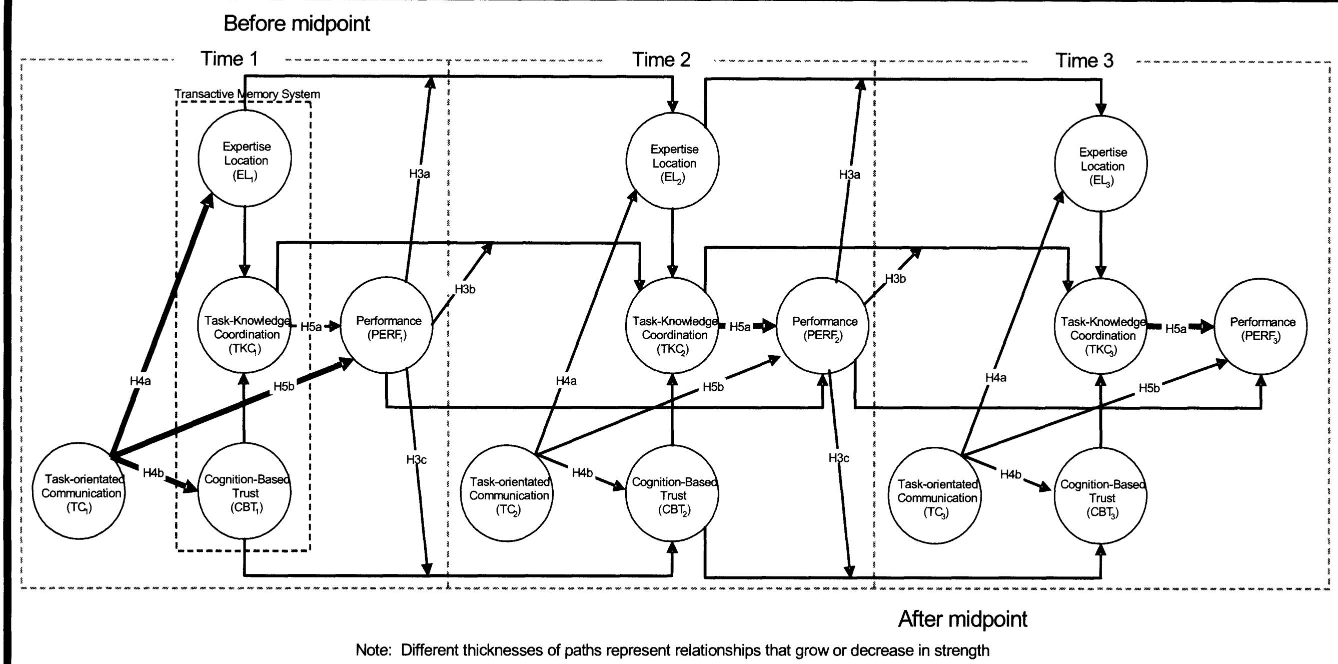

Figure 2. Temporal Model of TMS in Virtual Teams

Participants

Participants were recruited through an e-mail announcement that was broadcast via an Internet list-serve popular among faculty members in the information systems area. Six different MBA courses taught by five professors in four different countries were included for the study.[4]

A total of 146 MBA students (100 males, 46 females) of 10 different nationalities[5] participated in the study. The project accounted for 5 to 25 percent of the course credit depending on the professors.[6] The average age and work experience of the participants were 28 and 5 years, respectively. Students took part in the project as part of their course and were randomly assigned to 40, four-member teams. Teams were comprised of students from four different universities; two teams had two members from the same university. During the course of the project, two teams and six individual members were removed from the game due to their inactivity. This left 146 participants and 38 teams for the data analysis, six of which had three participants.

Task

A web-based, complex, and realistic business simulation game, Inc. 2000®, was used for the study. The engine of the game was developed by the first author and his colleagues and has been used regularly in both academic institutions and corporations in more than 100 sessions over the last 6 years. Inc. 2000 is a strategic business simulation game built on generic business concepts. It equally emphasizes all four major functional areas of business: marketing, finance, production and operations, and human resources.

The game is framed around the assumption that every team has been in business for 2 years. All teams start with the same position in terms of market share, financial resources, human resources, inventory, etc. Each team manages a $356 million company, producing and selling high-end server computers and competing against the other teams. The goal is to maximize the shareholder wealth of the company, which is influenced by several firm performance indicators including

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[4]The second author taught two of the courses.

[5]Australian, Chinese, Mongolian, Indian, Pakistani, Singaporean, Thai, German, Hungarian, and American.

[6]For the two classes that the second author taught, 25 percent of the course credit was assigned. Other classes assigned 5 percent (one class), 10 percent (two classes), and 20 percent (one class).

market share, profit, unit cost, ROA, and ROE. To outperform other teams, teams need to make a long-term strategic decision for the next seven periods rather than making a series of decisions on a period-by-period basis.

For the current study, teams needed to make a weekly decision regarding 25 variables that covered four functional areas. At the end of the week (after all decisions were submitted), the game administrator processed these decisions. Each team's weekly performance results were then distributed. The outcomes from prior weeks were taken into account in the subsequent week. The game was conducted over an 8-week period. A team's performance was assessed based on the decisions they made as well as the decisions made by other teams. Therefore, in each decision round, each team had to review its own performance in addition to analyzing and anticipating the movements of the other teams. As a result, teams could not simply *guess* the formula of the game. This model provides a dynamic and uncertain decision-making context that requires the integration of inputs and knowledge of all members if the team is to be successful.

Each team member was randomly assigned to one of four business roles: VP of marketing, VP of productions and operations, VP of finance, and VP of human resources. Apart from the first week of the project, during which team members became acquainted with one another, read the game manual, and collectively set the vision and objectives for their companies, team members devoted their interactions to discussing how they should run their company for the subsequent weeks two through eight using text-based, computer-mediated communication.

For the current study, a web-based interface of Inc. 2000 was designed to support and facilitate communication and knowledge coordination among team members in different places. The interface allowed the participants (1) to enter/edit/view their decisions and see their team's performance and (2) to communicate and exchange ideas/information from anywhere at any time through a web-based discussion database that is tightly integrated into the game. In addition to the web-based discussion database, members were provided an electronic mailing list for e-mail communications. All e-mail messages sent via the mailing lists were archived.

The web interface is purposely designed to allow *only* the member assigned to a particular functional area the ability to input decision variables in that area, while other members are able only to view these variables once they are entered. The ability of individual members to effectively interrelate their actions through communication therefore became critical to the team's performance. While the decision variables for four functional areas were predetermined, the ways in which teams deliberate their decisions were not. It was up to each team to decide how to coordinate and integrate inputs and knowledge from each member. This required not only the knowledge of four functional areas, but also the use of various communication and computing resources (e.g., spreadsheets and other modeling tools) and process skills.

