Delineating Cognitive Maps in Teams: The Structure, Antecedents, and Consequences of Transactive Memory Systems

A DISSERTATION
SUBMITTED TO THE FACULTY OF THE GRADUATE SCHOOL
OF THE UNIVERSITY OF MINNESOTA
BY

Xi Zhu

IN PARTIAL FULFILLMENT OF THE REQUIREMENTS
FOR THE DEGREE OF
DOCTOR OF PHILOSOPHY

Adviser: Professor David H. Knoke

July, 2011

Acknowledgements

The work reported in this dissertation was supported by a number of funding sources. A Graduate Student Support Initiative Fellowship from the College of Liberal Arts and the Department of Sociology, University of Minnesota helped me to develop some initial research ideas and skills in social network analysis. The collection of data for this research was funded by a National Science Foundation grant, "The Effect of Social Networks and Team Climate on Team Innovation and Client Outcomes in Health Care Teams" (SES-0719257), awarded to Professors Douglas Wholey and David Knoke. The analysis and the writing of this dissertation were supported by an Interdisciplinary Doctoral Fellowship from the University of Minnesota Graduate School and Minnesota Population Center. I thank these funding agencies for their generous financial support.

Many people have helped me develop and carry out this research and I owe them a great debt of gratitude. The members of my dissertation committee deserve special acknowledgements as mentors and friends. David Knoke has been generous with his time and advices across the many steps that led to the completion of my dissertation. He graciously read through and provided critical and constructive comments on my prelim paper, prospectus, numerous grant proposals, fellowship applications, and various versions of the dissertation, often under high time pressure. His unreserved support has infused me with confidence that I could accomplish what seemed to be impossible. I also owe him for introducing me to organization theory and social network analysis – two research areas that became my intellectual identity. Dave was a role model for me in teaching, student mentoring, and professional ethics. As I increasingly realized, I will benefit from David's mentoring for a lifetime.

Douglas Wholey is an inspiring mentor and colleague as any junior academic could hope for. I remember that my first meeting with him yielded several pages of research ideas from our discussion (and out of my expectation, Doug jotted down and sent me the list of ideas after the meeting to make sure that we could follow them through). This kind of idea-generating interaction continued in the past four years as we worked together on the INTACT (Improving Networks and Teamwork in Assertive Community Treatment) project and drove around the state of Minnesota for data collection. I also learned a great deal in data analysis and programming from Doug. Andrew Van de Ven's seminars on Micro Organizational Behavior and Theory Building and Research Design have set the theoretical and epistemological foundations for my dissertation research. I was very fortunate to have Andy serving on my committee and pushing me on issues of theory, method, and engaged scholarship. Erin Kelly always offered insightful suggestions on my research ideas and helped me think creatively of the research findings. Her knowledge of the sociological literature on work, organization, and health helped me ground my thinking in my home discipline – Sociology. Yanjie Bian helped me on issues related to network analysis, especially on how to substantively interpret various network structures. Yanjie was also a continuing source of inspiration to me for conducting high-quality sociological research in China.

Besides my dissertation committee, I benefitted greatly from interacting with a group of organization scholars at the University of Minnesota. Many of them have made extensive contributions to the INTACT project. They are Pri Shah, Pinar Karaca-Mandic, Michelle Duffy, Mary Zellmer-Bruhn, Katie White, David Knutson, and Yuqing Ren. The members of Minnesota ACT teams and Tom Witheridge, Gary Mager, and Dean Carter from the Minnesota Department of Human Services made this research possible with their voluntary participation and kind support. My friends and fellow sociology graduate students have shared so much laughter and a few tears during these years of dream pursuing. I thank them for their friendship: Erika Busse, Eric Dahlin, Rachael Kulick, Aaron Bommarito, Reiping Huang, Shawn Wick, Yu-Ju Chien, Laura Fischer, Wenjie Liao, Liying Luo, Minzee Kim, Jack Lam, Susan Mlangwa, Rehema Kilonzo, Mayumi Uno, Jin Jun, Xinxiang Chen, and Dong Dong. I thank the staff and other faculty members of the Department of Sociology for their continuous support. I am grateful to my friends in China, especially Tianlu Xia, Miao Zhu, Zhiqiang Dong, Yuting Zhou, Yi Guo, Sen Wang, and Minzhi Guo, for many years of emotional support.

Finally, my deepest gratitude goes to my families. My parents, Shi-Fei Song and Qi-Yun Zhu, provided me with their unconditional love and support. They have been extremely patient and acceptant as I undertook a long journey to develop my career. I dedicate this dissertation to them. I thank my brother, Wei Song, for keeping faith with me even when some of my ideas went wild and became tedious to his artistic mind. During my years in Minnesota, I was very blessed to meet and become part of the Levitan family, including Lance Sr., Eleni, Lance Jr., Kathy, Grant, Bryn, Bill, Angie Bowyer, and Helen Donahoe. I am grateful for their companionship that made the journey more enjoyable and sometimes less sober (just what I needed!). And because of them, Minnesota became another place that I now fondly call home.

To my parents, Shi-Fei Song and Qi-Yun Zhu

Abstract

This research examines the structure, antecedents, and consequences of transactive memory system (TMS), a team's shared cognition of who knows what and the process of collectively encoding, storing, and retrieving knowledge. For the structure of TMS, I conceptually distinguish teams' cognitive and knowledge structures (i.e., cognitive accuracy, consensus, and knowledge distribution) from cognitive processes (i.e., coordinate and trust in encoding, storing, and retrieving knowledge), and develop a new method to measure the TMS structure. For antecedents of TMS, I examine how patterns of social interactions among team members (as captured by the structures of various social networks and individuals' positions in networks) affect cognitive accuracy and consensus of teams and individuals. For consequences of TMS, I examine the effects of cognitive accuracy and consensus on team performance and individual job burnout.

Empirical analyses for this research are based on three waves of survey data collected from 26 multidisciplinary mental health care teams over a two-year research period. The results demonstrate that the structures of social networks are important predictors of team cognitive properties. Particularly, highly accurate and consensual TMS are found in teams with centralized and less dense task-help networks. Individuals' network positions have certain but limited implications for individual cognitive outcomes, which reinforces the idea that shared team cognition is fundamentally a team-level phenomenon. Additionally, I explain where cognitive inaccuracy comes from with a dyadic-level analysis. The results suggest that cognitive inaccuracy arises in dense task-

help networks because team members tend to overstate others' expertise when receiving task-related assistance from the others. Examining consequences of TMS, I show that cognitive accuracy and consensus interact with team knowledge stock in affecting team performance, with accuracy and consensus having greater positive effects on performance in teams with higher knowledge stock. At the individual level, I find that cognitive accuracy alleviates job burnout for team members. But this effect is limited to one dimension of job burnout – burnout related to ineffectiveness. Together, the empirical results provide a strong support for the arguments that shared team cognition is constructed through social interactions in teams and that shared team cognition has positive effects on teams and individuals.

Table of Contents

List of Tables

List of Figures

CHAPTER ONE

INTRODUCTION

1.1 Introduction

On March 17th 2011, the *New York Times* featured an article entitled "What Makes a Hospital Great." The article offered an insider's view on how excellence was achieved in a hospital famous for taking care of patients undergoing difficult surgery. Dr. Pauline Chen, a liver transplant and cancer surgeon, once believed that this nationally top-ranked hospital had excellent results because the surgeons were great and skillful. When she undertook her subspecialty training there, she soon became convinced that it was something about the entire system that distinguished this hospital:

> "*… I had only been working there a short time when it became clear that in day-to-day patient care, good or even superb operative skills weren't enough to make a hospital's reputation. It was having a well-oiled team of clinicians who believed in supporting one another and doing their best.*"

What shadows this inspiring sample are recurrent reports on how pervasively medical errors and operational mistakes occur in hospitals (Kohn, Corrigan, and Donaldson 2000; Landrigan et al. 2010). These reports highlighted a pressing challenge faced by all hospitals in the U.S.: How to create a well-functioning system that assures safety and quality in patient care? More broadly, the same challenge is faced by all modern organizations: the challenge to organize people and resources (tangible or intangible), to coordinate actions and work processes, and ultimately to accomplish the organizations' goals. Dr. Chen's observation points to one possible solution: to create well-oiled teams. But, the practical challenge is *how* to create such teams (if the characteristics of such teams can first be clearly specified).

Concomitant with this practical challenge is the increased research interest in how coordination unfolds in workplaces. This dissertation sets out to examine one critical aspect of the "well-oiled" teams: the cognitive underpinning of team coordination. Specifically, I explore the idea that teams with an accurate and shared cognitive representation of their knowledge repositories (i.e., transactive memory system) will exhibit smooth coordination in day-to-day work, which in turn will contribute to team effectiveness. I further examine what personal, interpersonal, and collective factors contribute to the development of an accurate and shared team cognition on knowledge distribution, and what impact such a team cognition has on teams and individuals. Methodologically, I develop and validate a method for measuring this shared team cognition.

To account for the antecedents of the shared team cognition on knowledge distribution, I draw on relevant theories from organization research, sociology, and psychology to form an integrated perspective. The common ground that these theories share is the recognition that socially shared cognition is constructed through social interaction processes. However, researchers have not reached an agreement on how social interactions should be operationalized and examined in empirical research. In this research, I use social network analysis to examine the impact of social interactions on team cognition. Social network analysis is capable of capturing interaction patterns and dynamics unfolding at various levels (individual-, dyadic-, and higher-level), which closely corresponds to the multilevel nature of shared team cognition. Empirically, I examine the measurement of transactive memory system and test hypotheses about the relationships between transactive memory system and its antecedents and consequences using data collected from multidisciplinary mental health care teams.

The scope of this research is restricted to work teams that exhibit high task interdependence and involve intensive coordination and interpersonal interactions. This excludes larger organizational systems (e.g., multinational corporations, universities) where coordination is channeled through other mechanisms (e.g., information systems and formal procedures). Although the research findings may be informative and have implications for larger organizations, inferences should be cautiously extended beyond work teams. I choose to examine the cognitive underpinning of coordination in health care teams because it is particularly pressing for health care teams to improve their coordination and effectiveness. If any teams' failure to achieve good coordination would pose a threat to somebody's wellbeing or even create a life or death difference, it should be health care teams (some other cases of intensive coordination have been examined in air crews and aircraft carrier operation teams; see Weick and Roberts 1993).

1.2 The Central Concept and Research Objectives

The central concept examined in this dissertation is transactive memory system (TMS). Wegner (1987:186) originally defined TMS as "a set of individual memory systems in combination with the communication that takes place between individuals." This definition has been extended in recent literature to mean: 1) knowledge/memory/information possessed by individuals combined with a shared awareness of who knows what (Moreland 1999; Austin 2003); and 2) a collective and cooperative system for encoding, storing, and retrieving information (Wegner, Erber, and Raymond 1991; Lewis 2003).

TMS is a critical antecedent for team coordination. Hilgard (1980) classified mental activities that determine human behaviors into three categories: cognition (knowing), affection (feeling), and conation (willing). Among the three, cognition is more closely related to the competence for social actions, while the other two are more closely related to motivational determinants of social behaviors. TMS, as a team-level cognitive system, determines a team's competence to coordinate. It is a *transactive* system in the sense that based on a shared awareness of who knows what, team members can access knowledge and information stored by other members. They divide the cognitive labor of memorizing by relying on experts in specific knowledge domains to encode and store new information in those domains. When needed, team members will retrieve specialized information from the experts. Each individual acts like a memory unit in a connected system in which knowledge and information are distributively stored and exchanged through retrieving processes.

Accumulating evidence from laboratory and field research shows that TMS exists in various types of teams and has a positive impact on team performance (Liang, Moreland, and Argote 1995; Moreland and Myaskovsky 2000; Austin 2003; Rau 2005;

Zhang et al. 2007). Other benefits of TMS include facilitating team learning (Lewis, Lange, and Gillis 2005) and serving as a knowledge management tool (Argote, McEvily, and Reagans 2003; London, Polzer, and Omoregie 2005). Despite the burgeoning interest in TMS, confusion about the construct's conceptual dimensionality and disagreement on how to measure the construct still characterize the current status of the field (Peltokorpi 2008). Moreover, research on antecedents of TMS is scarce, especially in real organizational settings (Hodgkinson and Healey 2008).

In this research, I aim to achieve three objectives. First, I extend current TMS theory by elaborating on a conceptual distinction between the structural and process aspects of TMS. TMS is a multi-faceted construct pertaining both to a team's cognitive structure and to its cognitive processes. To use Marks, Mathieu, and Zaccaro's (2001) terms, TMS describes both cognitive emergent states and cognitive team processes. Although the concept has gained increased popularity in empirical studies, the structure versus process distinction and the relationship between the two aspects were rarely explicated in prior research. I discuss this conceptual issue in chapter two. The lack of conceptual clarity may have further contributed to a misalignment between theory and methods as researchers sometimes employed process measures to address structural questions or vice versa. Thus, enhancing conceptual clarity will also inform measurement development, which is my second objective.

Second, building on prior research on TMS measurement, I propose a new method for measuring the TMS structure. This method considers each individual's cognition of team knowledge distribution as a cognitive map and captures this map with a person-by-expertise matrix. Measures for TMS structural properties, including knowledge stock, transactive memory (TM) accuracy, and TM consensus, and knowledge specialization can be derived from a complete set of team members' cognitive matrices. I test psychometric properties of these measures using data collected from real teams. Because the team knowledge distribution is described as person-by-expertise connections, I use the terms team knowledge distribution and team expertise distribution interchangeably in this dissertation.

Third, I examine the antecedents and consequences of TMS with selective focuses. Specifically, I explore two research questions: 1) How do social networks affect team TM accuracy and consensus? 2) How do TMS properties affect team performance and individual burnout? I develop hypotheses regarding the effects of social networks on TMS properties at both the team and individual levels. Empirical analyses are conducted based on three waves of survey data collected from 26 multidisciplinary mental health care teams. Examining its consequences, I assess how team-level TMS properties affect team performance and how individual-level TM accuracy affects job burnout. Together, the empirical results provide a strong support for the arguments that shared team cognition is constructed through social interactions and bears significant influence from social networks and that shared team cognition has positive effects on teams and individuals.

1.3 Organization of the Dissertation

In Chapter 1, I described the problem of coordination as a pressing challenge for modern organizations and teams, and introduced the concept of TMS as an important antecedent for effective coordination. I discussed the objectives of this research, which revolve around extending our understanding of TMS through theoretical, methodological, and empirical inquiries. The rest of dissertation is organized as follows.

In Chapter 2, I review literature on team and team cognition and compare TMS with other similar team-cognitive concepts. I then inspect the multi-faced concept of TMS through a structure-process lens and propose a framework to integrate various conceptual dimensions discussed in prior research.

Chapter 3 presents hypotheses regarding the antecedents and consequences of TMS. The hypotheses for antecedents focus on network structures and positions as predictors of TMS outcomes for teams and individuals respectively. Although hypotheses are proposed at both the team- and individual-levels, I consider team as the primary level of analysis. The hypotheses for TMS-team performance relationship are presented to replicate existing research and to explore the question how different dimensions of TMS interact to affect team performance. Finally, I extend research on TMS consequences to the individual level by exploring how cognitive accuracy is related to job burnout.

Chapter 4 describes the research setting, data, measurement, and analytic methods. Specifically, I describe the development and validation of a new method for measuring TMS. The method is based on the notion of individual cognitive maps.

Chapter 5 presents empirical results from testing the hypotheses developed in Chapter 3. I discuss the results in accordance with the types of hypotheses (first antecedents, then consequences) and the levels of analyses (first team-level, then individual-level). Network structures are shown to affect team TMS properties in ways that contradict my predictions. In an attempt to explain the surprising results, I present post-hoc analyses that break down the aggregate network effects to the dyadic level. Lastly, I present selective analyses for modeling changes in TMS and its consequences.

Chapter 6 concludes the dissertation by summarizing the major findings and discussing the contributions, implications, and limitations of this research.

CHAPTER TWO

TRANSACTIVE MEMORY SYSTEMS IN TEAMS

The study of transactive memory system (TMS) is situated in a broader stream of research on social and team cognitions in which many related concepts have been introduced and examined. In this chapter, I aim to build a conceptual foundation for this dissertation. I begin with defining team and team cognition and comparing TMS with similar team-cognitive concepts such as team mental model and shared cognition. I then delineate conceptual dimensions of TMS based on a structure versus process distinction and discuss how different dimensions are related.

2.1 Team and Team Cognition

Work teams are the building blocks of contemporary organizations. A variety of changes occurring in organizational environments, such as increasing competition, growing task complexity, and mounting demands for innovation and efficiency, are driving various organizations to adopt team-based structures (Lawler, Mohrman, and Ledford 1995; Kozlowski and Ilgen 2006). Scholars and managers generally believe that teams are more capable than individuals of tackling difficult and complex tasks because teams can coordinate and utilize diverse knowledge and skills possessed by their members. This promise has spurred a burgeoning stream of research on teams in the last two decades (see recent reviews by Cohen and Bailey 1997; Salas, Stagl, and Burke 2004; Ilgen et al. 2005; Kozlowski and Ilgen 2006; Mathieu et al. 2008).

As the precursor to current team research, small group research was a topic in social psychology for more than a century (McGrath, Arrow, and Berdahl 2000). However, in recent literature, researchers have accentuated a conceptual difference between teams and groups. For instance, Salas et al. (1992:4) defined a team as “a distinguishable set of two or more people who interact dynamically, interdependently, and adaptively toward a common and valued goal/object/mission, who have each been assigned specific roles or functions to perform, and who have a limited life span of membership.” Similarly, Kozlowski and Ilgen (2006:79) defined a team as “(a) two or more individuals who (b) socially interact (face-to-face or, increasingly, virtually); (c) possess one or more common goals; (d) are brought together to perform organizationally relevant tasks; (e) exhibit interdependencies with respect to workflow, goals, and outcomes; (f) have different roles and responsibilities; and (g) are together embedded in an encompassing organizational system, with boundaries and linkages to the broader system context and task environment.” These definitions emphasize that teams are special types of groups that exhibit dynamic interaction, clear role differentiation, and high interdependence. As will become clear in the next chapter, I embrace these defining features of teams and consider social interaction and interdependence as critical antecedents of TMS.

The idea that groups have cognitive properties similar to individual cognitions has been around for a long time (e.g., Durkheim’s [1893/1997] notion of collective consciousness). But the formal test of this idea in groups and teams has been a relatively recent development (Gibson 20001; Salas and Fiore 2004). Cooke, Gorman, and Winner

(2007:240) defined team cognition as “cognitive activity that occurs at a team level.” This definition applies a process view on team cognition and differs from the conventional view that describes team cognition as cognitive existence or structures. In recent years, two related concepts, TMS and team mental model, have dominated the team cognition literature (Ilgen et al. 2005; Pearsall, Ellis, and Bell 2010). TMS is defined as knowledge possessed by individuals combined with a shared awareness of who knows what among team members (Moreland 1999). Team mental model is defined as an organized and shared understanding of relevant knowledge among team members (Mohammed and Dumville 2001). Researchers suggested at least four content domains for team mental model: equipment model, task model, team (or team-member) model, and team interaction model (Cannon-Bowers, Salas, and Converse 1993; Mohammed, Klimoski, and Rentsch 2000). Some scholars have compared team mental model with TMS (Cannon-Bowers and Salas 2001; Peltokorpi 2008), but no crystal-clear conceptual relationship between the two has been proposed. Team mental model is defined more broadly and one may consider TMS as a unique type of team mental model: the team-member mental model – a mental representation of what team members know and their skills, preferences, and habits (Cannon-Bowers et al. 1993; Mohammed et al. 2000). But, I argue that team-member model does not convey all meanings of TMS. Current team mental model literature tends to emphasize shared beliefs as the main feature of team mental model, whereas TMS has multiple dimensions pertaining to both shared and distributed features. In summary, compared with team mental model, TMS has a more specific content focus (team members’ knowledge), but its dimensionality is more complex.

TMS is also closely related to several other concepts in social psychology literature, particularly shared cognition (Cannon-Bowers and Salas 2001) and distributed cognition (Hutchins 1991). Cannon-Bowers and Salas (2001) reflected on the notion of shared cognition and suggested that there were multiple meanings attached to the term shared. They described four broad categories. The first category is overlapping, which refers to the situation where team members have common knowledge. The second category is similar or identical where team members hold similar or identical knowledge. The third category is complementary or compatible, meaning that team members can have different knowledge but they must be able to draw similar expectations based on their knowledge. The fourth category is distributed for which the key issue is effective across-team knowledge appointment. Thompson and Fine (1999:280) offered a slightly different classification. They discussed three possible meanings for the term shared: "divided up into portions", "held in common", and "partaking in an agreement." What these authors did not explicitly consider is the distinction between lower-order, higher-order, and location information.

Wegner and Wegner (1995) defined these three types of information. Lower-order information is specific facts or details. Higher-order information is the label for lower-order information. Location information is the directory associating higher-order information with group members. According to these definitions, what we usually refer to as knowledge (whether it is context-specific or general knowledge) belongs to lower-order information. Higher-order information can be considered as a classification and labeling system that people use to categorize lower-order information into domains (e.g., details about foods, recipe, and cooking tips all belong to knowledge of cooking). Location information associates people with domains (e.g., John knows about cooking). With the described distinction, we can explicate the term shared better in the definition of TMS. Shared denotes to overlap, being similar or identical (the difference between overlapping, similar, and identical discussed in Cannon-Bowers and Salas [2001] seems to be a difference in degree rather than in form). What should be shared in TMS is higher-order and location information, whereas lower-order information can be distributed (complementary and divided up into portions). The advantages of TMS can only be realized when both shared and distributed features are attained.

2.2 Delineating the Central Concept

In this section, I further delineate the conceptual dimensions of TMS and discuss the relationships between dimensions.

Wegner's (1987) original conceptualization described a TMS as a set of individual memories and a group information-processing system based on a shared awareness of group members' expertise. He speculated that the development of a TMS begins when individuals in a group learn something about one another's domains of expertise. A transactive system emerges over time as experts in a specific knowledge domain are held responsible for encoding and storing new information in that domain and group members rely on one another for specialized memories and retrieve information from others when needed. Ideally, a group should have experts covering every knowledge domain that is relevant to its functioning and an accurate and shared cognitive representation of who are experts in what domains to facilitate information retrieving.

Wegner's conceptualization has stimulated an active line of empirical research on TMS (see Peltokorpi 2008 for a review). In these studies, researchers adopted two modified definitions: 1) TMS as a set of knowledge possessed by individuals combined with a shared awareness of who knows what (Moreland 1999; Yoo and Kanawattanachai 2001; Austin 2003; Akgün et al. 2005; Peltokorpi and Manka 2008); or 2) TMS as a cooperative system for encoding, storing, and retrieving information (Wegner et al. 1991; Lewis 2003; Yuan, Fulk, and Monge 2007). These two definitions, although interrelated, pertain to two distinctive aspects of the phenomenon described in Wegner's conceptualization. The first definition emphasizes the memory aspect: what knowledge do group members have and what do they know about one another's knowledge? The second definition emphasizes the transactive aspect: what do group members do to collectively encode, store, and retrieve information? Following Lewis et al. (2007), I refer to the first aspect as TMS structure and the second as TMS processes.

Although rarely explicated in prior research (Lewis et al. [2007] and Zhu [2009] are two exceptions), the structure versus process distinction is not a trivial one and should be elaborated to advance TMS research. Van de Ven and Poole (2005) argued that a fundamental issue influencing how scholars theorize organizational phenomena is whether they view organizations as consisting of things (substances) or processes. They found both views deeply embedded in contemporary organization theories. They suggested that the substantive and process views of organizations are complementary (and neither one is superior to the other), but appropriate theories and methods should be developed to examine the phenomenon at hand contingent on researchers' ontological views. In team research, Marks et al. (2001) articulated a similar perspective by differentiating emergent states from team processes. They argued that two types of constructs fall under the team process umbrella, namely processes and emergent states. The first type describes the nature of interactions among team members (i.e., processes) and the second describes qualities of a team that represent team members' cognitive, motivational, and affective states (i.e., emergent states). Building on these arguments, I seek to clarify the meanings of the TMS by elaborating a distinction between its structural and process aspects and discussing how these two aspects are related from a temporal viewpoint.

As evident in Wegner's conceptualization, TMS is a multi-faceted construct that pertains to both substances (a set of individual knowledge and a shared awareness) and processes (an information-processing system). The structure versus process distinction is consistent with the difference between substantive and process views of organizations and teams. TMS structure captures a team's cognitive state regarding team knowledge distribution, which reflects a substantive view of TMS. Properties characterizing a team's TMS structure include the quantity and distribution of the team's knowledge and the accuracy of and the agreement in team members' cognitions of the team knowledge distribution. In contrast, TMS processes describe team interactions that derive from as well as shape a team's TMS structure, reflecting a process view of TMS. TMS processes include team members learning one another's expertise, coordinating information encoding and storing based on either an explicit (e.g., role assignment) or an implicit (e.g., emerging coordination) division of labor, retrieving information from known experts while performing tasks, and refining their cognitions of who knows what. A transactive system emerges and becomes reinforced as team members specialize in particular knowledge domains and rely on one another for knowledge in other domains. From a temporal viewpoint, a TMS involves both the emergent cognitive structure and cognitive processes that are intertwined as the system evolves. The emergent structure characterizes the qualities of a team's cognitive state at specific time points and is constantly changing. The processes involve interactions such as coordination and differentiation that transform the cognitive structure from one state to another. The two aspects are intertwined because, on one hand, TMS structure can be considered as both the input and the output of TMS processes. On the other hand, TMS processes occur only when certain TMS structure is in place.

Theoretically, the distinction between TMS structure and processes provides a useful framework for integrating different TMS dimensions proposed by researchers. Researchers have offered alternative conceptualizations of TMS dimensions. Wegner's (1987) conceptualization consisted of two dimensions: individual memories and a shared awareness of group members' expertise. Moreland (1999) proposed a three-dimensional framework consisting of complexity, accuracy, and agreement of group members' beliefs about the expertise distribution. Lewis (2003) discerned three TMS dimensions: specialization (the differentiated structure of members' knowledge), credibility (members' beliefs of the reliability of others' knowledge), and coordination (effective, orchestrated knowledge processing). Austin (2003) integrated Wegner's and Moreland's work and classified four dimensions: knowledge stock, knowledge specialization, transactive memory (TM) accuracy, and TM consensus. Building on these conceptualizations and applying the structure-process framework, I classify these dimensions into two categories: 1) structural dimensions that characterize teams' cognitive states (knowledge stock, TM accuracy, and TM consensus); and 2) process dimensions that characterize actions related to utilizing teams' cognitive states (coordination and credibility). Knowledge specialization needs further consideration because it can mean either the degree to which individual knowledge differs (specialization as a structural property) or the process through which individuals become specialized in knowledge domains (specializing as a process). Because current literature focuses exclusively on the first meaning of specialization, I consider knowledge specialization as a structural dimension.

The four structural dimensions can be further classified into two sub-categories. Knowledge stock and specialization are properties of a team's knowledge structure (i.e., the quantity and distribution of a team's knowledge). TM accuracy and consensus are properties related to a team's shared cognition of its knowledge structure, thus are properties of a team's cognitive structure. To use Wegner and Wegner's (1995) terminology, knowledge stock and specialization are properties of lower-order information and TM accuracy and consensus characterize properties of higher-order and location information. When referring to the cognitive-structural dimensions (i.e., accuracy and consensus), I use transactive memory (TM) instead of transactive memory system (TMS) to denote them because these dimensions are entirely cognitive (related to the memory aspect) and are only part of the system.

The relationships among TMS structural dimensions can be complex and context specific. Theoretically, the initial knowledge stock and specialization are results of team design (i.e., who should be on the team and what knowledge/expertise they should bring to the team). Knowledge stock and specialization can change over time as team members learn from one another and from external sources; thus, they are influenced by team processes. In contrast, TM accuracy and TM consensus emerge completely from repeated social interactions within the team; thus are results of team processes. Austin (2003) predicted that knowledge specialization, TM consensus, and TM accuracy are likely to correlate with one another because they are interpersonal dimensions. Particularly, he predicted that specialization and consensus would have the strongest correlation because they both grow from a clear-cut division of expertise. In a field study of 27 product line groups in an apparel and sporting goods firm, Austin (2003) found support for his predictions. He found that TM accuracy had positive correlations with knowledge stock and TM consensus, and consensus and specialization had the strongest positive correlation among all.

For relationships between structural and process dimensions, Lewis et al.'s (2007) research on how group membership change affects group cognition and performance offered some good insights. In a laboratory study, they found that TMS processes mediated the impact of TMS structure on performance. When experiencing partial membership change, groups that relied on old team members' TMS structure had inefficient TMS processes, which in turn led to poor task performance. Lewis et al. found that when groups reflected together upon their collective knowledge, which potentially adjusted the TMS structure, they exhibited more efficient TMS processes and better subsequent task performance. An important insight from this research is that TMS processes mediate the relationship between TMS structure and team performance, which is consistent with the temporal view that I elaborated above. In a field study, Zhu (2009) examined relationships between structural and process TMS dimensions in a sample of 92 charter school boards. She measured TMS structure and processes (or TMS manifestation in her terminology) using Austin's (2003) and Lewis's (2003) scales respectively. She found that the two process dimensions, coordination and credibility, were positively correlated. The process dimensions were correlated with knowledge specialization, but were distinct from other structural dimensions such as accuracy and consensus. Consistent with Lewis et al. (2007), Zhu (2009) found that TMS processes mediated the effect of TMS structure on team performance. These findings provide support for the argument that TMS structure and TMS processes are distinct aspects of the phenomenon. However, there is still a lack of systematic research on how TMS dimensions are related to one another. I speculate that different task and knowledge contexts may lead to different configurations among TMS dimensions.

CHAPTER THREE

ANTECEDENTS AND CONSEQUENCES OF TRANSACTIVE MEMORY ACCURACY AND CONSENSUS

Reflected in the conceptual discussion, I view transactive memory system (TMS) structure and processes as two distinct yet interrelated aspects of the cognitive phenomenon described in Wegner (1987). As a collaborative-cognitive system, TMS is embedded in a broader social interaction system in and around a team. Team training, task performance, and membership change all affect the development and the properties of TMS (Liang et al. 1995; Brandon and Hollingshead 2004; Lewis et al. 2007). The TMS in turn affects team functioning and performance (Austin 2003; Rau 2005; Ellis 2006; Zhang et al. 2007). However, social interactions among people, the fundamental condition for TMS emergence, have not been directly examined in previous research. In this dissertation, I focus on the cognitive-structural dimensions of TMS and examine the interpersonal antecedents of transactive memory (TM) accuracy and consensus. In this chapter, I state an overall assumption that TMS is constructed through social interactions and develop research hypotheses regarding how social networks, which capture patterns of social interactions, affect TM accuracy and consensus. I then reestablish the hypotheses existing in the literature about the TMS' impact on team performance, and extend the theory to the interactive effects of TMS dimensions on team performance and to the individual consequences of TMS.

3.1 Socially Constructed Cognition

Social psychologists maintain that cognition is fundamentally a social phenomenon (Fiske and Taylor 1991). This perspective was further accentuated by the recent paradigm shift in social psychology from individualistic cognition to the idea of socially shared and situated cognition (Resnick, Levine, and Teasley 1991; Levine, Resnick, and Higgins 1993). Levine et al. (1993) reviewed the development of perspectives on socially situated cognitions and discussed several ways in which social factors influence cognitive processes and outcomes (e.g., by the presence of others, by social roles, positions, and identities, and by social interactions). They challenged the traditional assumption that "cognition is exclusively an individual act, clearly distinguishable from external social processes that may influence it" and argued that "the social and the cognitive are more intimately intertwined … and that much thinking must be understood as a form of social interaction" (Levine et al. 1993:588).

In sociology, a parallel perspective was developed in Berger and Luckmann's (1966) classic treatment of knowledge as socially constructed reality. The central idea of this perspective is that actors construct intersubjective realities through repeated social interactions. When persons and groups interact in a social system, they develop mental representations of one another. Such representations over time become institutionalized (as roles, identities) and exist beyond the parties that have created them; thus become socially constructed reality. In agreement with this view, I state the overall assumption for this research: TMS is an intersubjective system that is constructed and continuously reconstructed through social interactions among team members. Social interactions over time form typifications and mental representations of team members and shape the team's cognitive outcomes.

3.2 Work Interdependence, Interpersonal Interactions, and TMS

In ongoing work teams, social interactions are particularly important antecedents for the emergence of TMS. Many scholars have recognized the importance of social interactions in the development of social cognitions. For instance, Levine et al. (1993) contended that social interaction is the principal site for the development and practice of cognition. In teams, social interactions are a primary mechanism for sense making, information sharing, and expectation forming (Ibarra and Andrews 1993; Borgatti and Cross 2003). London et al. (2005) argued that the formation of shared cognitive representation is an interpersonal process at both the dyadic and group level. Although the importance of social interactions is evident in theoretical writing about TMS (e.g., Wegner 1987; Moreland 1999), the impact of social interactions on TMS has seldom been examined in empirical research.

In organizations, social interactions have two fundamental causes. First, opportunities for interaction are created by work interdependence. Work interdependence arises when multiple individuals, resources, and actions are needed to accomplish a task in a synchronized way. Thompson (1967) defined interdependence in terms of workflow. Van de Ven, Delbecq, and Koenig (1976) related interdependence with different modes of coordination and argued that increased workflow interdependence is associated with the use of coordination, especially the group coordination mechanism. Conceptually, work interdependence is a result of organizational/task design. Second, individuals in workplaces are not merely components of a machinery system. They interact socially and develop networks of relations beyond their job descriptions. Various kinds of interpersonal processes, such as helping, learning, and coping, unfold in workplaces on a daily basis; and are likely to affect individuals cognitively. I propose that social network analysis can advance our understanding of the impact of both types of interactions on team cognition. Social networks capture patterns of these interactions, which may explain information flow, interpersonal influence, and other group dynamics that affect teams' cognitive states (Kilduff and Krackhardt 2008). Social networks not only can determine from *where* team members develop interpersonal perceptions, but also can affect *how* team members develop such perceptions. Bunderson (2003) argued that, in groups, attributions of expertise are affected by both specific status cues (i.e., task-relevant and specific) and diffuse status cues (i.e., social categorical), and group contexts affect which type of status cues are more likely to be used. Members of decentralized teams are more likely to use specific status cues to develop expertise perceptions. By contrast, diffuse cues tend to be used in centralized teams.

In this research, I focus on two work-related social networks, namely the work-close network and the task-help network. The work-close network captures the interdependence in work and the extent to which team members interact with one another. It is a result of both task design and interpersonal processes (Wageman 1995). The task-help network, on the other hand, captures the flow of interpersonal assistance in which team members engage *beyond* their job requirements, and thus is a result of interpersonal processes.

Theorists agree that social interactions matter in shaping team cognition, but the question is how? One stream of research relevant for this inquiry is the research on communities of practice (Lave and Wenger 1991; Wenger 1998). The communities-of-practice theory suggests that shared ideas emerge among individuals who commit to common interests and engage in close interactions. A parallel argument can be found in social influence theory (Friedkin 1998; Friedkin and Johnsen 1999), which predicts that people's perceptions, attitudes, and behavior become similar as they interact more with one another. Both theories suggest that more interactions lead to more similarity in individual perceptions and attitudes. Based on these arguments, I hypothesize that TM consensus is likely to emerge in teams with dense work-related social networks. The density of the work-related social networks is also likely to affect TM accuracy because dense interactions lead to more information sharing and exposing, which would result in more accurate perceptions of one another's expertise. Therefore, I predict that the densities of the work-close and task-help networks will be positively related to TM accuracy. These predictions are summarized in Hypotheses 1A and 2A.

Both the communities-of-practice and the social influence arguments draw on a communal notion of social networks and consider cohesive structures as a positive feature of the networks. Alternatively, Burt (1992, 2005) argued that individual network advantages often come from centralized, disconnected, or differentiated structures. This argument emphasizes the importance of the broker's positions (i.e., some positions that are uniquely central to the network and will disconnect the network if the actors occupying these positions are removed). The brokerage argument and the cohesion argument are competing theories about network advantages. Based on the brokerage argument, I offer two alternative hypotheses at the team level about the positive effects of network centralization on team TM accuracy and consensus (summarized in Hypotheses 1B and 2B).

Hypothesis 1A: High densities of the work-close and task-help networks are positively related to team TM accuracy.

Hypothesis 1B: High centralization of the work-close and task-help networks is positively related to team TM accuracy.

Hypothesis 2A: High densities of the work-close and task-help networks are positively related to team TM consensus.

Hypothesis 2B: High centralization of the work-close and task-help networks is positively related to team TM consensus.

Although the group-level properties of TMS have attracted most research attention, the TMS is a multi-level construct that is rooted in individual cognitions. At the individual level, the most relevant TMS properties are individual TM accuracy and deviation (corresponding to team TM accuracy and consensus respectively). I define individual TM accuracy as the degree to which an individual's cognitive representation matches a team's actual expertise distribution. Individual TM deviation can be defined as the degree with which an individual's cognitive representation deviates from a team's average cognitive representation of team expertise distribution.

Cognitive accuracy and deviation have important individual implications, thus they deserve further investigation of their antecedents and consequences. At the individual level, an actor's position in social networks is a strong predictor of his or her behavior and cognitions. Sparrowe et al. (2001) suggested that degree centrality (i.e., the number of ties a focal actor have to other actors in the network) reflects an individual's involvement in exchanging ideas and assistance with others. Their empirical evidence showed that individuals central in social networks would, over time, accumulate more task-related knowledge and perform better than non-central individuals. Ibarra and Andrews (1993) studied the relationship between network centrality and employees' job-related perceptions. They found that network centrality had a strong and consistent effect on job-related perceptions, highlighting the importance of centrality in influencing individual cognitive outcomes in workplaces. Following this line of research, I argue that central actors in a team's work-related social networks will obtain more information about others' expertise and develop more accurate transactive memories than non-central actors. I use the degree centrality (Wasserman and Faust 1994) to measure actors' central positions because it is more in-line with the information-flow argument compared to other centrality measures (e.g., betweenness centrality and closeness centrality).

Hypothesis 3: High degree centralities in the work-close and task-help networks are positively related to individual TM accuracy.

The degree centrality also indicates an individual's proximity to others. Assimilation processes operate more evidently among socially approximate actors. Thus, I anticipate that central actors' cognitive representations of the team's expertise distribution are less likely to deviate from the team's commonplace perception.

Hypothesis 4: High degree centralities in the work-close and task-help networks are negatively related to individual TM deviation.

3.3 Consequences of TMS

Much of the research on TMS was fueled by the practical need to improve team coordination and performance. Evidence from both laboratory and field research suggests that TMS has a positive effect on performance. TMS is an important determinant of team performance for two reasons. First, it is a team's binding mechanism for synchronizing diverse skills into coordinated actions. Team cognition is particularly important for implicit coordination (Espinosa, Lerch, and Kraut 2004); that is, team members coordinate without intentionally planning or having to ask. An effective team should coordinate individual team members' expertise and effort to complete the team's tasks. Effective coordination requires team members to know what other people know. Second, TMS facilitates group information processing in ways that a team relies on individuals with expertise to process specialized information. The division of cognitive labor among team members will increase information repository, reduce cognitive overload, and improve effectiveness for teams.

Liang et al.'s (1995) experiment research showed that teams with their members trained together performed better than teams with their members trained separately. Members from trained-together teams exhibited clear specialization in remembering task skills, better coordination, and greater trust in one another's competence. Several follow-up studies modified Liang et al.'s experiment by better controlling for confounding factors (e.g., training procedures); and results of these experiments consistently suggested that TMS is positively related to team performance (Moreland 1999). In field settings, Faraj and Sproull (2000) examined the effect of expertise coordination process on team performance in software development teams. Their findings showed that knowing expertise location was positively related to team effectiveness.

Austin (2003) articulated how different TMS dimensions improve team performance: 1) knowledge stock minimizes the need for the team to seek external assistance; 2) TM consensus reduces coordination miscues; and 3) TM accuracy enables correct use of available knowledge resources. Empirically, Austin found that task-related TM accuracy had a consistent and positive effect on team performance measured by goal attainment, external evaluation, and internal evaluation. Edwards et al. (2006) and Lim and Klein (2006) found similar results that team cognitive accuracy was a strong predictor of team performance. Edwards et al. (2006) posited that in situations with one best way or a limited set of effective ways to successfully perform the task, accuracy is more predictive than consensus of performance. In line with Austin's (2003) theorization, I restate the hypotheses that knowledge stock, TM accuracy, and TM consensus are positively related to team performance.

Hypothesis 5A: Team TM accuracy is positively related to team performance.

Hypothesis 5B: Team TM consensus is positively related to team performance.

Hypothesis 5C: Team knowledge stock is positively related to team performance.

Although the premise of TMS is theoretically sound, empirical evidence, especially evidence from field research, for the TMS-performance relationship is still slim and inconsistent with the theory. For example, Austin (2003) found only one dimension (TM accuracy) of the task TMS had a consistent positive effect, and none of the external relationship TMS dimensions had an effect on team performance. In the same study, evidence showed that task-related knowledge stock was negatively associated with internally evaluated team performance. This inconsistency suggests that the effects of TMS dimensions on team performance may not be simply additive, but rather interactive. Among the structural dimensions of TMS, knowledge stock indicates the size of a team's knowledge repository. It can be considered as an input variable under the classic input-process-output framework for team performance (McGrath 1984; Hackman 1987). Knowledge stock is more likely to be affected by team design, staffing, and training than by interactions among team members. By contrast, TM accuracy and consensus are properties of a team's emergent cognitive state and they can be considered as outcomes of team processes. Knowledge stock sets the foundation for team performance because it determines how much knowledge resources a team can utilize.

TM accuracy and consensus facilitate team coordination and utilization of the knowledge stock. I anticipate that the positive effects of TM accuracy and consensus on team performance will be more evident when the team has a large knowledge stock. When the knowledge stock is low, TM accuracy and consensus may not be as influential because the team does not have the necessary resources to start with. According to this argument, I hypothesize that TM accuracy and consensus interact with knowledge stock in affecting team performance.

Hypothesis 6A: Team TM accuracy and knowledge stock interact in affecting team performance, with accuracy having a greater positive impact on performance in teams with high knowledge stock than in teams with low knowledge stock.

Hypothesis 6B: Team TM consensus and knowledge stock interact in affecting team performance, with consensus having a greater positive impact on performance in teams with high knowledge stock than in teams with low knowledge stock.

So far, research on TMS consequences has focused exclusively on its impact on team performance. However, team members are also affected by TMS. Team member outcomes (i.e., satisfaction, viability, burnout, and affective reactions) are important criteria for evaluating team effectiveness (Kozlowski and Ilgen 2006; Mathieu et al. 2008). For team members, one advantage of working in teams is that they can secure valued outcomes through exercising socially mediated agency (also called proxy agency, Bandura 2001). People seek assistance, support, and feedback from one another, and their experience in doing so affects their emotional, cognitive, and behavioral outcomes. TMS enables the exercise of proxy agency from an individual's perspective. TM accuracy is expected to promote individual cognitive efficiency. With more accurate cognitions, team members can locate distributed expertise promptly, seek assistance from the right teammates, and face fewer bounced-back requests. A potential benefit of the cognitive efficiency generated by accurate transactive memories is reducing team members' job burnout (Maslach, Schaufeli, and Leiter 2001).

I focus on job burnout as the individual outcome for this research because TMS is a cognition-based concept for which theoretical reasoning about its impact is largely based on the efficiency/competence argument (Wegner 1987; Moreland 1999). In other words, TMS affects the efficiency of interpersonal coordination, a characteristic of the immediate work context in which individuals perform tasks. The burnout literature suggests that job burnout is a psychological syndrome in response to cumulated interpersonal stressors and is affected by the immediate work context (Maslach et al. 2001). In contrast, other team member outcomes (e.g., satisfaction) are affected by both the immediate work context and other factors (e.g., compensation). Thus, I anticipate a direct relationship between TMS and job burnout. The relationships between TMS and other team member outcomes can be indirect and complex and need to be examined in conjunction with other confounding factors, which is beyond the scope of this research. In sum, I anticipate that individual TM accuracy will be negatively related to team members' job burnout.

Hypothesis 7: Individual TM accuracy is negatively related to team member burnout.

To summarize, I proposed four sets of research hypotheses in this chapter. Hypotheses 1 and 2 take up the network antecedents of TM accuracy and consensus at the team level. Hypotheses 3 and 4 link network positions to individual TM outcomes. Hypothesis 5 restates the relationship between TMS and team performance. Hypothesis 6 introduces the interactive effects of TMS dimensions on team performance. Finally, Hypothesis 7 proposes a relationship between cognitive accuracy and job burnout at the individual level.