During the summer of 2000, we conducted a pilot study to test the usability and reliability of the web-based business simulation game with 55 students on 13 teams who played the game over an 8-week period. Minor errors were corrected and small changes were made in the instructions as a result of the pilot test.

Measures

A survey was administered three times: at the end of weeks 2 (T1), 5 (T2), and 8 (T3). Since not all teams had every team member signed in during week 1 and the business game did not begin until week 2, we chose to measure T1 at the end of week 2. The questionnaire was administered via a web page as soon as all decisions were submitted for the week, but *before* teams received weekly performance feedback. A reminder e-mail was automatically sent out one day before the deadline to participants who had not yet completed the questionnaire. (All items are listed in Table 3.)

Team Performance (PERF)

Team performance was measured by the stock price (generated by Inc. 2000) in each period. Among other performance indicators from the game, we chose to use stock price since participants were told that the goal of the game was to maximize their company's shareholder wealth.

Task-orientated Communication (TC)

All e-mail messages sent through the provided mailing lists were automatically archived and included for analysis. Participants were also asked to forward other e-mail messages that were sent directly to their teammates via a special account. The entire set of messages exchanged by the participants was subject to content analysis.

One of the frequently used methods to study communication contents in small group research is Bales' (1950) interaction protocol analysis (IPA). This method has been used in numerous studies to examine interactions among team members in both face-to-face and computer-mediated communication settings (Hiltz and Johnson 1990; Hiltz et al. 1986; Rice and Love 1987; Siegel et al. 1986; Weisband 1992) with a high degree of reliability. IPA has 12 different categories of communication behaviors, 6 of which are task-oriented and the other 6 socio-emotional. Task-oriented content is defined as interactions that request or provide information or opinions; socio-emotional content is defined as interactions that show solidarity, tension relief, agreement, antagonism, tension, and disagreement.

According to Neuendorf (2002), the unit of analysis for content coding can either be determined in advance (an *etic* approach) or generated during the analysis (an *emic* approach). While an emic approach is more appropriate for interpretive or critical studies of communication, an etic approach is more appropriate for positivistic content analysis, as in our study. Furthermore, when using an etic approach, one needs to use the smallest identifiable unit that can be practically and reliably coded for the purpose of the study. In our study, the unit of coding was a complete message following a strategy similar to that used by Hiltz et al. (1986) as the individual message constituted the smallest unit of communicative actions that could be objectively observed and reliably coded.

We hired two coders and trained them with Bales' IPA training manual. We chose 80 sample messages that covered a wide range of communications by selecting the first and last 10 messages from two high- and two low-performing teams to train the coders. One of the authors and two coders read the IPA manual before they separately coded the 80 sample messages. Each message was coded into one of the 12 communication behaviors of IPA.

After the initial coder training was completed, both coders independently coded the same 400 messages from four teams, a number that exceeded 10 percent of the entire messages as suggested by Straus (1997). Again, coders assigned one of the 12 IPA categories to each individual message. We then calculated the inter-rater reliability as measured by kappa, which at .80 indicated substantial agreement (Landis and Koch 1977). Coders then met and resolved the differences until they reached 100 percent agreement. After that, we divided the remaining messages into two groups and coders coded them separately. In the end, a total of 3,259 messages were coded, each categorized into one of the 12 IPA categories. Appendix A shows four sample messages that were coded by both coders. Messages coded as one of the six task-oriented categories of IPA were identified as task-oriented messages.

We then calculated task-oriented communication frequency by calculating the total number of task-oriented messages posted on the web pages and the e-mail messages exchanged during the week. We also calculated task-oriented communication volume by calculating the total number of characters in task-oriented messages exchanged during the week. In calculating task-oriented communication volume, we only include the characters in the body of the message. Also, if the message was a response to an earlier message, we only counted the number of characters in the response, excluding the texts from the original message. We then combined task-oriented communication frequency and task-oriented volume as formative indicators of task-oriented communication for our data analysis. We used formative indicators because task-oriented communication is a function of task-oriented e-mail frequency and task-oriented e-mail volume, not the other way around (Diamantopoulos and Winklhofer 2001; Jarvis et al. 2003).

Expertise Location (EL)

Members' meta knowledge of each other's areas of expertise was measured using the expertise location measure developed and used by Faraj and Sproull (2000). Expertise location was assessed by asking three, 5-point Likert scale questions about team members' knowledge of who knows what. Since the measure was developed relatively recently, we examined the reliability of these items through a pilot study (pilot test alpha = .88).

Task–Knowledge Coordination (TKC)

Members' perception of their ability to coordinate task and knowledge was measured using a new measure we developed. Based on Weick and Roberts (1993), 11 candidate items were initially developed to capture the three main behavioral aspects of the coordination of knowledge: contribution (acting); representation (understanding); and interrelation (interrelating). Items were rated on a scale from 1 (strongly disagree) to 5 (strongly agree). Through the procedure recommended by Churchill (1979), which included the pilot study mentioned above, these 11 items were trimmed to the final four used in the current study (pilot test alpha of final four items = .85).

Cognition-Based Trust (CBT)

We drew upon instruments developed by Cook and Wall (1980) and McAllister (1995) to measure cognition-based trust. Three items from each of these prior studies were used to develop the original six items. Because the original items were developed at the dyad level (supervisor/subordinate), some wording was modified to suit the group level measurement. For example, items from the original question, "This person approaches his/her job with professionalism and dedication," were reworded to reflect the team context: "Most of my teammates approach their job with professionalism and dedication." Respondents assessed items by rating them on a scale ranging from 1 (strongly disagree) to 5 (strongly agree). Since the measure was developed for a different context, we reexamined the reliability of these modified items through the aforementioned pilot study. From the pool of six items, two items were further removed due to poor reliability (pilot test alpha of final four items = .85).

Analyses and Results

We conducted our analyses in three steps. First, we examined the psychometric properties of the scales through both exploratory and confirmatory factor analysis. Second, we conducted statistical tests to justify the appropriateness of aggregating individual-level scores into a team-level score. Finally, we tested hypotheses by testing the proposed path model using the structural equation modeling tool, partial least square (PLS).

Test of the Measurement Model

Data were first analyzed using exploratory factor analysis and a reliability test in SPSS that utilized individual participants' responses (Nunnally and Bernstein 1994) for perceptual measures. A more rigorous method, commonly known as confirmatory factor analysis, was then conducted using the EQS 5.7b package.