CHAPTER FOUR

DATA, MEASUREMENT, AND METHODS

In this chapter, I describe the research setting, data, measurement, and analytic methods used in this research. First, I outline the composition and structure of Assertive Community Treatment (ACT) teams and characterize the teams' task environments. The purpose is to familiarize the reader with the context where the transactive memory system (TMS) in this research develops and functions. Second, I describe the data sources and the procedures for data collection. This research applied a longitudinal survey design and collected data from 26 ACT teams in Minnesota. Third, I describe the key measures used in the analyses. Specifically, I introduce and validate a matrix-based measure for TMS. The measurement issue is particularly important in this research because eliciting and assessing team cognition from individuals is a challenging task for team cognition research (Mohammed et al. 2000; Cooke et al. 2007). Last, I briefly discuss the general linear mixed models used in regression analyses for hypotheses testing.

4.1 Research Setting

This research was conducted on the ACT teams operating in Minnesota. ACT teams are multidisciplinary mental health care teams that provide continuous services to clients with severe and persistent mental illness. An ACT team consists of a designated team leader, at least one full-time psychiatrist, and several nurses, substance abuse specialists, and vocational specialists (Teague, Bond, and Drake 1998). In addition, many

ACT teams have social workers specialized in non-clinical services related to mental illness recovery (e.g., civil commitment, housing, and social security). Some teams also have peer support specialists on staff to provide peer counseling. The typical size of an ACT teams is twelve and the range is from eight to seventeen.

The program model for ACT teams was first developed by Mary Ann Test, Leonard Stein, and their colleagues at the Mendota Mental Health Institute in Madison Wisconsin in the 1970s (Test and Stein 1976; Stein and Test 1980). This innovative model aimed to provide integrated community services to patients discharged from psychiatric hospitals. The defining characteristics of the ACT model include multidisciplinary team approach, comprehensive and continuous services, stable staffing, low client-staff ratio, and a focus on rehabilitative interventions in communities (Witheridge 1991; Teague et al. 1998). Studies that evaluated the effectiveness of the ACT model have consistently found that, compared with other treatment models, ACT reduces psychiatric hospitalization, improves client engagement, and is associated with better client satisfaction (Test and Stein 1980; Stein and Test 1980; Weisbrod, Test, and Stein 1980; Olfson 1990; Burns and Santos 1995; Bond et al. 2001). Recent research demonstrated that ACT also increased housing stability, improved quality of life, and moderately reduced psychiatric symptoms for some clients (Burns and Santos 1995; Mueser et al. 1998). Currently, ACT is a national standard evidence-based practice for mental health treatment recognized by Substance Abuse and Mental Health Services Administration (SAMHSA).

In their everyday practice, ACT teams operate in community health care settings (e.g., community health centers, regional mental health consortiums, and non-profit health care agencies). The teams primarily use home visits and in vivo interventions to achieve rehabilitative goals (e.g., stabilize clients' conditions, build clients' life skills). Although client visits and interventions are usually performed by individual team members, a team as a whole is held responsible for the outcomes and the quality of its services. The ACT model emphasizes a total team approach that requires teams to avoid client dependence on particular team members. Accordingly, teams rotate client visits among team members and hold daily team meetings to discuss conditions observed in recent visits, share information, and plan for future interventions.

This research setting was selected for three reasons. First, ACT teams' work involves highly interdependent tasks, complex knowledge structures, and intensive coordination. These characteristics fit well with what Kozlowski and Bell (2003) described as features of *complex teams*. The complex features of ACT teamwork and its reliance on information coordination make ACT teams an interesting setting for studying TMS. Second, as a national standard evidence-based practice, practical guidelines (called program fidelity or fidelity in the ACT literature) has been developed that specifies the model's critical elements and operating principles (McGrew et al. 1994; Teague et al. 1998). The guidelines are implemented in ACT teams across states and settings, creating high degree of consistency in ACT teams' structures and practices. These conditions would eliminate certain confounding factors for this research (e.g., task structures may influence both how team members interact with one another and the properties of the emergent TMS – the independent and dependent variables in this research). Third, the

ACT program was introduced to Minnesota in 2005. At the time when the study began, 27 ACT teams had been operating in the state for about three years. By then, these ACT teams were mature teams with full operational capacity and had moderate levels of turnover (about a 15% turnover rate for the six-month intervals between surveys). Because of its interdisciplinary nature, I anticipated that TMS would be a critical component of ACT teams' work. Turnover and team learning would evoke changes in both teams' knowledge structures and cognitive representations of knowledge distributions, which make ACT teams an ideal subject for a longitudinal study of TMS.

4.2 Data

Data for this research were obtained from two sources: (1) survey data collected by the researchers from members of 26 ACT teams and (2) team performance and fidelity data collected by the Minnesota Department of Human Services (MNDHS) from the same teams.

First, this dissertation research is situated within a large project, INTACT (Improving Networks and Teamwork in Assertive Community Treatment), for which Professor Douglas Wholey, Professor David Knoke, and I collected survey data from the 26 ACT teams. The project was funded by the National Science Foundation (NSF) grant, "The Effect of Social Networks and Team Climate on Team Innovation and Client Outcomes in Health Care Teams" (Wholey and Knoke co-PIs, SES-0719257, IRB Study Number 0803S28603). With the INTACT project, we investigate teamwork in multidisciplinary health care teams by examining the relationships among various context, input, process, and output variables. We collected three waves of survey data from the 26 ACT teams spaced at approximately six-month intervals. The time frames for the surveys are May to July 2008 for wave one, January to March 2009 for wave two, and September to November 2009 for wave three. All 27 Minnesota ACT teams were invited to participate in this research. Among them, 26 teams accepted the invitation and participated throughout a two-year research period. During each wave of data collection, we administrated the surveys at a breakfast or luncheon meeting with each team. The participants were informed that participation was voluntary and were ensured confidentiality of their responses. The survey administration process provided opportunities for the researchers to talk with ACT team members and answer questions. Self-addressed mail-in envelopes were provided to individuals who were absent from the meeting or preferred to return the survey questionnaire later. We sent a follow-up letter to non-respondents a month after the meetings to encourage participation.

During the three waves of data collection, the survey questionnaires were distributed to 318, 312, and 304 targeted ACT team members. We received 287, 268, and 275 completed questionnaires, which resulted in an individual-level response rate higher than 85% in each wave (90.2%, 85.9%, and 90.5% in three waves respectively). To obtain high quality social network and TMS measures, high within-team response rates were also desirable. We obtained response rates higher than 80% in majority of the teams (22, 21, and 20 teams in three waves respectively). Seventy-two percent of the respondents were female. The racial composition of the sample was 92% Caucasian, 5% Asian, 2% African American, and 1% others.

Second, Professor Wholey and I integrated the survey data with team performance measures extracted from the Minnesota Program Outcomes Status Report (POSR) data. The MNDHS collected quarterly measures of client outcomes from all ACT teams using the POSR. The POSR data included a series of outcome measures such as days and times of hospitalization for mental illness, hospitalization for substance abuse, incarceration, and residential crisis for each client during the report period (3 months) and employment and residential status of the client at the end of the report period. The POSR data also included measures of individual risk factors such as age, gender, race and ethnicity, and diagnoses (including the Global Assessment of Function – GAF score, a widely used numeric scale for rating the psychological, social, and occupational functioning of adults). For each client outcome measure, we estimated a risk-adjusted fixed team effect model and extracted the least-squares means of the fixed team effects to measure team performance in the six months after each survey wave (see the discussion on team performance measures in the next section for details). To protect confidentiality of the ACT clients, this analysis was performed by MNDHS staff in a state-operated and secured facility. Only aggregated team performance measures were extracted and used for analysis.

Additionally, I used the expert-rated ACT program fidelity measure also collected by MNDHS. During site visits to the Minnesota ACT teams, state officials and ACT experts assessed the teams' structure and operation according to the Minnesota ACT standards, a close replication of the national standard Dartmouth ACT Scale (DACTS). This assessment was performed prior to the first wave of survey. Because clinical evidence consistently showed that ACT program fidelity had a significant impact on client outcomes (McGrew et al. 1994; McHugo et al. 1999), I included the fidelity measure as a control variable in models predicting team performance. Further, program fidelity captured certain structural aspects of the ACT teamwork, such as frequent team meeting, which I anticipated would influence the development of TMS. Therefore, I included the fidelity measure as a control variable in modeling team TMS outcomes.

4.3 Measurement

4.3.1 Measuring TMS

Review of Existing Approaches – Researchers have proposed several methods to measure TMS (Faraj and Sproull 2000; Yoo and Kanawattanachai 2001; Lewis 2003; Austin 2003; Rau 2005; Yuan et al. 2007). Among them, the measures proposed by Lewis (2003) and Austin (2003) are the most influential ones. These two measurement approaches, however, employed very different procedures to measure TMS and resulted in different types of scales. Lewis (2003) developed a 15-item Likert-type scale to elicit team members' reports on three TMS dimensions: specialization, credibility, and coordination. Lewis rigorously tested the psychometric properties of the scale in both laboratory and field settings. Her results indicated that the proposed scale had great internal consistency, clear dimensionality, and good convergent and discriminant validity. The Lewis scale is so far the only TMS measure that has been systematically validated. In addition to its validated psychometric properties, the Lewis scale has several strengths: 1) the scale measures both structural and process TMS dimensions (although only one structural dimension – specialization – was included); 2) the scale is not limited to particular knowledge structures and does not require researchers to specify knowledge domains in advance; 3) the items can easily be implemented in survey questionnaires, making the Lewis scale particularly appealing in field research. The limitation of the Lewis scale, however, is that it is an indirect measure of TMS; that is, instead of assessing what the construct really is, this measure assesses TMS through its manifestation.

Austin (2003) proposed a set of measures for TMS structural dimensions, including knowledge stock, knowledge specialization, TM accuracy, and TM consensus. Austin's approach was based on team members' self-evaluations of their own expertise and their identifications of others' expertise. He proposed procedures for calculating TMS structural measures using information gathered from the self-evaluations and expert identifications. To test the validity of the proposed measures, Austin analyzed the correlations between the self-report measures and a second set of measures derived from problem-solving scenarios. The high correlations between the two sets of measures demonstrated the convergent validity of the self-report measures and supported the use of these measures in field research. The Austin measures directly assess TMS properties using individual cognitions of the team expertise distribution. The limitations of Austin's approach are: 1) given the complex procedures proposed, applying the method in field research can be difficult and laborious; 2) the measurement mixes Likert-type scales (self-evaluations) and binary scales (expert identifications), which makes substantive interpretations of the resulting measures difficult.

A Matrix-Based Approach **–** In this research, I build on Austin's (2003) work and propose a new method for measuring TMS. I considered an individual's cognition of the team expertise distribution as a *cognitive map* and proposed to measure it in a person-by-expertise matrix. Just as a map shows spatial relationships between locations, a cognitive map gives a representation of relationships between people and knowledge domains in an individual's mind. According to this conceptualization, I used a person-by-expertise matrix to describe relationships between persons (rows) and knowledge domains (columns) in an individual's cognition and derived TMS measures from a team's members' cognitive matrices.

In the questionnaire, I included such a matrix-based question asking respondents to identify others who have a lot of expertise in a given set of knowledge domains (the survey question is included in Appendix A). A list of knowledge domains and a complete team roster were provided as columns and rows following the question. Respondents were instructed to evaluate their own expertise in the same question. For each respondent, the result of this question is a binary individual cognitive matrix that has person-by-expertise cells representing the respondent's perceptions of who are experts in which knowledge domains. Eight key knowledge domains for ACT were identified through observing ACT teams and consulting multiple team leaders and ACT experts (including ACT researchers and administrators). The eight key knowledge domains were psychiatry/medicine, nursing, substance abuse/IDDT (Integrated Dual Diagnosis Treatment), vocational rehabilitation/supported employment, court/civil commitment, housing/subsidies, public assistance/social security, and team coordination/shift management. Before conducting each wave of survey, I obtained the team roster from each team's leader and customized the questionnaire for each team.

With this survey instrument, a team member's cognition of the team expertise distribution was captured in an n×8 matrix (where n is the team size and 8 is the number of knowledge domains). For a team of size n, there were n individual cognitive matrices. Assuming that individuals have the best knowledge of their own expertise, I constructed an approximate measure of the team's actual expertise distribution by extracting the self-evaluation vector from each individual's cognitive matrix and organizing these vectors in the same order as in the individual cognitive matrices. The result was a team expertise distribution matrix, which had the same dimensionality as the individual cognitive matrices: n ×8. This approach is similar to Austin's use of self-evaluations as a baseline for comparisons. The difference is that the matrix-based approach uses the binary scale in both self-evaluation and expert identification, which will lead to direct comparisons between self and others' evaluations. This approach simplifies the data collection and processing procedures, avoids complex data manipulation in calculating TMS measures, and produces more interpretable measures.

From Matrices to TMS Measures – For each team, there are n individual cognitive matrices and one team expertise distribution matrix. Below I describe how TMS measures can be derived from these matrices.

I denote the individual cognitive matrix for respondent i of team s as K_{si}:

$$\mathrm{K}_{si} = \begin{array}{cc} & \begin{matrix} KD_1 & KD_2 & \cdots\cdots & KD_8 \end{matrix} \\ \begin{matrix} TM_{s1} \\ \cdots\cdots \\ TM_{sn} \end{matrix} & \begin{bmatrix} y_{i11} & y_{i12} & \cdots & y_{i18} \\ \cdots & \cdots & y_{ijk} & \cdots \\ y_{in1} & y_{in2} & \cdots & y_{in8} \end{bmatrix} \end{array}$$

where y_{ijk} represents team member *i*'s perception of team member *j*'s expertise in knowledge domain *k* on a binary scale (1 = team member *j* has a lot of expertise in knowledge domain *k*, 0 = team member *j* does not have a lot of expertise in knowledge domain *k*), KD stands for knowledge domain, and TM stands for team member.

For team *s*, I denote the team expertise distribution matrix as M_s. This matrix can be constructed by placing the *i*th row of K_{si} in the *i*th row of M_s for *i* = 1 to *n*. Note that M_s is only an approximate measure of the unobserved actual expertise distribution in team *s*.

$$\mathrm{M}_{s} = \begin{array}{cc} & \begin{matrix} KD_1 & KD_2 & \cdots\cdots & KD_8 \end{matrix} \\ \begin{matrix} SE_{s1} \\ \cdots\cdots \\ SE_{sn} \end{matrix} & \begin{bmatrix} y_{111} & y_{112} & \cdots & y_{118} \\ \cdots & \cdots & y_{iik} & \cdots \\ y_{nn1} & y_{nn2} & \cdots & y_{nn8} \end{bmatrix} \end{array}$$

I measured team knowledge stock by calculating the sum of all cells in M_s standardized by n×8. The result measures the standardized total amount of expertise possessed by the team's members. The standardization is needed for cross-team comparisons. In ACT teams and in many other teams, team size is related to task demands: larger teams are expected to accomplish more tasks. Therefore, resources (what knowledge stock describes) should be considered in a relative sense. The formula for calculating team knowledge stock is:

$$\mathrm{KS}_s = \sum_{i=1}^{\mathrm{n}} \sum_{k=1}^{8} \mathrm{M}_s /(n \times 8)$$

where function ∑ means sum up cells in the matrix according to the dimension defined.

For TM accuracy, I first calculated the difference between an individual's cognitive representation of and the team's expertise distribution by subtracting M_s from K_{si} and calculating the sum of the absolute value of the difference matrix. The sum was then standardized by (n-1)×8 and subtracted from one to create an individual TM accuracy score for team member i. Team size minus one (instead of n) was used in standardization because by nature i's self-evaluation would not contribute to the difference. Substantively, the individual TM accuracy score measures the proportion of person-by-expertise cells of which i has an accurate perception. Given within-group agreement, the team-level TM accuracy score can be calculated as the group mean of individual TM accuracy scores. The formulas for calculating individual and team TM accuracy are:

$$\mathrm{IA}_{si} = 1 - \sum_{j=1}^{\mathrm{n}} \sum_{k=1}^{8} | \mathrm{K}_{si} - \mathrm{M}_s | /[(n-1) \times 8]$$

$$\mathrm{TA}_s = \sum_{i=1}^{\mathrm{n}} \mathrm{IA}_{si} / n$$

Conceptually, TM consensus is the opposite of the dispersion in team members' cognitions of who knows what. Based on cognitive matrices of all individuals in a team, I first computed a standard deviation score for each person-by-expertise cell to measure the extent to which team members disagree on a specific person's expertise in a specific knowledge domain. I then calculated the mean of the standard deviation scores across all person-by-expertise cells and subtracted the mean from one to create the team's TM consensus score. The TM consensus score measures the extent to which team members agree on the overall expertise distribution in the team. The formula for calculating team TM consensus is:

$$\mathrm{C}_s = 1 - \sum_{j=1}^{n} \sum_{k=1}^{8} < \sqrt{\sum_{i=1}^{n} (\mathrm{K}_{si} - \sum_{i=1}^{n} \mathrm{K}_{si} / n)^2 / (n-1)} > / (n \times 8)$$

where function $< \quad >$ means the calculation within this function is performed at the element (cell) level.

An individual-level measure related to TM consensus is individual TM deviation. Individual TM deviation is the difference between an individual's cognition and the team's *average* cognition of team expertise distribution. The procedure for calculating individual TM deviation is similar to that for individual TM accuracy. But, instead of using M_s for comparison, I used the average of K_{si}. The formula is:

$$\mathrm{ID}_{si} = \sum_{j=1}^{n} \sum_{k=1}^{8} | \mathrm{K}_{si} - \sum_{i=1}^{n} \mathrm{K}_{si} / n | / (n \times 8)$$

Among the four TMS dimensions, knowledge specialization has attracted little theorization and operational elaboration. Wegner (1987) described that when TMS emerges, group members would split cognitive loads among themselves by focusing on particular knowledge domains. Specialization, therefore, is a property of a team's *de facto* expertise distribution, rather than of team members' perceptions. To construct a measure in accordance with this conceptualization, I started with the team's expertise distribution matrix M_s. I first calculated an individual specialization score as the standard deviation for each row in M_s, and then averaged the individual scores to create a team knowledge specialization score. This measure is similar to Austin's specialization measure except that I used self-evaluations instead of others' identifications as the basis for calculation. The formula for calculating knowledge specialization is:

$$\mathrm{S}_s = \sum_{i=1}^{\mathrm{n}} \left(\sqrt{\sum_{k=1}^{8} < M_s - \bigcap_{8} \left(\sum_{k=1}^{8} M_s / 8 \right) >^2 / (8-1)} \right) / n$$

where function ∩ means combine eight identical n×1 row-mean vectors to create a n×8 matrix. Theoretically, there is a lack of articulation on how knowledge specialization is related to other TMS dimensions and how it contributes to team performance. Regarding its operationalization, existing proposals all focused on individual specialization; that is, the extent to which team members concentrate on certain knowledge domains. However, an alternative approach is to measure expert specialization; that is, the extent to which a team relies on certain experts to collect, store, and offer knowledge in a particular knowledge domain. Further elaboration is needed to clarify how different conceptualizations and measures are related to one another and to theorize the antecedents and consequences of knowledge specialization. Because these tasks were beyond the scope of this research, I did not develop hypotheses related to the antecedents and consequences of knowledge specialization. Nor did I include knowledge specialization in any analytic models, which will be presented in the next chapter.

Reliability Tests and Aggregation Analysis – I examined the test-retest reliability of the matrix-based survey instrument by comparing individual cognitive matrices across three waves. Because of turnover, team compositions changed across survey waves.

Therefore, individual cognitive matrices had different row compositions in different waves and comparing individual responses using the matrices was problematic. To overcome this difficulty, I recoded survey responses as dyadic vectors representing egos' evaluation of alters' expertise. The recoding created 2,249 repeated dyads between the first two waves and 2,287 repeated dyads between wave 2 and wave 3. Among these repeated dyads, I compared responses and found that 81% of the responses were identical across both periods. These results suggest that respondents' perceptions of others' expertise were relatively stable over time and the matrix-based survey instrument had test-retest reliability.

To test the reliability of using self-evaluations to measure teams' actual expertise distributions, I constructed two alternative measures with the following steps. First, I created an average perception matrix for each team by calculating the team mean in each person-by-expertise cell based on all individual responses in the team. Second, I dichotomized the average perception matrix using 0.5 and 0.75 as cut-points. The results were two matrices representing the team expertise distribution based on above 50% or 75% of team members considering someone as an expert in a knowledge domain. I compared the self-evaluation matrix with the dichotomized average perception matrices. Using 0.5 as a cut-point, I found 81% of self-evaluations were identical to the average perceptions. Based on a 0.75 cut-point, the percentage of identical evaluations dropped slightly to 77%. These results suggest that the reliability of using self-evaluations to measure the team expertise distribution is acceptable. I compared the percentage measure across waves, teams, and knowledge domains and obtained very consistent results. The percentages were almost the same across waves and knowledge domains. Comparing across teams, I found small variations (standard deviations were 0.05 and 0.06 for 50% and 75% cut-points respectively).

The tests above demonstrate that individual cognitive matrices and team expertise distribution matrices provided reliable information on team members' cognitive representations of and the teams' actual expertise distributions. Further, creating team TM accuracy score from individual TM accuracy scores requires within-group agreement (Bliese 2000). I assessed the intraclass correlations ICC(1) and ICC(2) for individual TM accuracy scores to test within-group agreement and reliability of team means. The ICC(1)s were 0.32, 0.22, and 0.26 and the ICC(2)s were 0.84, 0.74, and 0.79 in three waves respectively, indicating good within-group agreement and good reliability of team means. Therefore, using team means of individual TM accuracy scores was justified.

4.3.2 Other Team-Level Measures

Team Performance **–** We extracted team performance measures from the Minnesota POSR data. The POSR client outcome measures included times of hospitalization for mental illness, hospitalization for substance abuse, incarceration, and residential crisis, employment status, and residential status for each client.

For each client outcome measure, we estimated a risk-adjusted fixed team effect model for all clients served by the teams in the six months after the surveys. The analysis was performed under the generalized linear mixed models (GLMM) framework using SAS GLIMMIX procedure (McCulloch, Searle, and Neuhaus 2008). Risk factors included in the model were individual diagnoses, age, gender, race, and new client (a variable measuring whether a client was newly admitted or continuing client). Two quarters of data were used in estimating team performance for each wave. So, we included a fixed quarter effect to control for the differences between the two quarters. The least-squares means of the fixed team effects were extracted to measure team performance. The least-squares means of the fixed team effects were estimators of marginal means for the classification variable – team. Substantively, the least-squares mean can be interpreted as the predicted average of a particular outcome variable for all clients served by the team after controlling for individual risk factors. For a times-type measures (e.g., times of hospitalization), this interpretation can be further simplified to the incidence of the particular outcome (i.e., hospitalization) among clients served by the team.

Although performance measures based on all client outcomes were estimated and used in analysis, the primary performance measure for this research is the incidence of mental-illness related hospitalization. I chose to focus on this measure because: 1) ACT literature suggested that keeping clients out of psychiatric hospitals was the primary goal for ACT programs (Weisbrod et al. 1980); 2) clinical research consistently found that well performing ACT teams had less client hospitalization for mental illness (Olfson, 1990; Burns and Santos 1995).

Network Density and Centralization – I assessed the pattern of work interdependence in a team by the team’s work-close network. This network was constructed by asking respondents to rate how closely they have worked with each of the other team members in the previous month on a 4-point scale (1 – not closely to 4 – very closely). I dichotomized the work-close network by cut-point at 4 because team members tended to work closely with one another under the ACT model and the survey responses were highly skewed to the left. The task-help network was constructed by asking respondents to identify which team members had frequently provided them task-related assistance beyond job requirements in the previous month. This network was originally measured on a binary scale. Survey questions for these two networks are included in Appendix A.

Two types of team-level network variables were calculated. First, network densities were calculated for both networks using the number of present ties divided the number of possible ties in the networks (Wasserman and Faust 1994). Second, network centralization scores were calculated as the degree centralization index (Freeman 1979; Wasserman and Faust 1994). The quantity of this index was computed by the sum of the difference between maximum individual degree centrality and each observed individual degree centrality divided by $(n-1) \times (n-2)$.

Team Climate – Three team climate constructs were measured based on prior research. First, team psychological safety is defined as a shared belief that the team is a safe place for interpersonal risk taking (Edmondson, 1999). Items for this measure were adopted from Edmonson (1999) and adjusted for the ACT context in pre-survey fieldwork. A sample item is "I felt that I could bring up mistakes and slips by my team in consumer care activities to my ACT team members." Second, constructive controversy is defined as the critical and open discussion of divergent perspectives in the team. Items for this measure were drawn from Shah, Dirks, and Chervany (2006). Third, safety and quality orientation is defined as a shared belief that the team should prioritize safety and quality goals over the productivity goal. Items for this measure were adopted from Zohar (2000). Items for all three team climate measures were assessed using a 4-point Likert scale (1 – strongly disagree to 4 – strongly agree). For these measures, I performed exploratory and confirmatory factor analyses and aggregation analyses. These analyses produced satisfactory results supporting the use of these measures. See Appendix A for a complete list of items for three team climate measures.

Team-Level Control Variables **–** Team size was measured by the total number of team members. Number of new hires was measured by the number of new team members hired in six months prior to the survey. Client-staff ratio was measured by the number of clients that a team served divided by the team size. Urban team was coded 1 for teams located in metropolitan areas and 0 for teams located in rural areas. Specialized team was coded 1 for teams serving special clients (e.g., homeless, immigrants) and 0 for teams serving general clients. Fidelity was measured using the Minnesota ACT fidelity scale, an expert-rated index ranging from 1 (low fidelity) to 5 (high fidelity).

4.3.3 Other Individual-Level Measures

Team Member Burnout **–** To measure team member burnout, I selected nine items from Maslach Burnout Inventory (Maslach, Jackson, and Leiter, 1996) to assess three work-related burnout dimensions (three items for each dimension): 1) emotional exhaustion – feeling emotionally drained from work; 2) ineffectiveness – feeling ineffective at work or lack of personal achievement; and 3) depersonalization – feeling less caring or callous toward clients. The nine items were selected from the Maslach

Burnout Inventory based on their factor loadings so that they had the strongest loadings on the targeted factor and the weakest loadings on other factors. A sample item is feeling "emotionally drained from your work on your ACT team." The items were assessed for the frequency of experiencing a situation on a 5-point scale (1 – never to 5 – everyday). The complete list of the items is included in Appendix A.

Network Centrality – I calculated individual degree centrality for both work-close and task-help networks. The centrality score was computed as the total number of ties that individual *i* had divided by (*n*-1). Conceptually, the work-close relationship is non-directional and the task-help relationship is directional (i.e., for individual *i*, an outgoing tie indicates that *i* received help and an incoming tie indicates that *i* provided help). Accordingly, I calculated both in-degree and out-degree centralities for the task-help network (Wasserman and Faust 1994). For the work-close network, centrality was measured by the mean of in-degree and out-degree centralities.

Individual-Level Control Variables – Gender was coded 1 for female and 0 for male. Team leader was coded 1 for team leaders and 0 for non-leaders. Tenure was measured by the number of months an individual had worked on the ACT team.

4.3.4 Dyadic-Level Measures

Several dyadic-level variables were constructed to model cognitive dynamics unfold between pairs of team members. A dyad consists of a pair of actors and the possible relations between them. Using network terminology, the focal actor in the pair is called *ego* and the other actor is called *alter*.

Sources of TM Inaccuracy – At the dyadic level, I differentiated two types of

TM inaccuracy. First, expertise overstatement was measured by the number of knowledge domains in which the ego considered the alter as an expert, but the alter did not identify herself as an expert. Second, expertise understatement was measured by the number of knowledge domains in which the alter self-identified as an expert, but the ego did not identify the alter as an expert. Both variables are discreet variables that range from zero to eight.

Network Relations – I recoded both work-close and task-help networks to create dyadic-level relations. At the dyadic level, a work-close relation represents the ego's evaluation on her work interdependence with the alter. Originally, this evaluation was made on a 4-point scale (1 – not closely to 4 – very closely). I dichotomized the measure by cut-point 4. A task-help relation represents the ego's evaluation on whether she has *received* task-related assistance from the alter.

Dyadic Homogeneity – Two homogeneity variables were coded based on individual characteristics. Same gender was coded as 1 if the dyad were from the same gender. Same position was coded as 1 if the dyad held the same position on the team. The following position categories were used in the survey questionnaire: team leader, psychiatrist, nurse, rehabilitation specialist, substance abuse specialist, vocational specialist, peer support specialist, administrative support, and other.

Joint Tenure – Joint tenure measured how long a pair of team members had worked together on the team. It was measured by the shorter individual tenure of the two individuals in a dyad.

4.4 Analytic Methods

To test the research hypotheses regarding antecedents and consequences of TMS, I estimated regression models under the generalized linear mixed (GLM) model framework (Wolfinger and O'Connell 1993; McCulloch et al. 2008). All analyses were conducted using the SAS GLMMIX procedure (SAS Institute 2006).

Before estimating the regression models, I examined the distributions of the dependent variables by plotting their cumulative distribution functions and compared them with theoretical normal distributions. Figures 1 to 4 present these distributions for pooled data (distributions by waves are comparable to the overall distributions). All dependent variables are normally distributed with good symmetric and continuous properties except the individual burnout variables. Two burnout variables, ineffectiveness and depersonalization, are slightly skewed to the right and burnout emotional exhaustion is symmetrically distributed, but the distribution is clustered around certain values. Accordingly, I estimated regression models based on both Gaussian and adjusted (e.g., log-normal) link functions and compared the parameter estimates and model fit indices of different models. Based on these tests, the impact of the burnout variables' distributional properties on the results was minimal.

[Insert Figure 1 to 4 about here]

Based on the level of analysis and the dependent variable, five sets of regression models were estimated:

1) Team-level models for testing antecedents of team TM accuracy and consensus;

2) Individual-level models for testing antecedents of individual TM accuracy and deviation;

3) Team-level models for testing the effects of team TMS properties on team performance;

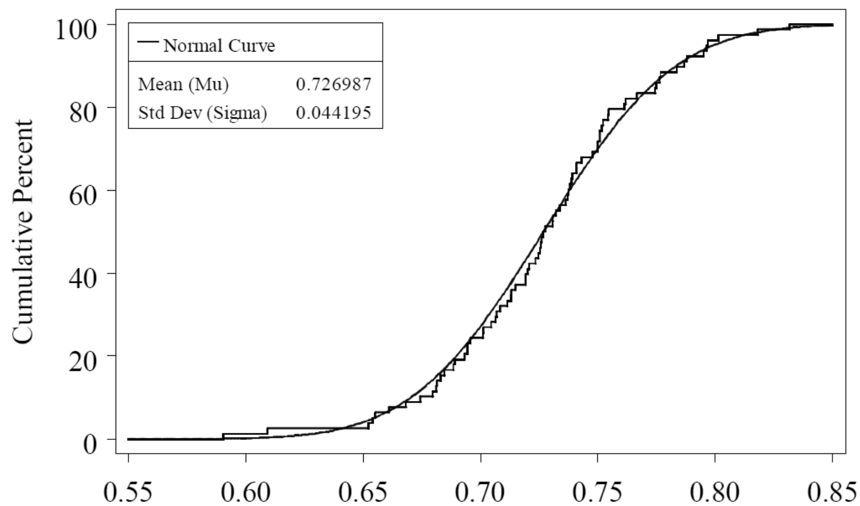
4) Individual-level models for testing the effects of individual TM accuracy on burnout.

5) Dyadic-level models for testing antecedents of dyadic expertise over- and understatements (as sources of TM inaccuracy);

For team-level analyses, regression models were estimated based on three waves of 26 observations for a total of 78 team-wave observations. Because teams were repeatedly observed over time, I included a fixed wave effect to control for unobserved differences between waves (e.g., the MNDHS started to implement the national standard client-staff ratios in Minnesota ACT teams in October 2008 – a time point between the first and the second wave, which was likely to affect ACT teams' functioning). Within-team correlated errors were controlled for by including a random team effect. At the individual level, three waves of approximately 780 observations were used in analyses. Two levels of hierarchical nestedness exist in this data structure: team members are nested within teams and repeatedly observed over waves. Therefore, I estimated the models with a fixed effect for wave and random effects for team and team member. For dyadic-level analyses, I included a fixed effect for wave and random effects for team, ego, and alter.

Figure 1. Distributions of Dependent Variables – Team-Level TMS Properties

Cumulative Distribution of Team TMS Accuracy



Cumulative Distribution of Team TMS Consensus

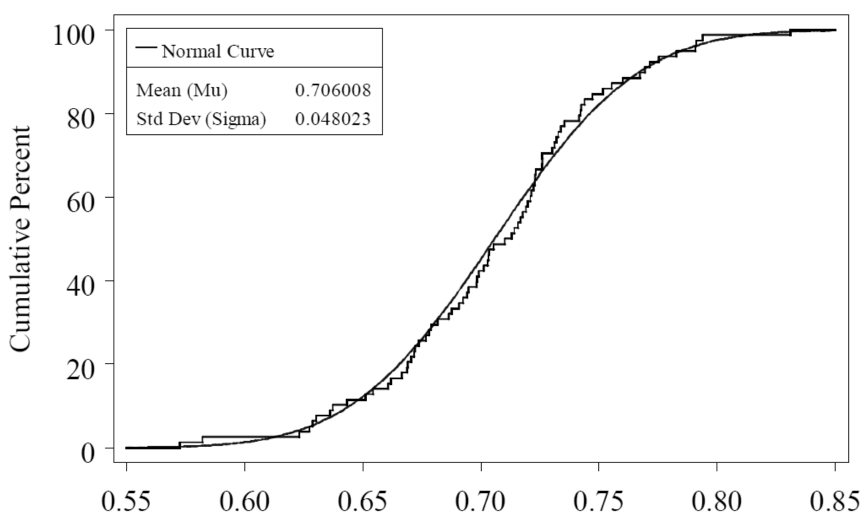
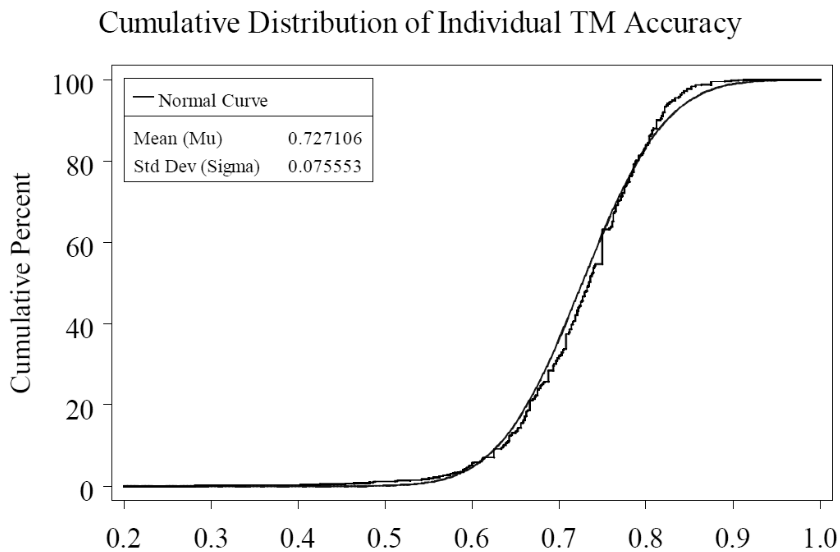


Figure 2. Distributions of Dependent Variables – Individual-Level TM Properties



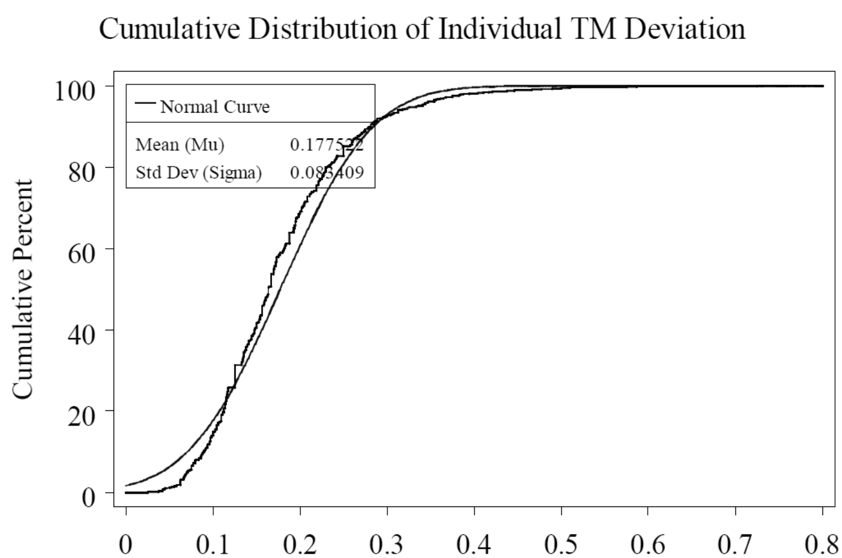


Figure 3. Distributions of Dependent Variables – Team Performance

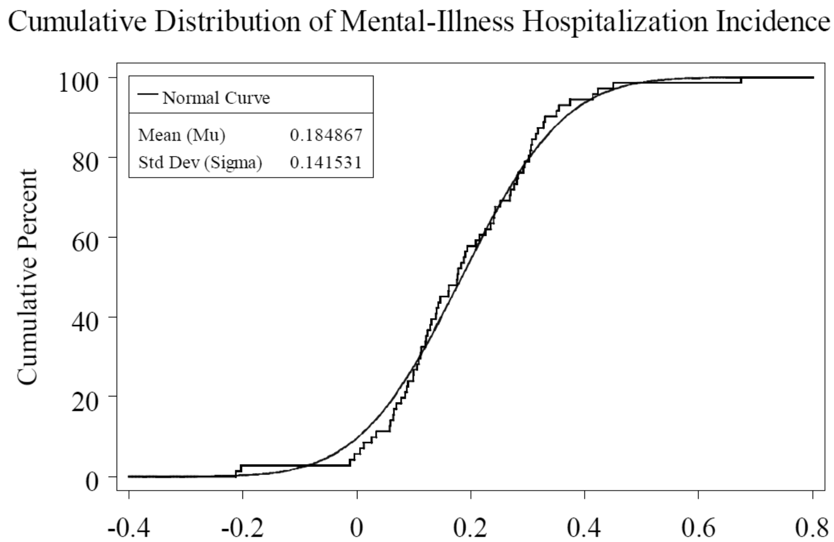
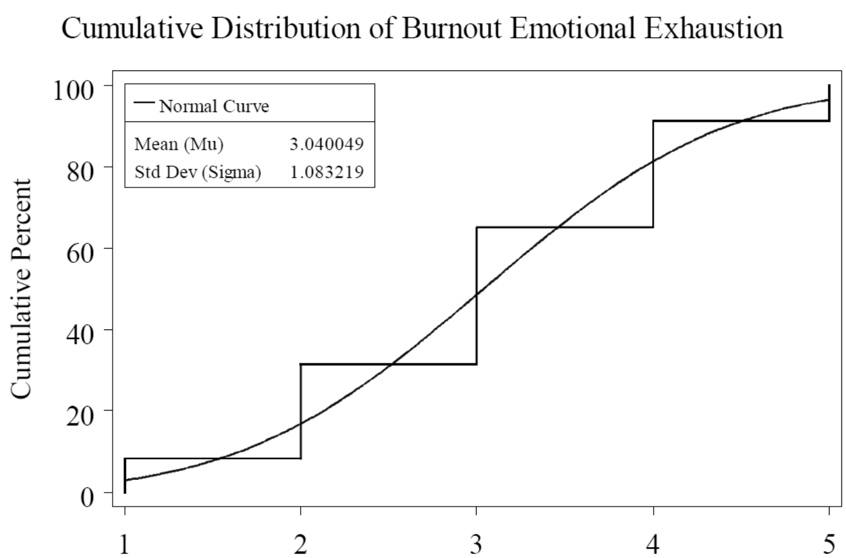
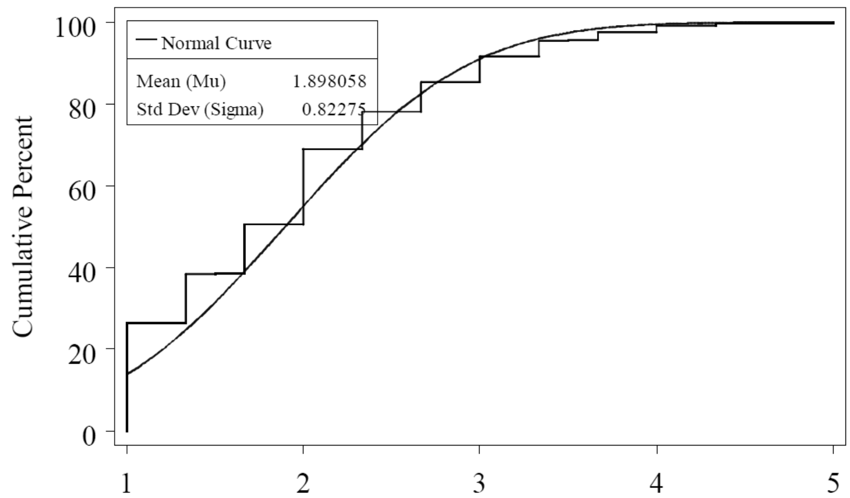


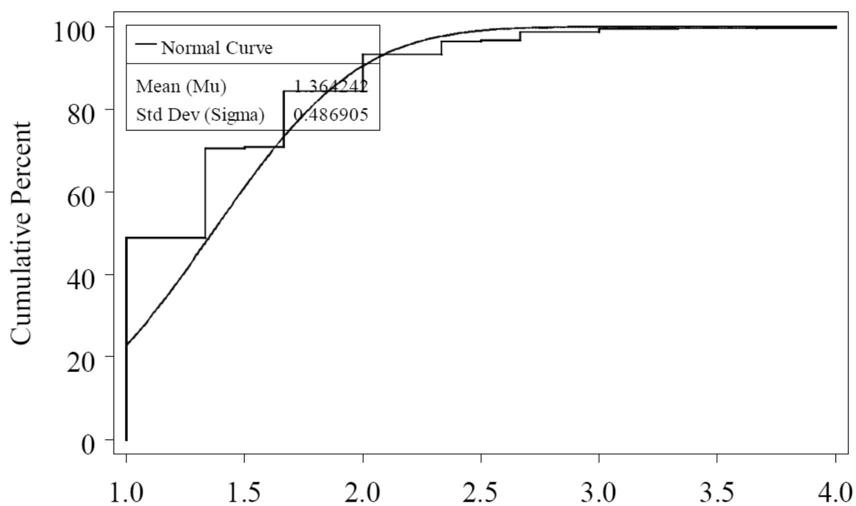
Figure 4. Distributions of Dependent Variables – Individual Burnout



Cumulative Distribution of Burnout Ineffectiveness



Cumulative Distribution of Burnout Depersonalization



CHAPTER FIVE

EMPRICAL RESULTS

In previous chapters, I examined the concept of transactive memory system (TMS) and distinguished its two conceptual aspects: the TMS structure and TMS processes. Two fundamental questions have motivated and continue to motivate researchers to examine this collaborative-cognitive phenomenon. First, they believe that TMS has positive consequences for teams (and other types of groups). So, a fundamental question is: Does TMS have the claimed positive consequences? Second, if in fact TMS has positive consequences, how can we create, manage, or improve TMS in teams? To put the second question in a more research-oriented form, we shall ask what antecedents contribute to the emergence and evolvement of TMS.

In this chapter, I empirically examine these two questions with selective focuses. First, for antecedents, I focus on how interactions among team members (as captured in the work-related social networks) affect team-level and individual-level TM accuracy and consensus (TM deviation at the individual level). The effects of personal (e.g., gender, team leader role, tenure) and collective factors (e.g., team climate) on TMS are also examined although the research focus is on interpersonal factors (i.e., social networks). Second, I examine how TMS and its different dimensions affect team performance and individual job burnout. Last, informed by the findings from the first two investigations, I conduct some analyses to further explore how social networks contribute to inaccuracy in TMS and to model the relationships between TMS and its antecedents and consequences from a change perspective.

5.1. Descriptive Statistics

Table 1 presents means, standard deviations, and Pearsonian correlations among team-level variables based on data pooled across three waves. At the team level, the mean TM accuracy is 0.73, indicating that on average 73% of the team members' identifications of others' expertise are accurate. This interpretation is consistent with the measurement design: team TM accuracy is the group mean of individual TM accuracy, which measures the proportion of person-by-expertise cells in an individual's cognitive matrix that matches the experts' self-identified team expertise distribution matrix. Teams also had high level of consensus on their teams' expertise distributions. The mean TM consensus score is 0.71. The mean team knowledge stock is 0.34, which is the proportion of knowledge domains in which team members collectively self-identified as experts averaged across teams. The teams had moderately dense work-close networks. On average, team members worked very closely with 40% of their teammates (mean density = 0.40). The mean density for task-help networks (0.60) is higher than that of work-close networks, suggesting that team members helped each other beyond their job requirements extensively. Overall, the Assertive Community Treatment (ACT) teams had high program fidelity (the mean is 4.15 on a 5-point scale) and low incidence of client hospitalization for mental illness during the study period. The average incidence of hospitalization for six months is 0.20 (risk-adjusted), meaning that ACT clients on average experience one-fifth time of hospitalization for each six months. It is a relatively low incidence of hospitalization for persons with several and persistent mental illness.