Exploratory Factor Analysis

In an exploratory factor analysis, a maximum likelihood method is used to extract the initial factors and the oblique method is used in the rotation phase in order to take into account correlation among factors (Pedhazur and Schmelkin 1991, p. 615). The results, as shown in Table 1, support a three-factor solution for EL, TKC, and CBT. All factor loading scores were as expected without any significant cross-factor loadings, with the exception of one item of TKC in period 3. These three factors accounted for 76.64 percent, 81.70 percent, and 84.21 percent of total variances for T1, T2, and T3, respectively. Finally, all factors achieved a high reliability with Cronbach's alpha greater than .85 (see Table 1). Table 2 shows the correlation among the individual items.

Confirmatory Factor Analysis

Since we measured three constructs (EL, TKC, and CBT) using the same questionnaire items at three different times, we conducted three separate confirmatory factor analyses for T1, T2, and T3. The CFA model was constrained in such a way that each item loads on only one underlying factor and error terms among items are not allowed to be correlated (Anderson and Gerbing 1982). The results (Table 3) showed that all loadings were significant and greater than .70 for all phases. All goodness of fit indexes, except chi-square, which is sensitive to the sample size (Green et al. 1997), clearly indicated that the model fit well with the data for all periods (NFI and CFI greater than .96).

Although the three constructs are theoretically and empirically distinct, as indicated by clean factor loadings in both the exploratory and confirmatory factor analyses, they are highly correlated to one another (factor correlation ranged from .58 to .78). Thus, to ensure discriminant validity, we compared four different measurement models using a hierarchical model comparison strategy (Anderson and Gerbing 1988). The results support the hypothesized measurement model with three factors. Details of the hierarchical model comparison are provided in Appendix B.

We further examined discriminant validity using the square root of the average variance extracted (Fornell and Larcker 1981). As shown in Table 4, all square roots of the average variance extracted and displayed on a diagonal of a correlation matrix are greater than the off-diagonal construct correlations in the corresponding rows and columns for each separate time period. Combined with the results of the confirmatory factor analyses, this indicates that each construct shared more variance with its items than it shared with other constructs, thereby demonstrating the discriminant validity.

We then estimated the reliability of the measures using Fornell and Larcker's (1981) construct reliability. All factors achieved a high reliability (greater than 0.85 across three times as shown in Table 3). Taken together, results from CFA provided strong evidence of the convergent and discriminant validity of the measures used in the study. Finally, Table 4 shows the descriptive statistics and the correlation matrix of all measures for all three phases of measurement.

Table 1. Results from Exploratory Factor Analysis

	T1 (n = 130)			T2 (n = 127)			T3 (n = 116)		
	Factors			Factors			Factors		
	1	2	3	1	2	3	1	2	3
CBT1	**0.74**	0.04	0.15	**0.80**	0.03	0.04	**0.74**	0.05	0.13
CBT2	**0.87**	0.00	-0.04	**0.89**	0.09	-0.08	**0.78**	0.04	0.08
CBT3	**0.79**	-0.01	0.01	**0.71**	0.08	0.08	**0.94**	0.11	-0.13
CBT4	**0.66**	0.00	0.18	**0.91**	-0.09	0.08	**0.68**	-0.09	0.32
EL1	-0.16	**0.85**	0.18	0.05	**0.85**	0.03	0.13	**0.81**	0.01
EL2	0.23	**0.86**	-0.20	0.15	**0.81**	-0.01	-0.09	**0.87**	0.14
EL3	-0.03	**0.73**	0.11	-0.09	**0.89**	0.07	0.06	**0.90**	-0.11
TKC1	-0.00	0.05	**0.74**	-0.15	0.21	**0.75**	0.18	0.38	0.36
TKC2	0.03	0.14	**0.77**	0.13	0.02	**0.75**	0.06	0.29	**0.60**
TKC3	0.08	-0.06	**0.82**	0.28	-0.09	**0.70**	0.10	-0.10	**0.87**
TKC4	0.14	-0.00	**0.63**	0.19	0.08	**0.60**	0.04	0.23	**0.66**
α	0.86	0.89	0.88	0.92	0.90	0.92	0.89	0.93	0.92
Factor correlation matrix									
	1	2	3	1	2	3	1	2	3
1	1.00			1.00			1.00		
2	0.58	1.00		0.62	1.00		0.72	1.00	
3	0.70	0.67	1.00	0.76	0.70	1.00	0.78	0.77	1.00

Note: Extraction Method: Maximum Likelihood.
Rotation Method: Promax with Kaiser Normalization.

Table 2. Correlation Matrix Between Items

	EL1	EL2	EL3	TKC1	TKC2	TKC3	TKC4	CBT1	CBT2	CBT3	CBT4
EL1	1.00										
EL2	0.80	1.00									
EL3	0.76	0.75	1.00								
TKC1	0.61	0.56	0.58	1.00							
TKC2	0.67	0.62	0.59	0.73	1.00						
TKC3	0.56	0.53	0.49	0.63	0.74	1.00					
TKC4	0.58	0.61	0.57	0.62	0.69	0.73	1.00				
CBT1	0.55	0.58	0.51	0.58	0.65	0.63	0.62	1.00			
CBT2	0.50	0.55	0.49	0.53	0.59	0.63	0.58	0.75	1.00		
CBT3	0.53	0.55	0.48	0.55	0.60	0.60	0.56	0.71	0.76	1.00	
CBT4	0.53	0.53	0.47	0.57	0.68	0.63	0.61	0.77	0.72	0.72	1.00

All items are significantly correlated ($p < .01$; 2-tailed).