[Insert Table 1 about here]

The correlations reveal relationships among TMS dimensions that are rather different from what previous research suggested. First, TM accuracy and TM consensus have a stronger correlation in this sample ($r = .83$, $p < .01$) than the correlations found in other research. I argued in Chapter Two that TM accuracy and consensus are properties of a team's cognitive structure, and knowledge stock and specialization are properties of a team's knowledge structure. Conceptually, TM accuracy measures the lack of cognitive deviation from the *actual* knowledge distribution and TM consensus measure the lack of cognitive deviation from the *average* perception of the knowledge distribution in a team. I expected these two dimensions to be more closely related to each other than to knowledge stock and specialization. But, the particularly strong correlation (not only at the team level, but also at the individual level as presented later) observed in this study may be context-specific. ACT teams are multidisciplinary teams for which key functional areas and knowledge domains are well-defined in the program model (with detailed standards). The protocol for ACT knowledge structure is well understood by ACT practitioners because ACT teams have undergone initial and continued training and continuous program evaluation. In this context, expert statuses are tied to specific knowledge domains and the team average perception is likely to be very close to the actual knowledge distribution (the validity test showed 81% overlap between the two as discussed in Chapter Four). This resulted in the strong correlation between TM accuracy and TM consensus. In other contexts, accuracy and consensus may measure substantively different team cognitive properties. For instance, when knowledge domains are less specified and the boundaries between domains are blurry, team members may agree on who is expert in a general sense based on status or other signals. This creates high consensus but not necessarily high accuracy. In contrast, if a team's tasks require members to have a wide spectrum of knowledge, team members may recognize anecdotal (but different) aspects of others' expertise, which leads to somewhat accurate assessments but not necessarily high consensus.

Second, contrary to Austin's (2003) findings, knowledge stock is negatively correlated with TM accuracy (r = -.44, p < .01) and consensus (r = -.45, p < .01) in the sample. The correlations of knowledge specialization with TM accuracy is .09 (p = .41), with TM consensus is .09 (p = .42), and with knowledge stock is .38 (p < .01). The evidence suggests that higher knowledge stock is associated with less accurate cognitive inference, low consensus on knowledge distribution, and high knowledge specialization. But, knowledge specialization is unrelated to either accuracy or consensus of the team's cognitive representation of knowledge distribution.

Table 2 displays descriptive statistics and correlations for individual-level variables based on all respondents pooled across three waves. As expected, the overall mean for individual TM accuracy is 0.73 (i.e., same as the team-level TM accuracy mean). The individual TM deviation is negatively correlated with TM accuracy (r = -.70, p < .01). ACT team members experienced moderately high level of emotional burnout (the mean is 3.04 on a 5-point scale) and low-levels of burnout related to ineffectiveness (mean = 1.90) and depersonalization (mean = 1.36).

[Insert Table 2 & Table 3 about here]

Table 3 displays descriptive statistics and correlations for dyadic-level variables based on all pairs of individuals in the same team pooled across 26 teams and three waves. On average, overstatements and understatements both are made in less than one knowledge domain (the means are 0.82 and 0.98). The two variables are negatively correlated ($r = -.22$, $p < .01$), suggesting that at the dyadic-level egos tend to make inaccurate identifications of alters' expertise in one or the other direction.

5.2. What Contributes to TM Accuracy and Consensus?

5.2.1 Network Structures and Team-Level TMS Properties

How do social networks affect teams' cognitive outcomes? This section tests competing hypotheses on the relationships between network structures and team TM accuracy and consensus. Table 4 presents results from the generalized linear mixed (GLM) regression models for team TM accuracy. Model 1 includes control variables only. Model 2 and Model 3 examine the main effects of team climate and network densities respectively. Model 4 includes both team climate and network densities as predictors. Model 5 assesses the impact of an alternative structure – network centralization. Models for network density and network centralization are separately estimated because the density and centralization measures for the same network are highly correlated ($r = -.43$, $p < .001$ for the work-close network; $r = -.84$, $p < .001$ for the task-help network). Because teams were repeatedly observed over time, the possible unmeasured between-wave differences and within-team (across-wave) correlated errors violate the independent observation assumption of regression analyses. Thus, I included a fixed wave effect to control for unmeasured differences between waves and a random team effect to control for within-team correlated errors in all models. However, coefficients for the fixed wave effect are not significant. The lack of difference between waves is consistently found in all models reported in this chapter. So, I suppress the fixed wave effect from all tables for presentational convenience.

Hypothesis 1A predicts that both work-close and task-help networks' densities are positively related to team TM accuracy. Results of the regression models, however, do not support this hypothesis. Model 4 shows the work-close network density is not related to team TM accuracy. Contrary to the prediction, the task-help network density has a significant and negative effect on TM accuracy ($b = -.16$, $p < .001$). This finding suggests that, aggregated to the team level, a high volume of task-related assistance is detrimental to teams' cognitive accuracy regarding who knows what. Edmondson (1999) argued that psychological safe facilitates open communication and team learning. Model 4 shows that psychological safety improves team TM accuracy ($b = .11$, $p < .01$). Model 5 tests the hypothesis that predicts the positive relationship between network centralization and team TM accuracy. The result shows that the centralization of the task-help network is positively related to team TM accuracy ($b = .24$, $p < .001$), which offers partial support for Hypothesis 1B. The network centralization measures used in this analysis assess the variability in team members' degree centrality (Wasserman and Faust 1994). High centralization implies the existence of one or a few central actors that are connected to many others, but the rest of actors are only connected to a few others (most likely to the central actors). Low centralization implies that actors are more equally connected to one another. The positive relationship between task-help network centralization and team TM accuracy may be explained by an efficiency argument that networks with central players are more efficient in channeling information flows and facilitating team members to recognize one another's expertise. An alternative explanation is that with high TM accuracy, team members can unmistakably identify and request assistance from highly visible experts. Experts in those high-demand areas may face more help requests and become central actors in the task-help network. The present analysis, however, cannot disentangle and test these competing explanations. Models 3, 4, and 5 have equivalently small Akaike Information Criteria (AIC), suggesting that these models fit the data better than models without network variables.

[Insert Table 4 & Table 5 about here]

Table 5 reports results from regression models for team TM consensus. The model specifications are the same as those of Table 4. Results show that the effects of network structures on team TM consensus are comparable to their effects on team TM accuracy. The density and centralization of the work-close network are unrelated to TM consensus. For the task-help network, density is negatively related to team TM consensus (b = -.19, $p < .001$) and centralization is positively related to team TM consensus (b = .26, $p < .001$). These findings contradict Hypothesis 2A and support Hypothesis 2B. Psychological safety is only marginally related to team TM consensus (b = .07, $p < .10$). Among the five models, Model 3 has the best model fit in predicting team TM consensus.

The covariance-parameter estimates for random team effects in all reported TM accuracy and TM consensus models are insignificant. To compare the random effect models with more parsimonious models, I estimated a set of Ordinary Least Squares (OLS) regressions and conducted likelihood ratio tests using the method developed by Vuong (1989). The tests suggest that models without the random team effect fit the data equivalently well as the random effect models. Because the coefficient estimates of the OLS regressions are comparable to the random effect models, I report the latter because they produce more conservative estimates.

5.2.2 Network Positions and Individual-Level TMS Outcomes

Do social networks affect individuals' cognitive outcomes similarly? Or, does the impact of networks on cognitive outcomes vary by individuals' network positions? Table 6 presents results of regression models for individual-level TM accuracy. Three nested models are displayed. Model 1 includes control variables only. Model 2 and Model 3 consecutively add the main effects of team climate and individual network centralities. Similar to the team-level analyses, both teams and individuals were repeatedly observed over time, which creates possible unmeasured between-wave differences and correlated errors within team and individual. Thus, all models include a fixed effect for wave, a random effect for team, and a random effect for individual.

Hypothesis 3 predicts that individual centrality in both work-close and task-help networks is positively related to individual TM accuracy. This hypothesis is not supported. The out-degree centrality in task-help network has a marginally negative effect on individual TM accuracy (b = -.017, $p < .10$). The results suggest that network positions do not have a significant impact on individual cognitive accuracy. Of the individual characteristics, we see that team leaders have more accurate perceptions of expertise distributions ($b = .03$, $p < .05$) and tenure is positively related to TM accuracy ($b = .0006$, $p < .01$). Echoing the finding from the team-level analysis, psychological safety has a positive effect on individual TM accuracy ($b = .06$, $p < .01$).

[Insert Table 6 & Table 7 about here]

In Table 7, I replicate the regression analyses for individual TM deviation. The results show that the out-degree centrality in task-help network significantly increases individual TM deviation ($b = .05$, $p < .001$). This result suggests that individuals in the position of receiving a lot of task-related assistance are more likely to have cognitive representations that stray from the team's average cognitive representation, which contradicts Hypothesis 4. Among the individual characteristics, only tenure has a stable effect on TM deviation across models. The negative coefficient suggests that individuals who have worked on the team for longer time are more likely to conform to the team's average cognitive representation of expertise distribution ($b = -.0005$, $p < .05$). The coefficient for tenure is small because it is unstandardized coefficient and the dependent and independent variables are measured on difference scales. The variable tenure measures the number of months a team member has worked on the team and its value ranges from 0 to 68, while the dependent variable individual TM deviation ranges from 0 to 1.

The fit indices for both individual TM accuracy models and TM deviation models show that adding network position variables decreases the model fit (AIC for Model 3 > AIC for Model 1, indicating poorer fit). This test suggests that differences in individual

TM properties are well explained by individual characteristics rather than by network positions. I examined the covariance-parameter estimates for the random team and individual effects. The random team effects are not significant in both sets of models. But, the estimates for random individual effect are significant (τ^2= .0009, p < .01 for the accuracy model and τ^2= .0029, p < .001 for the deviation model), indicating that individuals differ in their baseline cognitive accuracy and deviation regarding team expertise distribution.

5.2.3 Discussion

The results presented in this section lend credence to the argument that TMS is an intersubjective system that is socially constructed and continuously reconstructed through interactions among team members. Regression analyses at the team level show that team TM accuracy and consensus both are significantly influenced by patterns of social interactions captured in the network-structural measures.

The results, however, do not converge with my initial predictions, which hypothesize that network densities are positively related to team TM accuracy and consensus. The negative effects of task-help network density on TM accuracy and consensus are unexpected, suggesting that the ways in which social interactions shape teams' cognitive outcomes may be complex and need further examination (the last section of this chapter presents one attempt at such examination). The positive relationships between the task network centralization on team TM accuracy and consensus seem to support the alternative hypotheses that were developed using the brokerage/efficiency argument. These results need to be interpreted with caution.

Conceptually, network density and centralization are different measures of network structures, with density capturing the total volume of ties and centralization capturing the dispersion in numbers of network ties among individuals. Empirically, the two measures are often strongly correlated especially in small networks. With 8 to 16 team members working on the ACT teams, the networks are small and may or may not exhibit meaningful structural differentiations. In that case, degree centralization may only indicate that the network is sparse (opposite of a dense network). Thus, the positive effects of network centralization on team TM accuracy and consensus may only reflect the same underlying dynamics that the network density effects have captured (this is especially true for the task-help network considering the correlation between network density and network centralization is -.84).

The finding that psychological safety improves team TM accuracy is consistent with the recent research showing that psychological safety contributes to open communication, information sharing, and learning in teams (Edmondson 1999). Feeling safe in the team and believing that others would not hold one's mistakes against them will encourage team members to communicate more openly about their strengths and weaknesses, which will result in more accurate expertise perceptions.

The results for the effects of network positions on individual TM accuracy and consensus tell a coherent story of social network effects. Being at the center of receiving a lot of task help is associated with poorer TM accuracy and greater TM deviation. However, these effects are not as strong as the effects found at the team level (task-help in-degree centrality only has a marginal effect on individual TM accuracy). This outcome supports the idea that TMS is primarily a team-level construct.

5.3. How Does TMS Affect Teams and Individuals?

5.3.1 TMS and Team Performance

Prior research suggests that a well-developed TMS (with high knowledge stock, high TM accuracy, and high TM consensus) offers a team multiple advantages by maximizing its knowledge/information repository, facilitating knowledge/information utilization, and improving coordination. Generally, researchers conjectured positive relationships between knowledge stock, TM accuracy, TM consensus and team performance (Liang et al. 1995; Faraj and Sproull 2000; Austin 2003). Table 8 reports GLM regression models that assess the effects of these TMS dimensions on team performance (measured by the incidence of mental-illness related hospitalization among ACT clients). Model 1 includes team characteristics and program fidelity as control variables. Model 2 examines the effects of team climate and network densities. Model 3 through 5 assess the main effects of three TMS dimensions. Separate models were estimated because the three TMS variables, especially TM accuracy and TM consensus, are strongly correlated. Model 6 and 7 add the interaction terms between TM accuracy and knowledge stock and between TM consensus and knowledge stock respectively. All models include a fixed wave effect and a random team effect.

[Insert Table 8 about here]

Regarding the main effects of TMS dimensions, Hypotheses 5A-5C predict that TM accuracy, TM consensus, and knowledge stock all have positive effects on team performance. Results of regression analyses offer support for Hypothesis 5A, but contradict Hypothesis 5C. The dependent variable for these analyses is the incidence of mental-illness related hospitalization among ACT clients. Therefore, a negative coefficient indicates that a variable has a positive effect on team performance (reducing client hospitalization) and a positive coefficient indicates a negative impact on team performance (increasing client hospitalization). Model 3 shows that higher team TM accuracy is related to fewer mental-illness hospitalization ($b = -.81$, $p < .05$). However, Model 5 shows that knowledge stock is positively related to the incidence of hospitalization; thus, has a negative impact on team performance ($b = .50$, $p < .05$). Team TM consensus has no significant impact on team performance when only its main effect is evaluated. In these models, most control and team climate variables have no significant effect on team performance. Psychological safety is marginally (sometimes significantly) and positively related to client hospitalization. However, this effect does not appear consistently. Fidelity, a strong predictor of ACT team performance in clinical research, has no significant impact after controlling for team characteristics and other team variables (including TMS). This result may be due to the fact that all Minnesota ACT teams were trained and instructed to operate in compliance with the DACTS; and there is little variation in these teams' fidelity scores (the standard deviation is 0.19 on a 5-point scale).

In Models 6 and 7, I test Hypotheses 6A and 6B, which states that teams' cognitive properties (TM accuracy and consensus) and team knowledge stock interact in affecting team performance. Specifically, I predict that cognitive accuracy and consensus will have a greater impact on performance in teams with high knowledge stock than in teams with low knowledge stock. Both hypotheses are supported. Model 6 shows that team TM accuracy and knowledge stock have a significant interaction term (b = -16.07, p < .001). A similar result is obtained in Model 7 for team TM consensus and knowledge stock interaction (b = -12.42, p < .001). As illustrated in Figure 5, when teams are well-resources and have high knowledge stock, team TM accuracy sharply decreases the incidence of client hospitalization. By contrast, when knowledge stock is low, team TM accuracy does not improve performance (rather, it slightly increases the incidence of hospitalization). The joint effect of team TM consensus and knowledge stock is almost identical to that of TM accuracy and knowledge stock (as illustrated in Figure 6).

[Insert Figure 5 & 6 about here]

Assessing model fit for team performance models, we see that Models 6 and 7 have considerably lower AICs, suggesting that the two interaction models fit the data better than the other models. The covariance-parameter estimates for random team effects are insignificant. However, the likelihood ratio tests suggest that models with the random team effect fit better. Therefore, results from the random effect models are presented.

I replicated the best fitting model (Model 6) on other team performance measures (based on different client outcomes) and present selective models in Table 9. For most client outcomes (e.g., substance-abuse related hospitalization, incarceration, employment status), teams' TMS properties have no significant impact. However, TM accuracy is found to have a positive effect (with a similar joint effect of knowledge stock for mental-illness related hospitalization) on clients' housing stability. Table 9 shows that team TM accuracy and knowledge stock jointly reduce the incidence of homeless and improve residential status for ACT clients. Note that residential status is measured as an ordinal variable that ranges from 1 (homeless/homeless shelter) to 5 (private and independent living), with higher value indicating better residential status and better team performance. Thus, the positive coefficient for the TM accuracy and knowledge stock interaction indicates positive interactive effect on team performance (b = 19.1, $p < .10$), which is contrary to the coefficients for other performance measures for which negative coefficients indicate positive effect.

[Insert Table 9 about here]

5.3.2 Cognitive Accuracy and Individual Burnout

The next set of analyses, presented in Table 10, focus on the relationship between individual TM accuracy and team member job burnout. Hypothesis 7 predicts that individual TM accuracy is negatively related to team members' burnout. I estimated models for three burnout dimensions separately because previous research suggested that these outcomes have different causes (Demerouti et al. 2001; Maslach et al. 2001). Regression results show that individual TM accuracy has a negative effect on burnout, but only on burnout related to ineffectiveness (b = -.81, $p < .05$).

Theories on job burnout suggest that causes of and the relationship between burnout dimensions are complex, but some evidence shows that emotional exhaustion and depersonalization are primarily caused by work overload and conflict, whereas inefficacy (lack of personal accomplishment and a sense of ineffectiveness) is caused by the lack of job resources (Maslach et al. 2001). My analyses show that individual TM accuracy only affects burnout related to ineffectiveness. This finding is consistent with the existing burnout research. In ACT teams, resources in the forms of knowledge are distributed and located largely in individual minds. An accurate cognitive representation of how knowledge is distributed may help an individual to correctly locate and utilize these resources, which in turn enhances personal accomplishment and alleviates inefficacy. However, individual TM accuracy can hardly reduce job demands or conflict; and therefore, is less likely to affect burnout dimensions caused by these factors. The lack of impact of individual TM accuracy on emotional exhaustion and depersonalization supports this argument. In fact, the impact of network centralities also hints that job demands may cause emotional burnout and depersonalization. Table 10 shows that working closely with many others (indicated by work-close centrality) and providing assistance to many others (indicated by task-help in-degree centrality) are positively related to emotional exhaustion and depersonalization.

[Insert Table 10 about here]

All models reported in Table 10 include a fixed wave effect and a random team effect (both are insignificant based on the fixed effect coefficient and the random effect covariance-parameter estimates). I also estimated models with random individual effects, but these models did not reveal any significant effect of individual TM accuracy. This is possibly due to the correlation between individual TM accuracy and some unobserved individual characteristics captured in the random effect models. I conducted the likelihood-ratio-based Vuong test and the result suggested that models with and without the random individual effect are equally distant from the true model. Therefore, I present the simple models without random individual effects.

5.3.3 Discussion

At the team level, TM accuracy appears to be a strong predictor of team performance. In assessing team performance, I used client outcomes measured for the six months after the surveys, and the data were collected by the state administrative agency separately. This unique data structure demonstrates what may be the most important strengths of this research: longitudinal research design and multiple data sources. Although the TMS-performance link has been the focus of TMS research since its commencement, this field research perhaps offers the strongest support for the claimed positive consequences of TMS to date.

The finding on interactions between TMS dimensions in affecting team performance is intriguing. As discussed in Chapter 2, knowledge stock (and knowledge specialization) is the property of a team's knowledge structure (or, to use Wegner and Wegner's [1995] term, the property of lower-order information). In contrast, TM accuracy and consensus both pertain to a team's cognitive structures (or, they are properties of higher-order information and location information). The effects of these different types of properties are likely to differ and possibly conditioned on one another. My analyses show that such an interactive effect exists.

The findings from the individual level again are weaker than those from the team level, suggesting that the benefits of TMS are more evident at the team level. Individual TM accuracy is only negatively associated with burnout related to ineffectiveness. This relationship is possibly spurious because adding a random individual effect would change the TM accuracy effect to insignificant.

5.4. Extended Analyses

5.4.1 Types of TM Inaccuracy

So far we have seen that social networks (more specifically the task-help network) do matter in shaping teams' cognitive outcomes at both the team and the individual level. But, the direction of this impact comes as a surprise. At the team level, my findings (displayed in Table 4 and 5) contradict Hypotheses 1A and 2A. These hypotheses predict that high densities of social networks are positively related to high team-level TM accuracy and consensus. The empirical results, however, show that the high density of task-help network is negatively related to team TM accuracy and consensus. These results appeared consistently across different model specifications that I have estimated (including the first-difference models that I will present later in this chapter).

To explore further why this counter-intuitive relationship exists, I draw on a hint provided by some individual-level results. As presented in Table 6 and 7, the out-degree centrality in the task-help network is negatively related to individual TM accuracy and positively related to individual TM deviation. By contrast, the in-degree centrality in the same network is unrelated to TM accuracy and deviation. Together, these results suggest task-help network in-degrees may have been the major source for TM inaccuracy. The survey question for the task-help network asked respondents which of their team members frequently provided them task related help. Accordingly, an in-degree in the task-help network indicates that the focal respondent has frequently received help from another team member. An out-degree indicates that the focal respondent has provided help to another team member (who identified having received help from the focal respondent). For narrative convenience, I refer to the focal respondent as *ego* and the other team member as *alter* hereafter. The individual-level findings suggest that receiving a lot of help (the in-degree centrality measures the total volume of help received standardized by team size minus one) decreases an ego's TM accuracy and increases the ego's TM deviation. By contrast, providing a lot of help does not have such effects.

Inspired by these findings, the surprising negative relationship between the task-help network density and team TM accuracy may be explained by certain cognitive dynamics unfold at the dyadic level. One possible scenario is that an ego is more likely to mistakenly perceive an alter as an expert if she has received assistance from the alter. Considered at the dyadic level, this scenario speaks to one of the two possible mistakes in recognizing expertise, which is *expertise overstatement* (or expertise exaggeration). The ego overstates the alter's expertise by identifying the alter as an expert when the alter does not have the expertise (i.e., does not self-identify as an expert according to the measurement operation in this research). The other possible mistake is *expertise understatement*, which occurs when the ego fail to identify the alter as an expert when the alter has the expertise.

I conducted dyadic-level analyses to test the hypothetical explanation elaborated above. For the dyadic-level analyses, I created two inaccuracy measures: 1) Expertise overstatement measures the number of knowledge domains in which an ego identifies an alter as expert, but the alter does not self-identify as expert. 2) Expertise understatement measures the number of knowledge domains in which the alter self-identifies as expert, but the ego does not identify the alter as expert (see the Measurement section in Chapter 4 for details about other dyadic-level variables).