Table 3. Results of Confirmatory Factor Analysis (Using EQS 5.7b) of Constructs for Each Time Period

	Time		
	T1	T2	T3
Expertise Location (EL) Construct reliability =	.88	.92	.92
1. The team has a good "map" of each others' talents and skills.	.88	.91	.91
2. Team members know what task-related skills and knowledge they each possess.	.83	.91	.91
3. Team members know who on the team has specialized skills and knowledge that is relevant to their work.	.80	.86	.85
Task–Knowledge Coordination (TKC) Construct reliability =	.88	.90	.92
1. Our team members had a global perspective that includes each other's decisions and the relationship among them.	.76	.76	.86
2. Our team members carefully interrelated actions to each other in this project.	.89	.86	.90
3. Our team members carefully made their decisions to maximize an overall team performance.	.82	.87	.82
4. Our team members had developed a clear understanding of how each business function should be coordinated.	.74	.82	.88
Cognition-Based Trust (CBT) Construct reliability =	.89	.92	.93
1. Most of my teammates approach their job with professionalism and dedication.	.88	.86	.89
2. I see no reason to doubt my teammates' competence and preparation for the job.	.82	.88	.87
3. I can rely on other teammates not to make my job more difficult by careless work.	.78	.82	.89
4. Most of my teammates can be relied upon to do as they say they will do.	.81	.90	.88
Goodness of fit index			
Chi-square (*df* = 41)	62.36	45.65	58.55
P	0.02	0.28	0.04
NFI	0.97	0.98	0.97
CFI	0.99	1.00	0.99
RMSEA	0.06	0.03	0.06
RMSEA (90% confidence interval)	(.03, .09)	(.00, .07)	(.02, .09)

Note: All loadings were significant; *t*-values ranged from 7.95 to 15.48. Construct reliability was based on Fornell and Larcker's (1981) formula.

Levels of Analysis and Multicollinearity

In order to warrant the appropriateness of aggregating individuals' perception scores into a team-level score, we conducted James' index (r_{wg}), commonly known as the interrater agreement index (James et al. 1984). James' index measures the homogeneity of members' perceptions. Generally, an aggregation is considered appropriate if the median r_{wg} of the scale is greater than 0.70 (George 1990). Our results show that r_{wg} medians of EL, TKC, and CBT were .81, .80, and .87, respectively. Thus, the aggregated scores of each variable were calculated by averaging each individual's variable scores for each team.

We then assessed multicollinearity among three perceptual variables (EL, TKC, CBT) across three times using the variance inflation factor (VIF) value. Our results showed that the VIF scores across three times ranged from 2.45 to 7.59, which were well below the threshold value of 10 (Myers 1990, p. 369), thus indicating that multicollinearity was not a problem in this study. In addition to the VIF, we also calculated the condition index (Belsley et al. 1980). Condition indices (of EL, TKC, and CBT across three times) from the SPSS regression module ranged from 1.59 to 9.37, which were well below the threshold value of 15, suggesting no multicollinearity.

Table 4. Means, Standard Deviations, and Correlation of Constructs at the Group Level (n = 38)

			Correlation Matrix[a]													
	Mean	SD	TC_1	EL_1	TKC_1	CBT_1	$PERF_1$	TC_2	EL_2	TKC_2	CBT_2	$PERF_2$	TC_3	EL_3	TKC_3	CBT_3
TC_1[b]	16.79	14.98	**n.a.**													
EL_1	2.64	.63	0.40**	**.91**												
TKC_1	3.03	.67	0.44**	.75**	**.91**											
CBT_1	3.22	.52	0.29*	.73**	.80**	**.87**										
$PERF_1$	98.09	1.65	0.18*	.04	-.02	.07	**n.a.**									
TC_2	9.39	7.19	0.16**	.11	.32*	.13	.02	**n.a.**								
EL_2	3.14	.65	-0.01	.35*	.48**	.39*	.20	0.14	**.94**							
TKC_2	3.37	.69	0.02	.27	.41**	.26	.21	-0.03	.77**	**.91**						
CBT_2	3.41	.59	0.05	.25	.32	.30	.33*	-0.01	.69**	.84**	**.90**					
$PERF_2$	91.05	9.15	0.09	.16	.18	.14	.49**	0.34**	.39*	.30	.42**	**n.a.**				
TC_3	4.24	4.36	0.19	.06	.29	.12	-.15	0.46**	.21	.22	.23	.13	**n.a.**			
EL_3	3.08	.65	-0.09	.23	.39*	.19	.09	-0.07	.69**	.75**	.58**	.24	0.25	**.92**		
TKC_3	3.13	.74	-0.06	.21	.33*	.17	.02	0.02	.65**	.70**	.53**	.22	0.29	.89**	**.92**	
CBT_3	3.18	.71	0.06	.22	.31	.30	.10	-0.06	.64**	.66**	.59**	.19	0.29	.78**	.86**	**.93**
$PERF_3$	80.01	15.37	0.08	.07	.17	.07	.34*	0.33*	.38*	.30	.39*	.86**	0.28	.34*	.42**	.32

Note: *Correlation is significant at the 0.05 level (2-tailed).

**Correlation is significant at the 0.01 level (2-tailed).

[a]Diagonal **boldface** elements were the square root of the average variance extracted.

[b]TC values shown in this table is based on the number of task-oriented messages.

Test of the Hypotheses

We used PLS to test hypotheses from both the structural and temporal models. A full model that contains the structural model (as shown in Figure 1) for all three phases, along with additional paths to test the temporal models (as shown in Figure 2), was constructed and tested. PLS not only generates estimates of standardized regression coefficients (i.e., beta coefficients) for the model's paths, but also takes measurement errors into account, which can then be used to measure the relationship between latent variables (Wold 1985). Additionally, the assumptions of normality and the interval scale data are not necessary (Chin 1998). Based on the features mentioned above, PLS is most suitable during the early stage of theory development because it works well with small sample sizes and complex models (Chin 1998). The statistical significance of path coefficients was estimated based on the bootstrapping technique, as recommended by Chin (1998).

One of the advantages of PLS is that we can run the model with a relatively small sample size. The accepted rule of thumb regarding the sample size of PLS is consistent with that of multiple regression (Chin 1998). Generally, the ratio between the number of observations and the number of independent variables needs to be within the range of 5 to 30 (Guadagnoli and Velicer 1988). In the case of PLS, we should apply this rule for the most complex portion of the model (Chin 1998). In our case, the most complex portion of the model has five independent variables[7] and our sample size is 38; thus the ratio is 7.6, which is within the recommended range.

Measures were assessed at three different points throughout the project. In an attempt to control the continuity effect of team performance, we included a direct link only between the adjacent phases (i.e., $PERF_1$ to $PERF_2$). This approach is normally known as the Markov simplex model or first-order autoregressive model (Dunn et al. 1993), which is widely accepted to be "well-suited for examining the time-specific relations between two constructs over time" (Curran and Bollen 2001, p. 109). Figure 3 shows the results of our PLS analysis.

Since the same structural model was tested three times, the hypotheses from the structural model were assessed and reported separately for each phase here. Then, we tested the hypotheses from the temporal models (particularly H4 and H5) by examining the changes in the significance of the structural relationships among constructs over time.