Table 11 presents results from the dyadic-level regression models for TM inaccuracy. For both expertise overstatement and expertise understatement, I estimated a base model that includes control variables only and a full model, which examines the effects of network ties. The full models show that when an ego has worked closely with an alter, she is more likely to overstate (b = .19, p < .001), but less likely to understate the alter's expertise (b = -.06, p < .10). Due to the opposite directions, these two effects may have canceled each other to some extent when TM (in)accuracy was modeled at both the individual and team level. Without differentiating the types of inaccuracy, the effects of work-close ties on TM accuracy become dubious because they increase expertise overstatement and simultaneously reduce expertise understatement. The task-help ties, by contrast, are only related to one type of inaccuracy. The results suggest that when an ego has frequently received task-related help from an alter, she is more likely to overstate the alter's expertise (b = .37, p < .001). Other noteworthy findings from this analysis are that an ego is less likely to make either type of inaccurate statement when she and the alter have the same gender, or the same position, or have work together on the team for a longer period of time.

[Insert Table 11 about here]

All models reported in Table 11 include a fixed effect for wave and random effects for team, ego, and alter. Both the fixed wave and the random team effects are insignificant. But the random effects for ego and alter are significant. Inspecting the model fit indices, we see that the full models with the network variables have much better fit than the base models.

5.4.2 Modeling Changes

Early in this chapter, I reported regression models that tested research hypotheses on the relationships between the TMS structure and its antecedents (social network structures and positions) and consequences (team performance and individual burnout). Although I controlled for cross-time differences by including a fixed wave effect, these models essentially assumed a static view of the hypothesized relationships. The longitudinal data collected for this research, however, provide the opportunity to examine the hypothesized relationships dynamically. In Table 12, I present selective first-difference models in attempt to test such dynamic relationships. For each dependent variable, I selected the full model (i.e., the model with all independent variables of interest) estimated above and run a first-difference regression with the same model specification. I applied the simple difference equation, in which changes in the dependent variable were regressed on changes in the independent variables. The unchanging independent variables are taken out of the models because the differences are by definition zero. The first-difference models have substantial advantages in modeling changes, especially when there are unmeasured, unchanging explanatory variables, when there are persistent measurement errors for observed explanatory variables, and when the panel data give more reliable measurement of changes than in the level of the explanatory variables (Liker, Augustyniak, and Duncan 1985).

[Insert Table 12 about here]

In Table 12, the first two models show that changes in task-help network density is negatively related to changes in team-level TM accuracy (b = -.18, p < .01) and consensus (b = -.20, p < .01). These results are consistent with results from previous analyses. Also consistent with previous individual-level analyses, changes in out-degree centralities in the task-help network are negatively related to changes in individual TM accuracy (b = -.04, p < .01) and positively related to changes in individual TM deviation (b = .05, p < .001). Together, the models show that the relationships between TMS properties and their network antecedents are evident not only from a static point of view, but also from a dynamic view.

The relationships between TMS properties and their consequences, however, are absent from a dynamic view. The model for the team performance outcome shows no significant relationship between changes in team TM accuracy and changes in team performance (neither does such relationship exist for TM consensus as found in an unreported model). The last three models show no relationship between changes in individual TM accuracy and changes in individual job burnout.

The absence of the relationship between team TM accuracy and team performance may occur because the performance of ACT teams was relatively stable during the study period. On the other hand, team TM accuracy (and social networks) changed evidently because of the high volume of turnover occurring between waves (The turnover between survey waves one and two was particularly high. The median turnover rate was 19.1%). Appendix B displays the time-series plots for the team performance measure and team TM accuracy and consensus depicted by teams. As shown in these figures, there are very little changes in the performance measure for most teams except two teams that have apparent curved lines. But, changes in team TM accuracy and consensus are more visible where most teams have curved lines. The changes in TM accuracy and consensus may have made the relationships between networks and these TMS properties more detectable in modeling.

Figure 5. TM Accuracy and Knowledge Stock Joint Effect on Team Performance

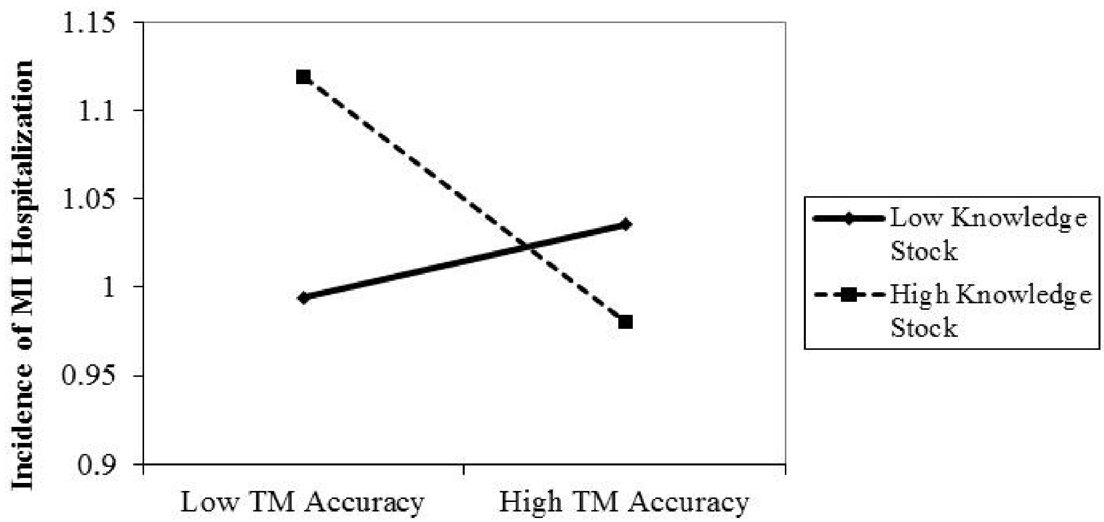


Figure 6. TM Consensus and Knowledge Stock Joint Effect on Team Performance

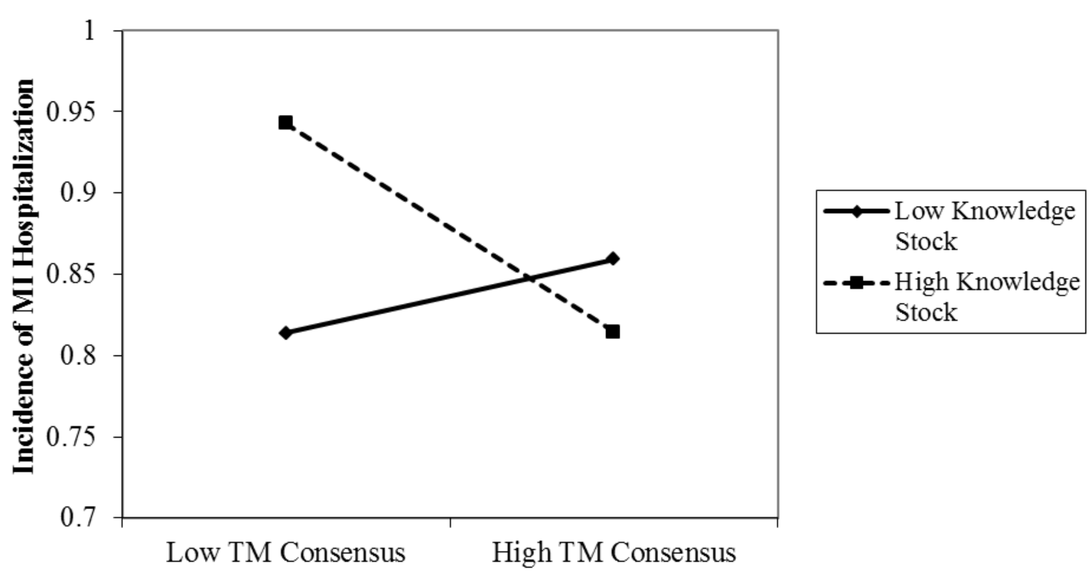


Table 1. Descriptive Statistics and Correlations among Team-Level Variables (N=78)

Variable	M.	S.D.	Correlations 1.	2.	3.	4.	5.	6.
1. Incidence MI Hospitalization	0.20	0.11						
2. TM Accuracy	0.73	0.04	-.23*					
3. TM Consensus	0.71	0.05	-.21	.83**				
4. Knowledge Stock	0.34	0.07	.38**	-.44**	-.45**			
5. Psychological Safety	3.44	0.21	-.07	.32**	.13	-.26*		
6. Constructive Controversy	3.30	0.30	-.11	.16	-.01	-.28*	.75**	
7. Safety & Quality Orientation	2.99	0.37	-.22*	.17	.00	-.24*	.53**	.55**
8. Work-Close Network Density	0.40	0.13	-.23*	.06	-.05	-.12	.49**	.38**
9. Task-Help Network Density	0.60	0.13	-.09	-.33**	-.44**	.04	.32**	.34**
10. Work-Close Centralization	0.43	0.08	.04	-.12	-.14	.05	-.26*	-.09
11. Task-Help Centralization	0.34	0.09	.10	.22*	.33**	-.02	-.41**	-.34**
12. Team Size	11.9	2.49	-.08	.06	.01	.07	-.21	-.02
13. No. of New Hires	1.86	1.74	.10	-.13	-.17	.27*	-.21	-.05
14. Client-Staff Ratio	6.18	1.16	.06	-.20	-.10	.31**	-.17	-.23*
15. Urban Team	0.65	0.48	-.02	-.25*	-.15	.32**	-.34**	-.23*
16. Specialized Team	0.15	0.36	-.28*	-.15	-.08	-.11	-.09	.02
17. Fidelity	4.15	0.19	-.23*	-.04	-.05	-.06	-.09	-.11

* *p*<.05 ** *p*<.01

Table 1. Descriptive Statistics & Correlations among Team-Level Variables – Continued

	Correlations									
Variable	7.	8.	9.	10.	11.	12.	13.	14.	15.	16.
1. Inc MI Hosp										
2. TM Accuracy										
3. TM Consens										
4. Knowl Stock										
5. Psych Safety										
6. Constr Contr										
7. S & Q Oritat										
8. W-C Density	.43**									
9. T-H Density	.31**	.42**								
10. W-C Ctrlzt	.07	-.42**	-.08							
11. T-H Ctrlzt	-.41**	-.41**	-.84**	.14						
12. Team Size	-.20	-.33**	-.16	.06	.15					
13. New Hires	-.24*	-.10	.04	-.11	.07	.24*				
14. Cl-St Ratio	-.35**	-.02	.14	-.05	-.11	-.07	.21			
15. Urban Team	-.28*	-.15	.02	-.06	.03	.30**	.44**	.62**		
16. Spec Team	.28**	-.04	.19	.18	-.17	.04	-.03	.01	.31**	
17. Fidelity	-.01	-.00	-.05	.17	.12	.29*	-.18	-.16	-.15	.14

Table 2. Descriptive Statistics and Correlations among Individual-Level Variables (N=781)

Variable	M.	S.D.	Correlations 1.	2.	3.	4.	5.	6.	7.	8.	9.	10.
1. Burnout Emotional Exhaustion	3.04	1.08										
2. Burnout Ineffectiveness	1.90	0.82	.10**									
3. Burnout Depersonalization	1.36	0.49	.29**	.22**								
4. Individual TM Accuracy	0.73	0.08	.02	-.07	.01							
5. Individual TM Deviation	0.18	0.08	-.00	.01	-.01	-.70**						
6. Work-Close Network Centrality	0.39	0.22	.07	-.15**	-.01	.11**	-.01					
7. Task-Help Network Out-Centrality	0.60	0.31	.00	-.16**	-.02	-.05	.16**	.32**				
8. Task-Help Network In-Centrality	0.61	0.22	.10**	-.07*	.06	.02	-.02	.41**	.26**			
9. Gender	0.71	0.45	.10**	.09**	.02	.08*	-.08*	.16**	-.06	.11**		
10. Team Leader	0.10	0.30	.06	-.04	-.08*	.12**	-.08*	.26**	.07*	.16**	.03	
11. Tenure	26.8	17.0	.01	-.05	.08*	.14**	-.10**	.11**	.01	.01	-.10**	.06

* *p*<.05 ** *p*<.01

Table 3. Descriptive Statistics and Correlations among Dyadic-Level Variables (N=8,445)

			Correlations					
Variable	**M.**	**S.D.**	1.	2.	3.	4.	5.	6.
1. # of Overstated Expertise Areas	0.82	1.25						
2. # of Understated Expertise Areas	0.98	1.35	-.22**					
3. Same Gender	0.56	0.50	.04**	.01**				
4. Same Position	0.21	0.40	-.09**	-.09**	.20**			
5. Joint Tenure	19.26	15.16	-.04**	-.06**	-.02**	.14**		
6. Work-Close Tie	0.34	0.48	.15**	-.06**	.01**	-.12**	.04**	
7. Task-Help Tie (Receiving)	0.55	0.50	.21**	-.02**	-.05**	-.15**	-.04**	.35**

* *p*<.05 ** *p*<.01

Table 4. GLM Regression for Team Transactive Memory Accuracy (N=78)

Variable	Team TM Accuracy				
	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**
Intercept	0.80 *** (0.13)	0.53 ** (0.15)	0.87 *** (0.16)	0.51 *** (0.13)	0.37 * (0.14)
Control					
Team Size	0.002 (0.003)	0.004 † (0.002)	0.002 (0.002)	0.003 (0.002)	0.004 * (0.002)
No. of New Hires	- 0.003 (0.003)	- 0.002 (0.003)	- 0.002 (0.003)	0.000 (0.002)	- 0.002 (0.003)
Fidelity	- 0.02 (0.03)	- 0.02 (0.03)	- 0.03 (0.03)	- 0.02 (0.02)	- 0.03 (0.03)
Team Climate					
Psychological Safety		0.10 ** (0.04)		0.11 ** (0.03)	0.12 ** (0.04)
Constructive Controversy		- 0.04 (0.03)		- 0.03 (0.02)	- 0.04 (0.02)
Safe & Quality Orientation		0.01 (0.02)		0.02 (0.02)	0.03 (0.02)
Network					
Work-Close Density			0.07 (0.06)	0.01 (0.04)	
Task-Help Density			- 0.14 ** (0.04)	- 0.16 *** (0.04)	
Work-Close Centralization					- 0.04 (0.06)
Task-Help Centralization					0.24 *** (0.06)
	Model Fit Index				
- 2 Log Likelihood	- 222.83	- 213.94	- 224.60	- 222.77	- 222.18
AIC	- 218.83	- 209.94	- 220.60	- 220.77	- 220.18

Note. Coefficient estimates are shown with standard errors in parentheses for all regression models.

† *p*<.10   * *p*<.05   ** *p*<.01   *** *p*<.001

Table 5. GLM Regression for Team Transactive Memory Consensus (N=78)

	Team TM Consensus				
Variable	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**
Intercept	0.78 *** (0.16)	0.70 ** (0.19)	0.90 *** (0.15)	0.71 *** (0.17)	0.56 ** (0.17)
Control					
Team Size	0.001 (0.003)	0.002 (0.003)	- 0.000 (0.003)	0.001 (0.003)	0.002 (0.003)
No. of New Hires	- 0.002 (0.003)	- 0.002 (0.003)	- 0.002 (0.003)	- 0.001 (0.003)	- 0.003 (0.003)
Fidelity	- 0.02 (0.04)	- 0.02 (0.04)	- 0.02 (0.04)	- 0.02 (0.03)	- 0.03 (0.03)
Team Climate					
Psychological Safety		0.06 (0.04)		0.07 † (0.04)	0.08 † (0.04)
Constructive Controversy		- 0.04 (0.03)		- 0.02 (0.03)	- 0.04 (0.03)
Safe & Quality Orientation		- 0.004 (0.02)		0.008 (0.02)	0.02 (0.02)
Network					
Work-Close Density			0.02 (0.05)	- 0.004 (0.05)	
Task-Help Density			- 0.18 *** (0.04)	- 0.19 *** (0.04)	
Work-Close Centralization					- 0.06 (0.06)
Task-Help Centralization					0.26 *** (0.07)
	Model Fit Index				
- 2 Log Likelihood	- 215.88	- 201.63	- 224.09	- 211.37	- 208.81
AIC	- 211.88	- 197.63	- 220.09	- 207.37	- 204.81

† *p*<.10 * *p*<.05 ** *p*<.01 *** *p*<.001

Table 6. GLM Regression for Individual Transactive Memory Accuracy (N=787)

Variable	Individual TM Accuracy		
	Model 1	**Model 2**	**Model 3**
Intercept	0.70 *** (0.01)	0.57 *** (0.06)	0.57 *** (0.06)
Control			
Gender	0.01 (0.007)	0.01 † (0.006)	0.01 (0.007)
Team Leader	0.03 ** (0.01)	0.03 ** (0.01)	0.03 * (0.01)
Tenure	0.0006 ** (0.0002)	0.0006 ** (0.0002)	0.0006 ** (0.0002)
Team Climate			
Psychological Safety		0.07 ** (0.02)	0.06 ** (0.02)
Constructive Controversy		- 0.03 (0.02)	- 0.03 (0.02)
Safe & Quality Orientation		0.001 (0.01)	0.001 (0.01)
Network Centrality			
Work-Close Centrality			0.011 (0.015)
Task-Help Out-Centrality			- 0.017 † (0.009)
Task-Help In-Centrality			0.007 (0.014)
	Model Fit Index		
- 2 Log Likelihood	- 1868.71	- 1856.99	- 1840.03
AIC	- 1862.71	- 1850.99	- 1834.03

† *p*<.10 * *p*<.05 ** *p*<.01 *** *p*<.001

Table 7. GLM Regression for Individual Transactive Memory Deviation (N=787)

Variable	Individual TM Deviation		
	Model 1	**Model 2**	**Model 3**
Intercept	0.20 ***	0.24 ***	0.25 ***
	(0.01)	(0.05)	(0.05)
Control			
Gender	- 0.02 †	- 0.02 †	- 0.01
	(0.01)	(0.01)	(0.01)
Team Leader	- 0.02 †	- 0.02	- 0.02 †
	(0.01)	(0.01)	(0.01)
Tenure	- 0.0005 *	- 0.0005 *	- 0.0005 *
	(0.0002)	(0.0002)	(0.0002)
Team Climate			
Psychological Safety		- 0.03	- 0.04 †
		(0.02)	(0.02)
Constructive Controversy		0.02	0.01
		(0.02)	(0.02)
Safe & Quality Orientation		0.01	0.01
		(0.01)	(0.01)
Network Centrality			
Work-Close Centrality			0.01
			(0.02)
Task-Help Out-Centrality			0.05 ***
			(0.01)
Task-Help In-Centrality			- 0.01
			(0.02)
	Model Fit Index		
- 2 Log Likelihood	- 1737.72	- 1720.34	- 1723.91
AIC	- 1731.72	- 1714.34	- 1717.91

† *p*<.10 * *p*<.05 ** *p*<.01 *** *p*<.001

Table 8. GLM Regression for Team Performance (N=78)

Variable	Incidence of Mental-Illness Hospitalization				
	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**
Intercept	0.60 (0.48)	0.22 (0.63)	0.78 (0.65)	0.71 (0.68)	0.19 (0.59)
Control					
Team Size	- 0.01 (0.01)	- 0.01 (0.01)	- 0.01 (0.01)	- 0.01 (0.01)	- 0.01 (0.01)
Client-Staff Ratio	- 0.02 (0.02)	- 0.02 (0.02)	- 0.03 (0.02)	- 0.03 (0.02)	- 0.02 (0.02)
Fidelity	- 0.04 (0.12)	- 0.05 (0.13)	- 0.06 (0.13)	- 0.06 (0.13)	- 0.06 (0.12)
Urban Team	0.04 (0.07)	0.04 (0.08)	0.04 (0.08)	0.05 (0.08)	0.02 (0.07)
Specialized Team	- 0.17 * (0.07)	- 0.15 † (0.09)	- 0.15 † (0.08)	- 0.14 (0.08)	- 0.11 (0.08)
Team Climate					
Psychological Safety		0.21 † (0.11)	0.27 * (0.11)	0.24 * (0.11)	0.18 (0.11)
Constructive Controversy		- 0.03 (0.07)	- 0.03 (0.07)	- 0.03 (0.07)	0.005 (0.07)
Safe & Quality Orientation		- 0.04 (0.06)	- 0.03 (0.06)	- 0.04 (0.06)	- 0.05 (0.06)
Network Density					
Work-Close Density		- 0.20 (0.14)	- 0.26 † (0.14)	- 0.24 (0.14)	- 0.20 (0.14)
Task-Help Density		0.02 (0.12)	- 0.10 (0.13)	- 0.08 (0.13)	- 0.02 (0.12)
TMS Dimensions					
Team TM Accuracy			- 0.81 * (0.33)		
Team TM Consensus				- 0.57 (0.34)	
Team Knowledge Stock					0.50 * (0.25)
Accuracy × K. Stock					
Consensus × K. Stock					
	Model Fit Index				
- 2 Log Likelihood	- 69.79	- 59.38	- 64.77	- 61.80	- 62.21
AIC	- 65.79	- 55.38	- 60.77	- 57.80	- 58.21

† *p*<.10 * *p*<.05 ** *p*<.01 *** *p*<.001

Table 8. GLM Regression for Team Performance – Continued

Variable	Incidence of Mental-Illness Hospitalization	
	Model 6	**Model 7**
Intercept	- 2.60 * (0.96)	- 1.95 † (1.08)
Control		
Team Size	- 0.01 (0.01)	- 0.01 (0.01)
Client-Staff Ratio	- 0.02 (0.02)	- 0.02 (0.02)
Fidelity	- 0.17 (0.10)	- 0.13 (0.11)
Urban Team	- 0.03 (0.06)	- 0.01 (0.07)
Specialized Team	- 0.08 (0.07)	- 0.07 (0.07)
Team Climate		
Psychological Safety	0.13 (0.10)	0.18 (0.11)
Constructive Controversy	- 0.07 (0.07)	- 0.05 (0.07)
Safe & Quality Orientation	- 0.01 (0.05)	- 0.05 (0.05)
Network Density		
Work-Close Density	- 0.16 (0.13)	- 0.19 (0.14)
Task-Help Density	- 0.11 (0.11)	- 0.09 (0.12)
TMS Dimensions		
Team TM Accuracy	4.86 ** (1.37)	
Team TM Consensus		3.81 * (1.53)
Team Knowledge Stock	11.98 *** (2.78)	9.12 ** (3.06)
Accuracy × Knowledge Stock	- 16.07 *** (3.85)	
Consensus × Knowledge Stock		- 12.42 ** (4.37)
	Model Fit Index	
- 2 Log Likelihood	- 85.46	- 75.86
AIC	- 81.46	- 71.86

Table 9. TMS Effect on Other Team Performance Measures (N=78)