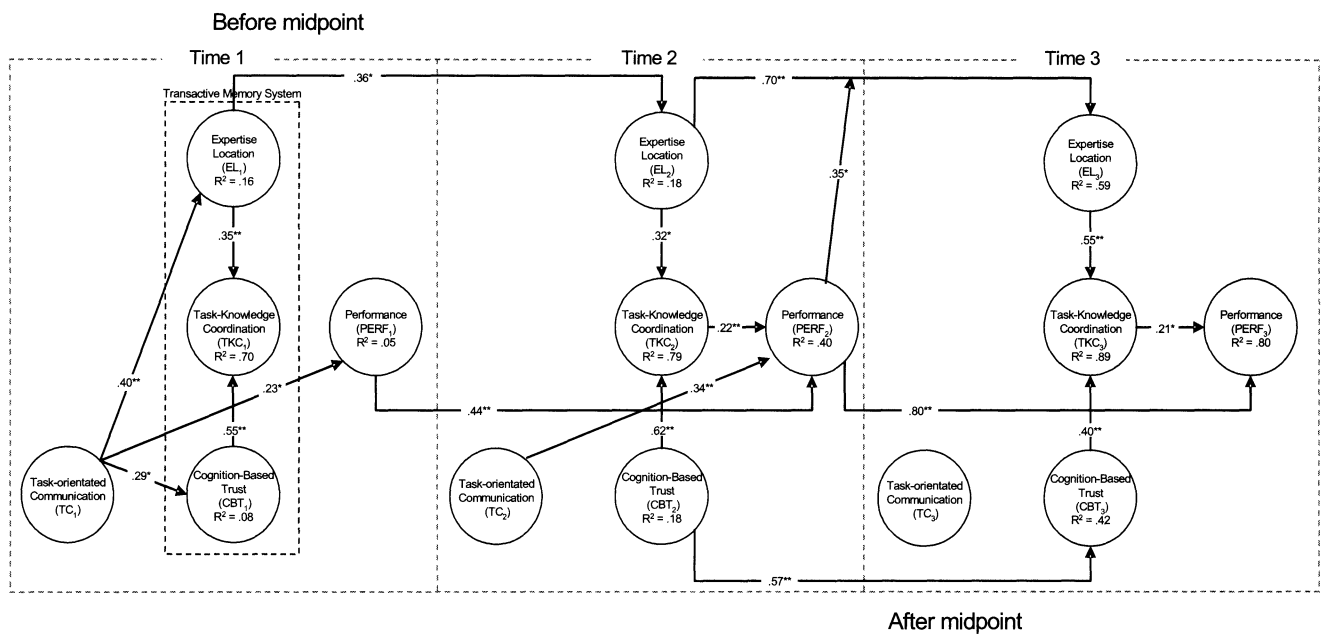
First, we examined the structural aspect of TMS in virtual teams through H1 and H2. With H1a through H1c, collectively, we examined the mediation effect of task–knowledge coordination on the impact of expertise location and cognition-based trust on virtual team performance. H1a and H1b were supported in all three periods, while H1c was supported only at T3. In order to examine full mediation, additional models were tested by including direct links from expertise location and cognition-based trust to team performance (Baron and Kenny 1986),[8] none of which were statistically significant. The results suggest that the impact of expertise location and cognition-based trust on virtual team performance is mediated by task–knowledge coordination.

With H2a through H2c, we examined the role of task-oriented communication in the formation of TMS and team performance. The PLS results show that, at T1, the path from task-oriented communication to expertise location (H2a) was significant as expected. The path from task-oriented communication to cognition-based trust (H2b) was marginally significant at T1 with the p-value of 0.056 (t-value = 1.59). However, H2a and H2b were not supported by either T2 or T3. Finally, the path from task-oriented communication to team performance (H2c) was significant at both T1 and T2, but not at T3.

Then, we examined the temporal aspect of TMS in virtual teams by examining the changes of the structural model and the role of performance feedback over time. With H3a through H3c, we examined the negative moderation effect of performance feedback on the impact of the past expertise location, task–knowledge coordination, and cognition-based trust on future expertise location, task–knowledge coordination, and cognition-based trust, respectively. To test these hypotheses, we included interaction effects between past performance and each of the three dimensions of TMS. We followed the procedure suggested by Chin et al. (2003) in modeling the interaction terms by multiplying the standardized indicators of main effects. We tested these hypotheses twice, once from T1 to T2 and again from T2 to T3. The results show that the interaction term is significant only for expertise location from T2 to T3, providing partial support for H3a. However, we did not find statistical support for H3b or H3c. Although we did not hypothesize the main effects of past performance and past dimensions of TMS, they had to be included in order to construct a proper model to test the hypothesized moderation effect (Baron and Kenny 1986; Chin et al. 2003). It is worth noting that we found that the results of the main effects show that expertise location (for all phases) and cognition-based trust (from T2 to T3) were posi-

[7]They are paths from $PERF_{t-1}$, TKC_{t-1}, EL_t, CBT_t, and TKC_{t-1} X $PERF_{t-1}$ to TKC_t.

[8]The results of the additional models are not reported here due to space constraints.



* Beta path coefficient is statistically significant at p < .05 (1-tailed).
** Beta path coefficient is statistically significant at p < .01 (1-tailed).

Figure 3. Results of the Model

Table 5. Summary of Hypotheses Testing

	Predictions	Results
Structural Model		
H1a	$EL_t \rightarrow TKC_t$	Supported at all phases
H1b	$CBT_t \rightarrow TKC_t$	Supported at all phases
H1c	$TKC_t \rightarrow PERF_t$	Supported only at T3
H2a	$TC_t \rightarrow EL_t$	Supported only at T1
H2b	$TC_t \rightarrow CBT_t$	Marginally supported only at T1
H2c	$TC_t \rightarrow PERF_t$	Supported only at T1 and T2
Temporal Model		
H3a	$PERF_{t-1} \times EL_{t-1} \rightarrow EL_t$	Supported only at T3
H3b	$PERF_{t-1} \times TKC_{t-1} \rightarrow TKC_t$	Not supported
H3c	$PERF_{t-1} \times CBT_{t-1} \rightarrow CBT_t$	Not supported
H4a	The impact of TC on EL will go down after the midpoint	Supported
H4b	The impact of TC on CBT will go down after the midpoint	Not supported
H5a	The impact of TKC on PERF will increase after the midpoint	Supported
H5b	The impact of TC on PERF will decrease after the midpoint	Supported

tively influenced by those of the previous phase, while task–knowledge coordination was not.

With H4a and H4b, we hypothesized the decreasing influence of task-oriented communication on expertise location and cognition-based trust after the midpoint. The paths from task-oriented communication to expertise location and cognition-based trust were statistically significant only in T1. This provides a strong support for H4a and H4b.