Variable	Team Performance		
	Incidence of Homeless	**Residential Crisis**	**Residential Status**
Intercept	- 1.17 (0.73)	0.63 † (0.33)	6.82 † (3.89)
Control			
Team Size	- 0.004 (0.007)	- 0.001 (0.003)	- 0.071 † (0.036)
Client-Staff Ratio	- 0.017 (0.012)	- 0.011 † (0.006)	- 0.058 (0.060)
Fidelity	- 0.018 (0.101)	- 0.022 (0.033)	0.80 (0.73)
Urban Team	0.03 (0.05)	0.03 (0.02)	0.09 (0.35)
Specialized Team	0.08 (0.06)	- 0.02 (0.02)	- 1.32 ** (0.42)
Team Climate			
Psychological Safety	0.04 (0.06)	- 0.01 (0.03)	- 0.47 † (0.27)
Constructive Controversy	- 0.02 (0.04)	0.05 * (0.02)	0.04 (0.14)
Safe & Quality Orientation	- 0.03 (0.03)	- 0.02 (0.02)	- 0.06 (0.14)
Network Density			
Work-Close Density	- 0.04 (0.07)	- 0.03 (0.04)	0.09 (0.34)
Task-Help Density	- 0.03 (0.07)	- 0.07 † (0.04)	0.78 * (0.31)
TMS Dimensions			
Team TM Accuracy	2.19 * (0.88)	- 0.59 † (0.34)	- 5.11 (3.92)
Team Knowledge Stock	4.73 * (1.81)	0.91 (0.94)	- 14.08 † (8.04)
Accuracy × Knowledge Stock	- 6.88 ** (2.52)	1.17 (1.31)	19.10 † (11.14)
	Model Fit Index		
- 2 Log Likelihood	- 127.58	- 205.62	51.11
AIC	- 123.58	- 201.62	55.11

† *p*<.10 * *p*<.05 ** *p*<.01 *** *p*<.001

Table 10. GLM Regression for Individual Burnout (N=781)

Variable	Individual Burnout		
	Emotional Exhaustion	**Ineffectiveness**	**Depersonalization**
Intercept	4.88 *** (0.75)	2.59 *** (0.59)	2.06 *** (0.35)
Control			
Gender	0.15 † (0.09)	0.17 ** (0.07)	0.00 (0.04)
Team Leader	- 0.02 (0.13)	0.01 (0.10)	- 0.19 ** (0.06)
Tenure	0.003 (0.002)	- 0.000 (0.002)	0.003 ** (0.001)
Team Climate			
Psychological Safety	- 0.03 (0.31)	0.41 † (0.24)	- 0.24 (0.15)
Constructive Controversy	- 0.31 (0.22)	- 0.33 † (0.17)	0.02 (0.10)
Safe & Quality Orientation	- 0.68 *** (0.15)	- 0.08 (0.12)	- 0.10 (0.07)
Network Centrality			
Work-Close Centrality	0.47 * (0.22)	- 0.49 ** (0.17)	0.04 (0.10)
Task-Help Out-Centrality	0.07 (0.13)	- 0.29 ** (0.10)	- 0.03 (0.06)
Task-Help In-Centrality	0.56 ** (0.19)	0.09 (0.15)	0.20 * (0.09)
TMS			
Individual TM Accuracy	0.70 (0.51)	- 0.81 * (0.39)	0.25 (0.24)
	Model Fit Index		
- 2 Log Likelihood	2287.42	1868.35	1092.63
AIC	2291.42	1872.35	1096.63

† *p*<.10 * *p*<.05 ** *p*<.01 *** *p*<.001

Table 11. GLM Regression for Dyadic TM Inaccuracy (N=8,445)

Variable	Types of TM Inaccuracy			
	Overstate		**Understate**	
Intercept	1.34 *** (0.08)	0.98 *** (0.08)	1.43 *** (0.08)	1.42 *** (0.08)
Ego Control				
Gender	- 0.04 (0.08)	- 0.04 (0.08)	0.07 (0.07)	0.07 (0.07)
Team Leader	- 0.36 ** (0.12)	- 0.40 *** (0.11)	0.06 (0.10)	0.07 (0.10)
Dyadic Control				
Same Gender	- 0.09 *** (0.03)	- 0.07 * (0.03)	- 0.18 *** (0.03)	- 0.18 *** (0.03)
Same Position	- 0.46 *** (0.03)	- 0.34 *** (0.03)	- 0.49 *** (0.03)	- 0.49 *** (0.03)
Joint Tenure	- 0.006 *** (0.001)	- 0.004 ** (0.001)	- 0.011 *** (0.001)	- 0.011 *** (0.001)
Network Ties				
Work Close		0.19 *** (0.03)		- 0.06 † (0.03)
Task Help (Receiving)		0.37 *** (0.03)		0.03 (0.03)
	Model Fit Index			
- 2 Log Likelihood	25181.58	24884.92	25174.27	25180.91
AIC	25187.58	24890.92	25180.27	25186.91

† *p*<.10 * *p*<.05 ** *p*<.01 *** *p*<.001

Table 12. First-Difference Models Summary

Variable	Team TMS		Performance	Individual TM		Individual Burnout		
	Team TM Accuracy	**Team TM Consensus**	**MI Hospi-talization**	**Indiv. TM Accuracy**	**Indiv. TM Deviation**	**Burnout Emotional**	**Burnout Ineffective**	**Burnout Depersonal**
Intercept	0.01 (0.01)	0.01 (0.01)	0.01 (0.03)	0.01 (0.007)	- 0.01 † (0.005)	0.21 ** (0.07)	- 0.07 (0.05)	0.08 * (0.03)
Team Climate								
Psychological Safety	0.05 (0.04)	0.03 (0.04)	0.30 * (0.11)	0.05 † (0.03)	- 0.03 (0.03)	0.43 (0.30)	0.02 (0.21)	- 0.29 † (0.15)
Constructive Controversy	- 0.03 (0.03)	- 0.02 (0.03)	- 0.07 (0.08)	- 0.01 (0.02)	0.01 (0.02)	- 0.09 (0.23)	- 0.14 (0.16)	0.14 (0.11)
Safe & Quality Orientation	0.01 (0.03)	- 0.003 (0.03)	- 0.04 (0.06)	0.02 (0.02)	- 0.001 (0.02)	- 0.43 * (0.18)	- 0.30 * (0.18)	- 0.10 (0.09)
Network Density								
Work-Close Density	- 0.02 (0.07)	- 0.03 (0.06)	- 0.20 (0.15)					
Task-Help Density	- 0.18 ** (0.06)	- 0.20 ** (0.06)	- 0.04 (0.15)					
Team TM Accuracy			- 0.04 (0.34)					
Network Centrality								
Work-Close Centrality				0.001 (0.02)	0.02 (0.02)	0.22 (0.25)	0.24 (0.18)	0.06 (0.13)
Task-Help Out-Centrality				- 0.04 ** (0.01)	0.05 *** (0.01)	- 0.43 ** (0.14)	- 0.12 (0.10)	- 0.15 * (0.07)
Task-Help In-Centrality				- 0.02 (0.02)	0.02 (0.02)	- 0.34 (0.23)	- 0.08 (0.16)	0.14 (0.11)
Individual TM Accuracy						0.41 (0.56)	0.04 (0.39)	0.19 (0.28)

† *p*<.10 * *p*<.05 ** *p*<.01 *** *p*<.001

CHAPTER SIX

CONCLUSION

6.1 Summary Remarks

From the outset, I specified three objectives for this dissertation research: to extend transactive memory system (TMS) theory by inspecting the concept's dimensionality and internal structure (i.e., the relationship between different conceptual dimensions), to develop a new method for measuring TMS, and to examine the antecedents and consequences of TMS with selective focuses (examining social interactions captured in work-related social networks for antecedents and team performance and individual burnout for consequences). Below, I summarize the major findings of this research.

First, by reviewing Wegner's (1987) original conceptualization of TMS and comparing TMS to similar team-cognitive concepts, I distinguished TMS structure and TMS processes as two distinct but intertwined conceptual aspects. The two aspects are intertwined in the sense that TMS structure sets the condition for TMS processes to unfold and TMS processes transform TMS structure from one state to another over time. Based on the structure-process distinction, I classified the conceptual dimensions of TMS discussed in previous research into two categories: structural dimensions (transactive memory [TM] accuracy, TM consensus, knowledge stock, and knowledge specialization) and process dimensions (coordination, credibility, and possibly a third dimension – specializing – that is undertheorized).

Second, I developed a new method for measuring structural TMS dimensions. I offered rationales for developing a new measurement based on appraising existing measurement approaches' strengths and weaknesses. The new measurement is based on individual cognitive maps of expertise distributions, where a cognitive map is a person-by-expertise matrix perceived/developed by and stored in an individual's mind. I proposed formulas for calculating measures for the four TMS structural dimensions. I tested the measurement properties with the empirical data collected from 26 Assertive Community Treatment (ACT) teams. The results showed that the new measurement has good test-retest reliability, reliability for self-evaluation, and within-group agreement (for aggregating individual scores to the team level). The results from examining the consequences of TMS provided support for the measurement's predictive validity. The tests supported the use of the new method in this and similar field studies.

Third, examining the effects of social networks on TM accuracy and consensus, I found that high density of the task-help network is detrimental to TM accuracy and consensus at the team level. Centralization of the task-help network on the other hand positively influences team-level TM accuracy and consensus. At the individual level, out-degree centrality in the task-help network is negatively related to individual TM accuracy and positively related to individual TM deviation. I conducted post-hoc analyses at the dyadic level and found that frequently receiving help from an alter contributes to TM inaccuracy by increasing the likelihood of the ego overstating the alter's expertise. Examining the consequences of TMS, I reestablished that team-level TM accuracy has a positive impact on team performance. Further, the results of the TMS-performance analysis provided strong support for the argument that TM accuracy and consensus interact with team knowledge stock in affecting team performance, with TM accuracy and consensus having a greater impact on team performance when team knowledge stock is high than when the knowledge stock is low. Finally, I extended the research on TMS consequences to the individual level, and found that high individual TM accuracy reduces job burnout related to ineffectiveness.

6.2 Contributions and Implications

In line with the three achieved research objectives, this dissertation makes several theoretical and methodological contributions. First, joining in an emerging effort to further crystalize the concept (Lewis et al. 2007; Palazzolo 2008; Zhu 2009), I accentuate the distinction and theorize the relationship between TMS' structural and process aspects. The idea is not new (see Wegner and Wegner's [1995] explicit account on the distinction). But, it has been missing from most of the empirical research, which has resulted in the ambiguity in research operationalization and difficulty in synthesizing research findings. This research improves the conceptual clarity of TMS and contributes to TMS theory.

Second, the matrix-based measurement developed in this dissertation makes a methodological contribution to the study of TMS. The new method offers direct measures of teams' knowledge and cognitive structures. In addition to good reliabilities, the measures have several other advantages including that the survey instrument is easy to implement in field research and that the measures are easy to derive and well interpretable.

Third, this study contributes to the growing literature on team cognition by bringing in a social network perspective to account for interpersonal antecedents of TMS. Social interactions have been considered as the fundamental cause for TMS. But, how social interactions affect TMS have not been examined directly. This research is the first attempt to examine the impact of social interactions on cognitive accuracy and consensus using social network analyses.

Finally, the impact of TMS on both team performance and individual team member morale is examined, which extends the current research that only focuses on TMS' impact on team performance outcomes. The interactions between TMS dimension in affecting team performance found in this research underlines the importance of understanding TMS not just as unitary concept, but as a system of constituent dimension that interact with one another. Theory regarding the interactions among TMS dimensions is needed to advance the field.

The research findings have several practical implications. First, teams need to develop a good TMS. Managers and scholars increasingly recognize that effective coordination in the use of knowledge is a principal source of organizational effectiveness and competitiveness (Gibson 2001). But, the challenge of how to effectively coordinate persists. This research suggests that TMS is the cognitive underpinning of effective coordination and is imperative for team performance. To use Dr. Chen's term, one characteristic for defining a "well-oiled team" is that the team has a good TMS, which means high knowledge stock, high cognitive accuracy, and high consensus regarding knowledge distribution in the team.

Second, among different TMS structural dimensions, cognitive accuracy appears to be particularly important. My findings suggest that TM accuracy not only improves team performance, but also helps to alleviate staff burnout related to ineffectiveness. Thus, managers and team leaders need to foster accurate interpersonal perceptions in their teams.

Third, regarding how to foster accurate and consensual TMS, this research suggests that managers and team leaders should develop and emphasize the team's psychological safety climate. Levine et al. (1993) argued that social interaction is the paramount site for the development and practice of collective cognition. This research provides evidence that patterns of social interactions are important predictors of team cognitive structures. However, the relationships between social networks and TMS are more complex than I originally predicted. One implication, derived from the research finding that task-related helping behavior is negatively related to TM accuracy, is that managers and team leaders should not play a passive role in the development of TMS and let the system emerge without intervention. Despite many benefits of the interpersonal helping behavior in organizations (Podsakoff et al. 2000), helping each other is likely to result in cognitive inaccuracy particularly for team members who have received help. Managers and team leaders can break the association between helping behavior and TM inaccuracy by organizing the teams to collectively reflect on their knowledge distribution.

6.3 Limitations

This research has several limitations. Although the research site has some unique features (e.g., clear functional specification, high task interdependence, and intense coordination) that allowed me to delineate team cognitive structures in a very detailed way, the uniqueness of this research site may reduce the generalizability of my empirical findings. The unique context may have contributed and constrained different aspects of my inquiry simultaneously. ACT teams are expected to benefit from TMS to a great extent because their work requires intense cross-disciplinary coordination. My analyses on the TMS-team performance relationship confirmed this expectation and TMS explained important variations in ACT teams' performance. However, because of their clear-cut functional divisions, all teams in the sample had very high levels of TM accuracy and consensus, which may have impaired the possibility of demonstrating the relationships of TM accuracy and consensus with their antecedents. Another limitation of this research is that I only included structural measures of TMS; therefore I could not test the relationships between the TMS structure and TMS processes and their joint impact on team effectiveness. Future research should test potential contextual effects by conducting similar studies in different field settings and examine the relationship between the TMS structure and TMS processes by incorporating valid measures for both aspects.

REFERENCES

Akgün, Ali E., John Byrne, Halit Keskin, Gary S. Lynn, and Salih Z. Imamoglu. 2005. "Knowledge Networks in New Product Development Projects: A Transactive Memory Perspective." *Information & Management* 42(8):1105-1120.

Argote, Linda, Bill McEvily, and Ray Reagans. 2003. "Managing Knowledge in Organizations: An Integrative Framework and Review of Emerging Themes." *Management Science* 49(4):571-582.

Austin, John R. 2003. "Transactive Memory in Organizational Groups: The Effects of Content, Consensus, Specialization, and Accuracy on Group Performance." *Journal of Applied Psychology* 88(5):866-878.

Bandura, Albert. 2001. "Social Cognitive Theory: An Agentic Perspective." *Annual Review of Psychology* 52(1):1-26.

Berger, Peter L. and Thomas Luckmann. 1967. *The Social Construction of Reality: A Treatise in the Sociology of Knowledge*. Garden City, NY: Doubleday & Company.

Bliese, Paul D. 2000. "Within-Group Agreement, Non-Independence, and Reliability: Implications for Data Aggregation and Analysis." Pp.349-381 in *Multilevel Theory, Research, and Methods in Organizations: Foundations, Extensions, and New Directions*, edited by K.J. Klein and S.W.J. Kozlowski. San Francisco, CA: Jossey-Bass.

Bond, Gary R., Robert E. Drake, Kim T. Mueser, and Eric Latimer. 2001. "Assertive Community Treatment for People with Severe Mental Illness: Critical Ingredients and Impact on Patients." *Disease Management & Health Outcomes* 9(3):141-159.

Borgatti, Stephen P. and Rob Cross. 2003. "A Relational View of Information Seeking and Learning in Social Networks." *Management Science* 49(4):432-445.

Brandon, David P. and Andrea B. Hollingshead. 2004. "Transactive Memory Systems in Organizations: Matching Tasks, Expertise, and People." *Organization Science* 15(6):633-644.

Bunderson, J. Stuart. 2003. "Recognizing and Utilizing Expertise in Work Groups: A Status Characteristics Perspective." *Administrative Science Quarterly* 48(4):557-591.

Burns, Barbara J. and Alberto B. Santos. 1995. "Assertive Community Treatment: An Update of Randomized Trials." *Psychiatric Services* 46(7):669-675.

Burt, Ronald S. 1992. *Structural Holes: The Social Structure of Competition*. Cambridge, MA: Harvard University Press.

Burt, Ronald S. 2005. *Brokerage and Closure: An Introduction to Social Capital*. New York: Oxford University Press.

Cannon-Bowers, Janis A., Eduardo Salas, and Sharolyn Converse. 1993. "Shared Mental Models in Expert Team Decision Making." Pp.221-246 *in Individual and Group Decision Making*, edited by N. J. Castellan. Hillsdale, NJ: Lawrence Erlbaum Associates.

Cannon-Bowers, Janis A. and Eduardo Salas. 2001. "Reflections on Shared Cognition." *Journal of Organizational Behavior* 22(2):195-202.

Cohen, Susan G. and Diane E. Bailey. 1997. "What Makes Teams Work: Group Effectiveness Research from the Shop Floor to the Executive Suite." *Journal of Management* 23(3):239-290.

Cooke, Nancy J., Jamie C. Gorman, and Jennifer L. Winner. 2007. "Team Cognition." Pp.239-268 in *Handbook of Applied Cognition, 2nd Edition*, edited by F. T. Durso. Chichester, UK: John Wiley & Sons.

Demerouti, Evangelia, Arnold B. Bakker, Friedhelm Nachreiner, and Wilmar B. Schaufeli. 2001. "The Job Demands-Resources Model of Burnout." *Journal of Applied Psychology* 86(3):499-512.

Durkheim, Emile. [1893] 1997. *The Division of Labor in Society*. New York: Free Press.

Edmondson, Amy. 1999. "Psychological Safety and Learning Behavior in Work Teams." *Administrative Science Quarterly* 44(2):350-383.

Edwards, Bryan D., Eric A. Day, Winfred Arthur Jr., and Suzanne T. Bell. 2006. "Relationships among Team Ability Composition, Team Mental Models, and Team Performance." *Journal of Applied Psychology* 91(3):727-736.

Ellis, Aleksander P. J. 2006. "System Breakdown: The Role of Mental Models and Transactive Memory in the Relationship between Acute Stress and Team Performance." *Academy of Management Journal* 49(3):576-589.

Espinosa, Alberto J., F. Javier Lerch, and Robert E. Kraut 2004. "Explicit vs. Implicit Coordination Mechanisms and Task Dependencies: One Size Does Not Fit All." Pp.107-129 in *Team Cognition: Understanding the Factors that Drive Process and*

Performance, edited by Eduardo Salas and Stephen M. Fiore. Washington, DC: American Psychological Association.

Faraj, Samer and Lee Sproull. 2000. "Coordinating Expertise in Software Development Teams." *Management Science* 46(12):1554-1568.

Fiske, Susan T. and Shelley E. Taylor. 1991. *Social Cognition*. New York: McGraw-Hill.

Freeman, Linton C. 1979. "Centrality in Social Networks Conceptual Clarification." *Social Networks* 1(3):215-239.

Friedkin, Noah E. 1998. *A Structural Theory of Social Influence*. Cambridge, UK: Cambridge University Press.

Friedkin, Noah E. and Eugene C. Johnsen. 1999. "Social Influence Networks and Opinion Change." *Advances in Group Processes* 16:1-29.

Gibson, Cristina B. 2001. "From Knowledge Accumulation to Accommodation: Cycles of Collective Cognition in Work Groups." *Journal of Organizational Behavior* 22(2):121-134.

Hackman, J. Richard. 1987. "The Design of Work Teams." Pp.315-342 in *Handbook of Organizational Behavior*, edited by J. W. Lorsch. Englewood Cliffs, NJ: Prentice-Hall.

Hilgard, Ernest R. 1980. "The Trilogy of Mind: Cognition, Affection, and Conation." *Journal of the History of the Behavioral Sciences* 16(2):107-117.

Hodgkinson, Gerard P. and Mark P. Healey. 2008. "Cognition in Organizations." *Annual Review of Psychology* 59(1):387-417.

Hutchins, Edwin. 1991. "The Social Organization of Distributed Cognition." Pp.283-307 in *Perspectives on Socially Shared Cognition*, edited by L.B. Resnick, J.M. Levine and S.D. Teasley. Washington, DC: American Psychological Association.

Ibarra, Hermirila and Steven B. Andrews. 1993. "Power, Social Influence, and Sense Making: Effects of Network Centrality and Proximity on Employee Perceptions." *Administrative Science Quarterly* 38(2):277-303.

Ilgen, Daniel R., John R. Hollenbeck, Michael Johnson, and Dustin Jundt. 2005. "Teams in Organizations: From Input-Process-Output Models to IMOI Models." *Annual Review of Psychology* 56(1):517-543.

Kilduff, Martin and David Krackhardt. 2008. *Interpersonal Networks in Organizations: Cognition, Personality, Dynamics, and Culture*. New York: Cambridge University Press.

Kohn, Linda T., Janet M. Corrigan, and Molla S. Donaldson. 2000. *To Err is Human: Building a Safer Health System*. Washington, D.C.: Institute of Medicine.

Kozlowski, Steve W. J. and Bradford S. Bell. 2003. "Work Groups and Teams in Organizations." Pp.333-375 in *Handbook of Psychology*, edited by W. C. Borman, D. R. Ilgen, and R. J. Klimoski. London: John Wiley & Sons.

Kozlowski, Steve W. J. and Daniel R. Ilgen. 2006. "Enhancing the Effectiveness of Work Groups and Teams." *Psychological Science in the Public Interest* 7(3):77-124.

Landrigan, Christopher P., Gareth J. Parry, Catherine B. Bones, Andrew D. Hackbarth, Donald A. Goldmann, and Paul J. Sharek. 2010. "Temporal Trends in Rates of

Patient Harm Resulting from Medical Care." *New England Journal of Medicine* 363(22):2124-2134.

Lave, Jean and Etienne Wenger. 1991. *Situated Learning: Legitimate Peripheral Participation*. Cambridge, UK: Cambridge University Press.

Lawler, Edward E., Susan A. Mohrman, and Gerald E. Ledford. 1995. *Creating High Performance Organizations: Practices and Results of Employee Involvement and Total Quality Management in Fortune 1000 Companies*. San Francisco: Jossey-Bass.

Levine, John M., Lauren B. Resnick, and E. T. Higgins. 1993. "Social Foundations of Cognition." *Annual Review of Psychology* 44(1):585-612.