Finally, with H5a we hypothesized the increasing influence of task–knowledge coordination on team performance after the midpoint. We also hypothesized the decreasing influence of task-oriented communication on team performance after the midpoint with H5b. The path from task–knowledge coordination to team performance was not significant in T1 and T2, but became significant in T3. At the same time, the path from task-oriented communication to team performance was significant in T1 and T2, but became insignificant in T3. These changing patterns provide moderate support for H5a and H5b. Table 5 summarizes the results of the hypotheses testing.

Discussion

Research on virtual teams is becoming more common, but there is a gap in our understanding of knowledge coordination and its impact on performance in virtual teams. To fill this gap, we explore how three key behavioral dimensions of TMS—expertise location, task–knowledge coordination, and cognition-based trust—impacting virtual team performance evolve over time. When taken together, our finding provides a basic picture of how TMS and their impact on team performance evolve over time in virtual teams.

When a new virtual team is assembled for the first time, our study indicates that it takes a few weeks before the members are able to fully recognize, trust, and coordinate their specialized knowledge in order to effectively perform the task. In that process, our findings suggest that early and frequent task-oriented communications play a critical role in forming the initial beliefs and trust of team members about each others' specialized knowledge. We also found that the volume and frequency of task-oriented communication is a significant determinant of team performance in the initial phase of the project. Furthermore, once such beliefs and trust set in, they appear to be difficult to change. Only negative team performance around the mid-point makes the team members recalibrate their beliefs about other team members' specialized knowledge. The importance of early task-oriented communications is consistent with the findings of Lewis (2004), who studied face-to-face teams. But contrary to Lewis' prediction, teams were able to form TMS based solely on computer-mediated communications.

Once virtual teams develop their TMS, simple hard work and frequent communication is not sufficient for improving team performance. Our study shows that the direct impact of task-oriented communication on team performance disappears over time, as task–knowledge coordination becomes an important determinant of team performance, fully mediating the impact of expertise location and cognition-based trust. This suggests that virtual teams with highly developed TMS can communicate "smart," minimizing the volume and frequency of task-oriented communications without affecting team performance. At the same time, our finding suggests that in virtual teams, it takes quite some time—perhaps much longer than in face-to-face teams—for TMS to fully develop and begin to influence team performance. It is important to note that our finding does not suggest that late task-oriented communication in virtual teams is not important. What we argue, instead, is that once a team develops its TMS, its members can economize their communication efforts. It is like a highly trained professional basketball team that can execute sophisticated plays with minimal on-court communication among players who know and trust each others' ability. Our finding suggests that such a phenomenon might be taking place among virtual teams that rely primarily on task-oriented communications when performing cognitive tasks.

We also observed that the three dimensions of TMS do not follow the same evolutionary path. Although expertise location and cognition-based trust seem to be quite stable once initially formed, we found that task–knowledge coordination was particularly dynamic. This is consistent with Faraj and Xiao (2006), who noted that knowledge coordination in complex task environments is emergent. Our finding also suggests that the three behavioral dimensions of TMS impact team performance differently. This finding is a significant departure from the prior studies of TMS, which have typically bundled them together.

Limitations

Despite several contributions to the literature, our study has several limitations that the reader should consider in evaluating the results. First, our study was conducted in a simulated environment with MBA students. Although Inc. 2000 provided a reasonably complex, distributed, collaborative decision-making environment, the real world often represents much more complex virtual team environments. For example, we arbitrarily assigned roles to participating students. In the real world, virtual team members are more likely to be assigned to a role based on their expertise and knowledge. We assumed that individuals would participate in only one team at a time. In the real world, individuals are often members of multiple teams, with different roles, expectations, and temporal rhythms. We assumed that individuals would have access to a fairly limited set of communication media. In the real world, individuals have access to a much broader set of communication media, including face-to-face meetings. Thus, one needs to consider these boundary conditions before trying to generalize our findings.

Second, it needs to be noted that our participants performed a structured task that required high interdependence among team members. While our results can be applied in similar task contexts, one needs to carefully examine the task structure before generalizing the results. We believe that if the task did not require interdependence, the behavioral dimensions of TMS may not be as important. Instead, other factors such as effective and efficient communication would be more important for team performance.

Third, since participants were selected from a handful of universities, they might have communicated locally among classmates across virtual teams. However, our content analysis did not provide any information that suggests this type of cross-team communication among students on the same campus. Furthermore, to see if there was any "university effect" on team performance, we ran a series of t-tests to compare the performance of teams that included a member from a university *vis-à-vis* the performance of all other teams. We conducted this analysis for all participating universities in all three phases and did not find any significant university effect. Thus, combined with our content analysis and the *post hoc* analysis of university effect, we believe that even if some participants communicated with other students on the same campus who belonged to another team, it did not affect their team performance.

Fourth, due to the complexity of this study, we did not manipulate team composition to include specific cultural (e.g., individualistic versus collectivistic) and temporal differences as factors in the selection process. This might have suppressed the influence of cultural and temporal differences that have been found to have a negative impact on the coordination (Maznevski and Chudoba 2000) and communication (Kayworth and Leidner 2000) of virtual teams.

Finally, another shortcoming is related to the measure of team performance. In this study, team performance is based solely on an objective measure provided by the simulation game. The accuracy of this objective measure is heavily dependent on how closely the mathematical model used in the simulation game represents the underlying assumptions of how the real business world works. Furthermore, the objective measure used here represents only one dimension of team effectiveness. Other affective measures such as satisfaction in a team's process and outcomes are by no means less important.

Directions for Future Research

Despite these limitations, a meaningful and interpretable pattern of relationships among the team's communication, expertise location, cognition-based trust, task–knowledge coordination, and performance over time has emerged. As an initial empirical study that explores the temporal aspects of TMS and performance in virtual teams, our study provides several implications for both future research and management practices.

For virtual team research, our study demonstrates the dynamic and complex relationship between task-oriented communications and the three dimensions of TMS in virtual teams and their impact on team performance over time. Although much remains to be answered about the development and impact of TMS in virtual teams, our study highlights the role of time in virtual teams and TMS research as noted by McGrath (1988), that "time is ubiquitous but understudied within the field of social psychology" (p. 255). As one of the first empirical studies on the changes in TMS in virtual teams, however, our study raises more questions than it answers. What drives the change in TMS? How is it strengthened or, conversely, how does it become weakened or broken? These are just a few of the questions that need to be addressed in future studies.