Lewis, Kyle. 2003. "Measuring Transactive Memory Systems in the Field: Scale Development and Validation." *Journal of Applied Psychology* 88(4):587-604.

Lewis, Kyle, Maura Belliveau, Benjamin Herndon, and Joshua Keller. 2007. "Group Cognition, Membership Change, and Performance: Investigating the Benefits and Detriments of Collective Knowledge." *Organizational Behavior and Human Decision Processes* 103(2):159-178.

Lewis, Kyle, Donald Lange, and Lynette Gillis. 2005. "Transactive Memory Systems, Learning, and Learning Transfer." *Organization Science* 16(6):581-598.

Liang, Diane W., Richard Moreland, and Linda Argote. 1995. "Group Versus Individual Training and Group Performance: The Mediating Role of Transactive Memory." *Personality and Social Psychology Bulletin* 21(4):384-393.

Liker, Jeffrey K., Sue Augustyniak, and Greg J. Duncan. 1985. "Panel Data and Models of Change: A Comparison of First Difference and Conventional Two-Wave Models." *Social Science Research* 14(1):80-101.

Lim, Beng-Chong and Katherine J. Klein. 2006. "Team Mental Models and Team Performance: A Field Study of the Effects of Team Mental Model Similarity and Accuracy." *Journal of Organizational Behavior* 27(4):403-418.

London, Manuel, Jeffrey T. Polzer, and Heather Omoregie. 2005. "Interpersonal Congruence, Transactive Memory, and Feedback Processes: An Integrative Model of Group Learning." *Human Resource Development Review* 4(2):114-135.

Marks, Michelle A., John E. Mathieu, and Stephen J. Zaccaro. 2001. "A Temporally Based Framework and Taxonomy of Team Processes." *Academy of Management Review* 26(3):356-376.

Maslach, Christina, Susan E. Jackson, and Michael P. Leiter. 1996. *Maslach Burnout Inventory: Manual*. Palo Alto, CA: Consulting Psychologists Press.

Maslach, Christina, Wilmar B. Schaufeli, and Michael P. Leiter. 2001. "Job Burnout." *Annual Review of Psychology* 52(1):397-422.

Mathieu, John, M. T. Maynard, Tammy Rapp, and Lucy Gilson. 2008. "Team Effectiveness 1997-2007: A Review of Recent Advancements and a Glimpse Into the Future." *Journal of Management* 34(3):410-476.

McCulloch, Charles E., Shayle R. Searle, and John M. Neuhaus. 2008. *Generalized, Linear, and Mixed Models, 2nd Edition*. Hoboken, NJ: John Wiley & Sons.

McGrath, Joseph E. 1984. *Groups: Interaction and Performance*. Englewood Cliffs, NJ: Prentice-Hall.

McGrath, Joseph E., Holly Arrow, and Jennifer L. Berdahl. 2000. "The Study of Groups: Past, Present, and Future." *Personality and Social Psychology Review* 4(1):95-105.

McGrew, John H., Gary R. Bond, Laura Dietzen, and Michelle Salyers. 1994. "Measuring the Fidelity of Implementation of a Mental Health Program Model." *Journal of Consulting and Clinical Psychology* 62(4):670-678.

McHugo, Gregory J., Robert E. Drake, Gregory B. Teague, and Haiyi Xie. 1999. "Fidelity to Assertive Community Treatment and Client Outcomes in the New Hampshire Dual Disorders Study." *Psychiatric Services* 50(6):818-824.

Mohammed, Susan and Brad C. Dumville. 2001. "Team Mental Models in a Team Knowledge Framework: Expanding Theory and Measurement across Disciplinary Boundaries." *Journal of Organizational Behavior* 22(2):89-106.

Mohammed, Susan, Richard Klimoski, and Joan R. Rentsch. 2000. "The Measurement of Team Mental Models: We Have No Shared Schema." *Organizational Research Methods* 3(2):123-165.

Moreland, Richard L. 1999. "Transactive Memory: Learning Who Knows What in Work Groups and Organizations." Pp.3-31 in *Shared Cognition in Organizations: The Management of Knowledge*, edited by L.L. Thompson, J.M. Levine, and D.M. Mesick. Mahwah, NJ: Erlbaum.

Moreland, Richard L. and Larissa Myaskovsky. 2000. "Exploring the Performance Benefits of Group Training: Transactive Memory or Improved Communication?" *Organizational Behavior and Human Decision Processes* 82(1):117-133.

Mueser, Kim T., Gary R. Bond, Robert E. Drake, and Sandra G. Resnick. 1998. "Models of Community Care for Severe Mental Illness: A Review of Research on Case Management." *Schizophrenia Bulletin* 24(1):37-74.

Olfson, Mark. 1990. "Assertive Community Treatment: An Evaluation of the Experimental Evidence." *Psychiatric Services* 41(6):634-641.

Palazzolo, Edward T. 2008. *Patterns of Information Retrieval in Communication Networks: A Study of Transactive Memory in Organizational Work Teams*. Saarbrücken, Germany: VDM Verlag.

Pearsall, Matthew J., Aleksander P. J. Ellis, and Bradford S. Bell. 2010. "Building the Infrastructure: The Effects of Role Identification Behaviors on Team Cognition Development and Performance." *Journal of Applied Psychology* 95(1):192-200.

Peltokorpi, Vesa. 2008. "Transactive Memory Systems." *Review of General Psychology* 12(4):378-394.

Peltokorpi, Vesa and Marja-Liisa Manka. 2008. "Antecedents and the Performance Outcome of Transactive Memory in Daycare Work Groups." *European Psychologist* 13(2):103-113.

Podsakoff, Philip M., Scott B. MacKenzie, Julie B. Paine, and Daniel G. Bachrach. 2000. "Organizational Citizenship Behaviors: A Critical Review of the Theoretical and

Empirical Literature and Suggestions for Future Research." *Journal of Management* 26(3):513-563.

Rau, Devaki. 2005. "The Influence of Relationship Conflict and Trust on the Transactive Memory." *Small Group Research* 36(6):746-771.

Resnick, Lauren B., John M. Levine, and Stephanie D. Teasley. 1991. *Perspectives on Socially Shared Cognition*. Washington, DC: American Psychological Association.

Salas, Eduardo, Terry L. Dickinson, Sharolyn A. Converse, and Scott I. Tannenbaum. 1992. "Toward an Understanding of Team Performance and Training." Pp.3-29 in *Teams: Their Training and Performance.*, edited by R.W. Swezey and E. Salas. Westport, CT: Ablex Publishing.

Salas, Eduardo and Stephen M. Fiore. 2004. "Why Team Cognition? An Overview." Pp.3-8 in *Team Cognition: Understanding the Factors that Drive Process and Performance.*, edited by E. Salas and S.M. Fiore. Washington, DC: American Psychological Association.

Salas, Eduardo, Kevin C. Stagl, and C. S. Burke. 2004. "25 Years of Team Effectiveness in Organizations: Research Themes and Emerging Needs." Pp.47-91 in *International Review of Industrial and Organizational Psychology Vol. 19*, edited by C. L. Cooper and I. T. Robertson. Chichester, UK: John Wiley & Sons.

SAS Institute. 2006. *The GLIMMIX Procedure, June 2006*. Cary, NC: SAS Institute.

Shah, Priti P., Kurt T. Dirks, and Norman Chervany. 2006. "The Multiple Pathways of High Performing Groups: The Interaction of Social Networks and Group Processes." *Journal of Organizational Behavior* 27(3):299-317.

Sparrowe, Raymond T., Robert C. Liden, Sandy J. Wayne, and Maria L. Kraimer. 2001. "Social Networks and the Performance of Individuals and Groups." *Academy of Management Journal* 44(2):316-325.

Stein, Leonard I. and Mary A. Test. 1980. "Alternative to Mental Hospital Treatment: I. Conceptual Model, Treatment Program, and Clinical Evaluation." *Archives of General Psychiatry* 37(4):392-397.

Teague, Gregory B., Gary R. Bond, and Robert E. Drake. 1998. "Program Fidelity in Assertive Community Treatment." *American Journal of Orthopsychiatry* 68(2):216-233.

Test, Mary A. and Leonard I. Stein. 1976. "Practical Guidelines for the Community Treatment of Markedly Impaired Patients." *Community Mental Health Journal* 12:72-82.

Test, Mary A. and Leonard I. Stein. 1980. "Alternative to Mental Hospital Treatment: III. Social Cost." *Archives of General Psychiatry* 37(4):409-412.

Thompson, James D. 1967. *Organization in Action*. Chicago: McGraw-Hill.

Thompson, Leigh and Gary A. Fine. 1999. "Socially Shared Cognition, Affect, and Behavior: A Review and Integration." *Personality and Social Psychology Review* 3(4):278-302.

Van de Ven, Andrew H. and Marshall S. Poole. 2005. "Alternative Approaches for Studying Organizational Change." *Organization Studies* 26(9):1377-1404.

Van de Ven, Andrew H., Andre L. Delbecq, and Richard Koenig Jr. 1976. "Determinants of Coordination Modes within Organizations." *American Sociological Review* 41(2):322-338.

Vuong, Quang H. 1989. "Likelihood Ratio Tests for Model Selection and Non-Nested Hypotheses." *Econometrica* 57(2):307-333.

Wageman, Ruth. 1995. "Interdependence and Group Effectiveness." *Administrative Science Quarterly* 40(1):145-180.

Wasserman, Stanley and Katherine Faust. 1994. *Social Network Analysis: Methods and Applications*. Cambridge, UK: Cambridge University Press.

Wegner, Daniel M. 1987. "Transactive Memory: A Contemporary Analysis of the Group Mind." Pp.185-208 in *Theories of Group Behavior*, edited by B. Mullen and G.R. Goethals. New York: Springer-Verlag.

Wegner, Daniel M., Ralph Erber, and Paula Raymond. 1991. "Transactive Memory in Close Relationships." *Journal of Personality and Social Psychology* 61(6):923-929.

Wegner, Toni G. and Daniel M. 1995. "Transactive Memory." Pp.654-656 in *The Blackwell Encyclopedia of Social Psychology*, edited by A. S. R. Manstead and M. Hewstone. Oxford, UK: Blackwell.

Weick, Karl E. and Karlene H. Roberts. 1993. "Collective Mind in Organizations: Heedful Interrelating on Flight Decks." *Administrative Science Quarterly* 38(3):357-381.

Weisbrod, Burton A., Mary A. Test, and Leonard I. Stein. 1980. "Alternative to Mental Hospital Treatment: II. Economic Benefit-Cost Analysis." *Archives of General Psychiatry* 37(4):400-405.

Wenger, Etienne. 1998. *Communities of Practice: Learning, Meaning, and Identity*. New York: Cambridge University Press.

Witheridge, Thomas F. 1991. "The 'Active Ingredients' of Assertive Outreach." *New Directions for Mental Health Services* 52:47-64.

Wolfinger, Russ and Michael O'Connell. 1993. "Generalized Linear Mixed Models: A Pseudo-Likelihood Approach." *Journal of Statistical Computation and Simulation* 4:233-243.

Yoo, Youngjin and Prasert Kanawattanachai. 2001. "Developments of Transactive Memory Systems and Collective Mind in Virtual Teams." *International Journal of Organizational Analysis* 9(2):187.

Yuan, Y. C., Janet Fulk, and Peter R. Monge. 2007. "Access to Information in Connective and Communal Transactive Memory Systems." *Communication Research* 34(2):131-155.

Zhang, Zhi-Xue, Paul S. Hempel, Yu-Lan Han, and Dean Tjosvold. 2007. "Transactive Memory System Links Work Team Characteristics and Performance." *Journal of Applied Psychology* 92(6):1722-1730.

Zhu, Jing. 2009. "Utilizing Expertise in Work Teams: The Role of Transactive Memory Systems." Unpublished Dissertation, University of Minnesota.

Zohar, Dov. 2000. "A Group-Level Model of Safety Climate: Testing the Effect of Group Climate on Microaccidents in Manufacturing Jobs." *Journal of Applied Psychology* 85(4):587-596.

APPENDIX A

SURVEY QUESTIONS, ITEMS, AND SCALES

1. Transactive Memory System

Question: Which of your ACT team members have a lot of expertise in (INCLUDE AN ANSWER FOR YOURSELF)

	Psychiatry /Medicine	Nursing	Sub. Abuse/IDDT	Vocational Rehabilitation/ Supported Employment
Team Member 1	☐	☐	☐	☐
Team Member 2	☐	☐	☐	☐
……				
Team Member N	☐	☐	☐	☐

	Courts/Civil Commitment	Housing/ Subsidies	Public Assistance/ Social Security	Team Coordination/ Shift Management
Team Member 1	☐	☐	☐	☐
Team Member 2	☐	☐	☐	☐
……				
Team Member N	☐	☐	☐	☐

2. Work-Close Network

Question: During the past month, how closely did you work with each of your other ACT team members? Leave the answer for yourself blank.

	Not closely	A little Closely	Somewhat closely	Very closely
Team Member 1	☐	☐	☐	☐
Team Member 2	☐	☐	☐	☐
……				
Team Member N	☐	☐	☐	☐

3. Task-Help Network

Question: During the past month, which of your ACT team members FREQUENTLY provided you Task Related Assistance beyond what their job role requires? For example, (1) help you when you have a heavy load or are absent; (2) help you with your work even though it is not required; or (3) volunteer to take extra responsibilities to help you when things get demanding at work. Leave the answer for yourself blank.

	Task Related Assistance
Team Member 1	□
Team Member 2	□
……	
Team Member N	□

4. Team Member Burnout

Question: These items ask how you felt about working on your ACT team. During the past month, how often did you feel?

Items:
- emotionally drained from your work on your ACT team.
- used up at the end of the workday from your work on your ACT team.
- you were working too hard on your ACT team.
- you were treating some consumers as if they were impersonal objects.
- you have become more callous toward people since you took this job.
- you don't really care what happens to some consumers.
- you dealt very effectively with the problems of your team's consumers. (Reverse coded)
- you were positively influencing other people's lives through your work. (Reverse coded)
- you had accomplished many worthwhile things in your job on your ACT team. (Reverse coded)

Scale: 1 – Never, 2 – Once or twice, 3 – A few times, 4 – A few times a week, 5 – Everyday.

5. Psychological Safety

Question: During the past month, how much do you agree with the following statements about your ability to bring up issues on your ACT team?
Items:
- I felt that I could bring up personal safety issues, such as working in dangerous neighborhoods, to my ACT team members.

- I felt that I could bring up mistakes and slips by my team in consumer care activities to my ACT team members.
- I felt that I could bring up problems and tough issues, such as unprofessional behavior or missing team meetings, to my ACT team members.
- I felt that if I made a mistake, other members of my ACT team would NOT hold it against me.
- I felt that it was safe to take a risk to try new things in my ACT team.
- I felt that my personal skills and talents were valued by other members of my ACT team.
- I felt that it was easy to ask for a change in the time of a visit.
- I felt that it was easy to ask for a partner to accompany me on a visit.

Scale: 1 – Strongly disagree, 2 – Somewhat disagree, 3 – Somewhat agree, 4 – Strongly agree.

6. Constructive Controversy

Question: During the past month, how much do you agree with the following statements about conflict and communication on your ACT team?

Items:
- I felt that even when we disagreed on my ACT team, we communicated with respect for each other.
- I felt that on my ACT team we used our opposing views to understand problems.

Scale: 1 – Strongly disagree, 2 – Somewhat disagree, 3 – Somewhat agree, 4 – Strongly agree.

7. Safety and Quality Orientation

Question: During the past month, how much do you agree with the following statements about your experience with balancing productivity, quality, and safety on your ACT team?

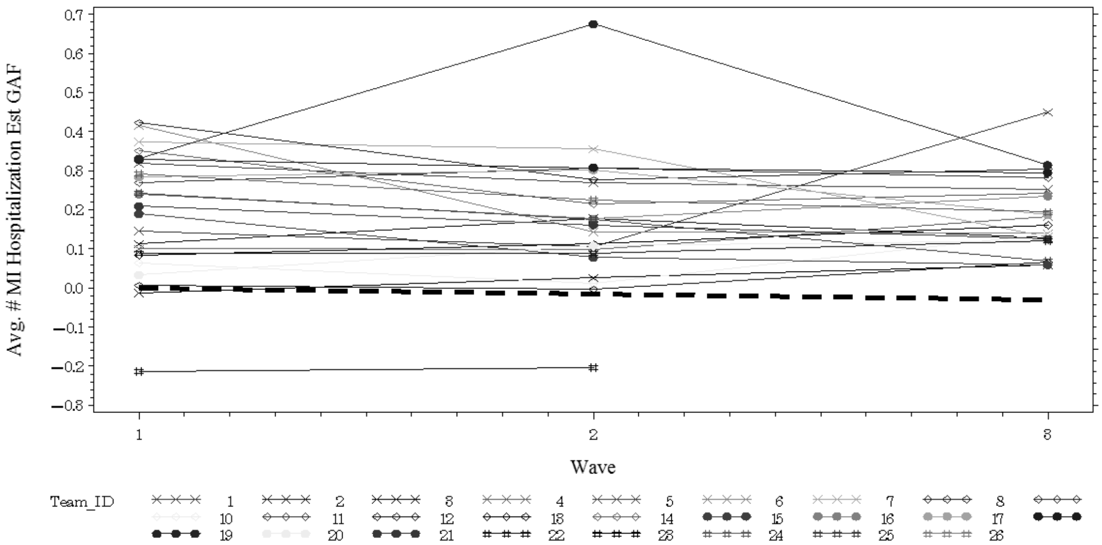
Items:
- I felt that I had the time during visits with consumers to assure safety for me or the consumers, even if it meant visiting fewer consumers.
- I felt that I had the time to assure high quality visits with consumers, even if it meant visiting fewer consumers.
- I felt that I had to make as many consumer visits as possible, even if it meant lower quality visits or less personal or consumer safety. (Reverse coded)

Scale: 1 – Strongly disagree, 2 – Somewhat disagree, 3 – Somewhat agree, 4 – Strongly agree.

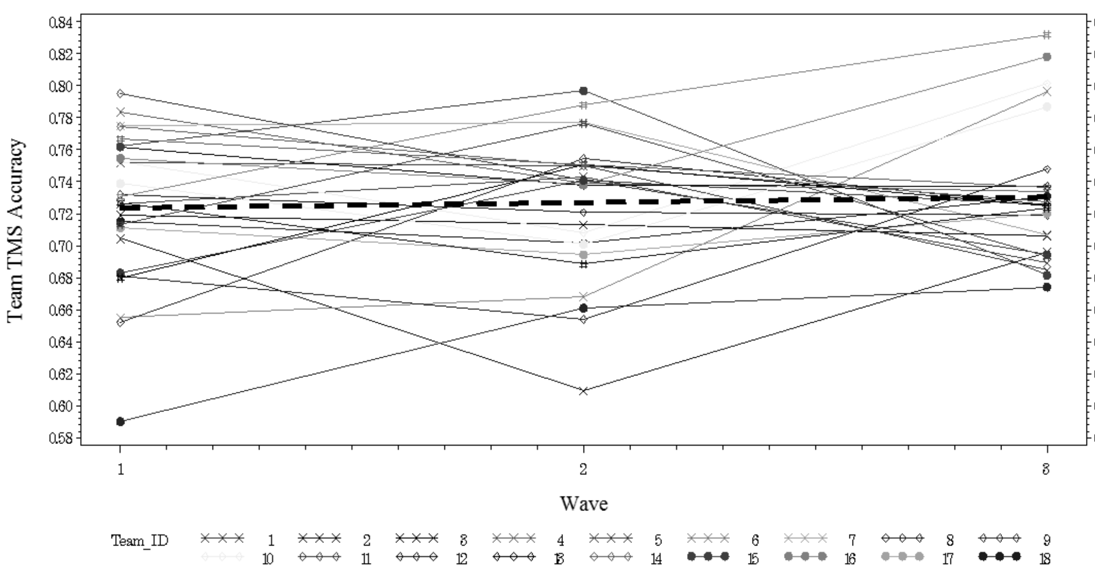
APPENDIX B

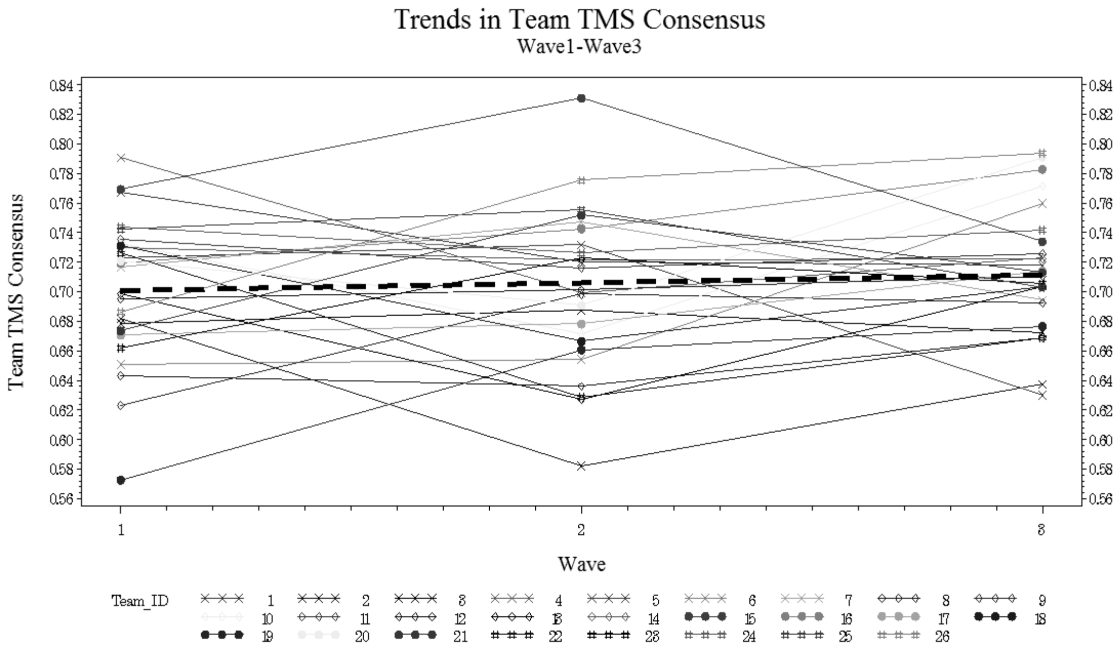
CHANGE PATTERNS IN TEAM-LEVEL DEPENDENT VARIABLES

Trends in Mental-Illness Hospitalization Incidence
Wave1-Wave3



Trends in Team TMS Accuracy
Wave1-Wave3





Trends in Team TMS Consensus
Wave1-Wave3
Team TMS Consensus
Wave
Team_ID