Second, further exploration of the relationship between different technologies of TMS is in order. Similarly, this study highlights the need for increased attention to the design and development of collaborative tools that facilitate the flow and creation of knowledge among individuals working on a complex, cognitive, interdependent task. Tools like the one developed by Boland et al. (1994) allow each member to express how he/she understands the overall problem and think systematically (Argyris and Schön 1978). Our study suggests that virtual teams require support for all three behavioral dimensions associated with TMS. While much of the past research on media and virtual team performance has focused on the fit between the media and the task, our study suggests that future research needs to examine the support of various factors associated with social cognition in virtual teams.

Finally, we examined only three dimensions—expertise location, task–knowledge coordination, and cognition-based trust—that are associated with TMS. However, we recognize that there are other factors that need to be examined. For example, people over time develop an awareness of who needs what as well as who knows what. Also, as pointed out in previous mental model studies (Brandon and Hollingshead 2004; Klimoski and Mohammed 1994), TMS in teams can be further associated with task, technology, team dynamics, and environments. Our study has merely scratched the surface of this rich and important area of inquiry.

Implications for Practice

Our results provide two important managerial implications for organizations that are using virtual teams for critical tasks. First, we suggest that organizations need to emphasize early and frequent task-oriented communications when they put together a new virtual team. While we fully acknowledge the importance of "ice-breaking" activities that emphasize social and emotional bonding among team members, it is equally, if not more, important to help members develop different aspects of TMS through these early task-oriented communications. At the same time, once teams develop effective TMS, they may be misdirecting their effort if managers continue to emphasize frequent task-oriented communication. Instead, managers should then focus on supporting the coordination of specialized knowledge of team members in the realm of the task requirements.

Our study also suggests that given the important role of expertise location and task–knowledge coordination that we found in this study, organizations can develop tools that facilitate their development and maintenance in virtual teams. Simple tools such as electronic directories that show members' domains of expertise could be a good starting point (Moreland 1999). Tools that help team members to build initial trust through simple indicators for past performance or peer reviews can be also effective given the importance of cognition-based trust. More sophisticated and dynamic tools that reflect members' changing profiles of knowledge and how it can be matched to various task-requirements could be even more effective.

Conclusion

Can virtual teams develop TMS without having face-to-face meetings? Based on our finding, the answer to that question is yes. Like in the case of their counterparts in face-to-face environments (Lewis 2004), for virtual teams early task-oriented communications seem to be most crucial in developing TMS. Do TMS that are formed without any face-to-face meetings influence team performance? Again, based on our finding, the answer is a cautious yes. In our case, it took 8 weeks before TMS began to influence team performance. Given most prior studies on TMS were done in laboratory settings which typically last no more than a day, our finding suggests that it might take longer to build effective TMS in virtual teams compared to face-to-face teams. Once developed, however, TMS play an important role in influencing team performance in virtual teams. As virtual teams take on increasingly important and knowledge intensive tasks, researchers and practitioners alike need to pay attention to the development and maintenance of TMS. The current study offers a small step toward the goal.

Acknowledgments

We would like to recognize Kalle Lyytinen and Karl Weick for their helpful comments on earlier versions of the paper. We acknowledge the help and support of Ritu Agarwal, of the associate editor, and of the three reviewers for their constructive feedback.

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Appendix A

Examples of Our Coding

The following examples are taken from 400 messages that were coded by both coders. Each message was coded using one of the 12 subcategories of the original IPA protocol shown in Table A1. The interrater reliability was calculated at the subcategory level.

Table A1. IPA Coding Categories (adopted from Bales 1950)

Socio-emotional area: Positive	1. **Shows solidarity**, raises other's status, gives help, reward
	2. **Shows tension release**, jokes, laughs, shows satisfaction
	3. **Agrees**, shows passive acceptance, understands, concurs, complies
Task area: neutral	4. **Gives suggestions**, direction, implying autonomy for others
	5. **Gives opinion**, evaluation, analysis, expresses feeling, wish
	6. **Gives orientation**, information repeats, clarifies, confirms
	7. **Asks for orientation**, information, repetition, confirmation
	8. **Asks for opinions**, evaluation, analysis, expression of feeling
	9. **Asks for suggestions**, direction, possible ways of action
Socio-emotional area: Negative	10. **Disagrees**, shows passive rejection, formality, withholds help
	11. **Shows tension**, asks for help, withdraws out of field
	12. **Shows antagonism**, deflates other's status, defends or asserts self

Examples of Task-Oriented Message (All Names are Disguised)

```
From:    Ben
To:      teamx@info.cwru.edu
Subject: More labors and advertising/promotion
Dear teammates,

I made my decision to product 4200 units and hopefully we can sell all of them.  I am
positive because 1)we have had a big R&D investment (which means our machine has a good
quality) 2)The market's still hot (index of 103) 3)our sale price is moderate.
```

```
Please note that our plant capacity is 5000.  In order to match our aggressive
production/sales strategy, we need more labor (currently 89; this quarter HR is hiring 13
but can we hire 11 more to catch a 4500 units production because each labor is for 40
machines in a regular basis) and sales person.

For Marketing VP, can you also dramatically increase the ad/promotion for marketing because
of this production increase?

Ben
VP production
```

Both coders coded this message as category 5, gives opinion.

```
From:    George
To:      teamx@info.cwru.edu
Subject: Re: Team Check   Received: 10/10/2000 4:12:10 PM
What is you plan for the next quarter.  You must have got the financial statement.  It
appears that our team is going good.  Will you discuss the possibility of increasing the
production level up to 3000.  I think considering our financial report we can take this
opportunity to increase our production in the coming quarters.
Pl.  send your comments.

George
```

Reviewer 1 coded this message as 4, gives suggestion, and reviewer 2 as 5, gives opinion. After the discussion, they agreed to code it as 4.

Examples of Socio-Emotional Messages

```
Discussion thread: [Quarter 10]->[ok...personal]
Sender: John, 9/28/2000 7:46:38 PM
The weather here is getting really nice...sunny, mid-20's.   It's Spring-time in Australia,
so the flowers are out in force at the moment.

I live my girlfriend of 6.5 years (Tracy) and we have a gorgeous black cat that has about
one hundred different names.   I think Grease was her original name, because she liked
getting under cars as a kitten and would get all greasy...that progressed to Monkey,
because she liked climbing things (and it's also a nice progression "Grease Monkey").   I
think we are calling her Beeby at the moment, or The Beeb!!

I have a sister - Cindy - who still lives at home with my parents.   As mentioned already,
I love golf and "intend" to get really fit over my Summer break before I start work at [a
company name] in February....I will have about 4 months off!!

How was that Sophia?

Regards,

John.

p.s.   I am going to try and save a short "movie" of me next week at work placement and I
will e-mail it to you all so that you can see what you are dealing with!!!
```

Both reviewers coded this message as 1, shows solidarity.

```
Discussion thread: [Quarter 11]->[Q10 review]
Sender: Mike, 10/5/2000 5:43:41 PM
Right, we seem to be on the right track guys.
But our stock price still rank last.  Although it is not a main concern for this time.  I
hope we can cooperate and collaborate more effectively this week.

Good Job,
Mike
VP of Marketing
```

Reviewer 1 coded this message as 11, shows tension, and reviewer 2 as 10, disagrees. After the discussion, they agreed to code it as 11.

Appendix B

Confirmatory Factor Analysis

Four models that were compared include the following: (1) a null model (M_0); (2) a single-factor model (M_1) having all final 11 items loaded on a single factor (Figure B1); (3) a three-factor model with correlation among factors fixed to one (M_2, see Figure B2); and (4) a three-factor model with factors being freely correlated (M_3, Figure B3). The difference in chi-square statistics was used to test the superiority of one measurement model over another in these comparisons. Table B1 shows the results of the hierarchical comparisons that we conducted based on data at T1.[9] The first three comparisons demonstrated the superiority of the three-factor model over null and one-factor models. The last comparison (M_2-M_3) demonstrated that the three underlying factors were indeed distinct from one another and that the correlations among them were statistically different from unity (Pedhazur and Schmelkin 1991, p. 681).

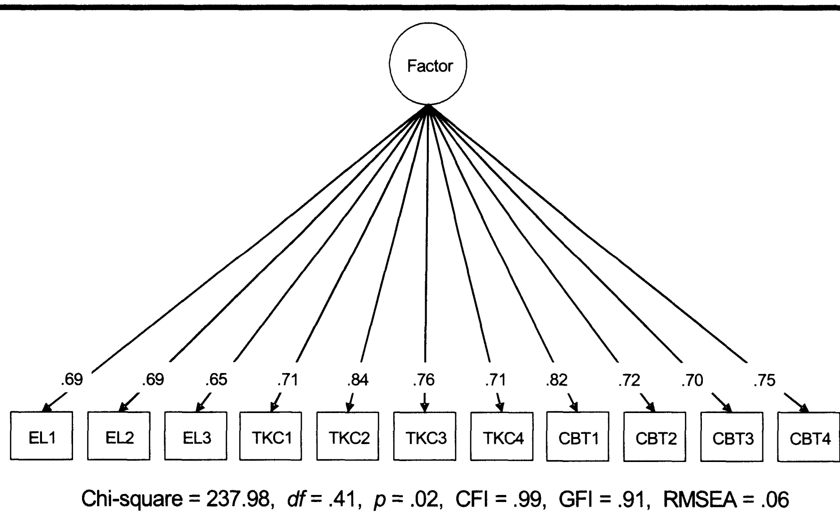
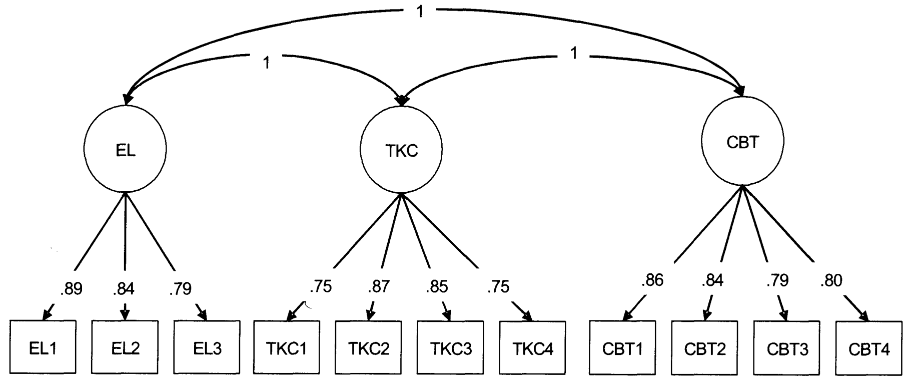


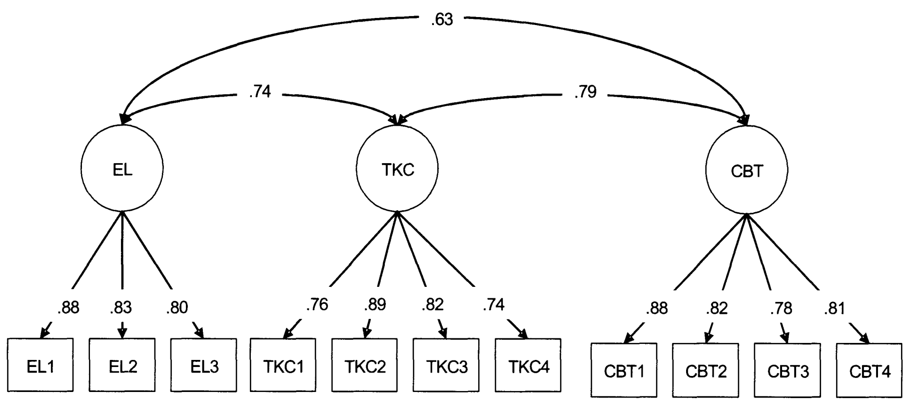
Figure B1. Model M_1 (Based on Data at T1)

[9]We also conducted the same test with data from T2 and T3 and the results were consistent with those with T1 data.



Chi-square = 190.95, df = 44, p < .001, CFI = .92, GFI = .76, RMSEA = 1.6

Figure B2. Model M_2 (Based on Data at T1)



Chi-square = 62.36, df = 41, p = .02, CFI = .99, GFI = .91, RMSEA = .06

Figure B3. Model M_3 (Based on Data at T1)

Table B1. Hierarchical Comparisons of Measurement Models (Based on Data at T1)

Model	Description	χ^2	*df*	
M_0	Null model	1005.03	55	
M_1	One-factor model	237.98	44	
M_2	Three-factor model (factor correlations fixed to 1)	190.95	44	
M_3	Three-factor model (factors are freely correlated)	62.36	41	
Model comparisons		$\Delta\chi^2$	Δdf	p
M_0-M_1	Test for the fit of the one-factor model over null model	767.05	11	0.0000
M_0-M_3	Test for the fit of the three-factor model over null model	942.67	14	0.0000
M_1-M_3	Test for the fit of the three-factor model	175.62	3	0.0000
M_2-M_3	Test for the discriminant validity of the three factors	128.59	3	0.0000