COMPUTATIONAL AND EMPIRICAL EXPLORATIONS OF WORK GROUP PERFORMANCE

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To my wife, Libby, and to my family,

whom I love beyond words…

I hope you'll accept these 40,392 as a start.

ABSTRACT

Computational methods combined with traditional empirical techniques offer a powerful new approach to the study of human performance. Scholars engaged in the study of work group and organizational behavior are increasingly calling for the use of integrated methods in conducting research, including the wider adoption of computational models for generating and testing new theory.

In this collection of three studies, I first review the state of modern computational modeling and find a steady increase in the incorporation of dynamic, adaptive, and realistic behaviors of agents in social network settings. However, my analysis suggests areas that can be addressed in the next generation of organizational simulation systems. I compare 28 models according to more than 200 evaluation criteria, ranging from simple representations of agent demographic and performance characteristics, to more richly defined instantiations of behavioral attributes, interaction with non-agent entities, model flexibility, communication channels, simulation types, knowledge, transactive memory, task complexity, and resource networks. I assess trends across these criteria, discuss practical applications, and propose an agenda for future research and development.

In the second study, using a modified version of one of the models reviewed in the first study, I examine the link between individual performance and group outcomes. Organizational behavior theories generally agree that human capital is critical to teams and organizations, but little guidance exists on the extent to which such theories accurately explain the relative contributions of individual actors to overall performance. Using newly created network-based measures of individual knowledge and task

exclusivity along with simulations based on empirical data obtained from a software development firm, I investigate the relative effectiveness of social network theory and resource dependency theory as predictors of individuals' contributions to group performance. Results indicate that individual impacts on group performance are even more closely associated with knowledge and task dimensions than with social network structure. Furthermore, given that knowledge may be assessed *a priori*, I explore factors that may provide useful guidance for structuring teams and predicting team performance.

In the third study, I integrate psychological, social network, and organizational learning theories to investigate the extent to which the amount and structure of a work group's transactive memory explains the relationship between the group's collective experience and its performance. I use network surveys and archival data obtained from 1,456 individuals and 87 managers on 118 diverse work teams in four Fortune 500 companies as the basis for analyzing relationships between transactive memory, group experience, and group performance. I find that group transactive memory partially mediates the link between group experience and performance. In addition, the degree of "small-worldness" exhibited in the structure of group transactive memory moderates the memory's mediating effect on group learning. I discuss the study's findings, practical implications, and limitations as well as how the findings may extend to inter-group, organization, inter-organizational, and even societal levels.

Finally, I provide a path for computational extensions of these studies in future research efforts. In particular, I propose modifications of the multi-agent model used in the second study ("Construct") that will enable dynamic simulation of agent-level learning that builds to group and organizational level learning. I also suggest a step-by-step methodology for calibrating, validating, and conducting a multi-agent simulation-based study of organizational learning.

PREFACE

In attempting to summarize a significant concentration of one's relatively short life in what one hopes will be even modestly useful research, there is a great temptation to wax philosophic in order to sustain the appearance of importance or comedic perhaps to mask the fear of insignificance. Alas, five years of intense doctoral study has wearied me of such vanity. Little more can be said than that I arrived thinking "look how far I have swum to get here" and that I depart thinking "but look how vast is the ocean in which I swim."

Even so, journeys are rarely truly solitary, particularly academic ones. And I embarked on mine with the support of parents whose love is and always has been action more than words, and with the constant encouragement of my wife, Libby, without whom whatever contribution I might claim would have been lost long ago to the exigencies and disappointments of academia. Perhaps the greatest lesson to be learned is not a scientific one at all, but rather one about life and love. It is the love within our dearest relationships that endures, transcending any truth we think we may have glimpsed along our journey's way.

Beyond the involvement of my family and my wife, the journey would not have been possible without the support and insight of many friends and colleagues, some of whom I will doubtless offend by forgetting to include them here. I apologize in advance if you are in that number. I wish to express gratitude to my advisor, Kathleen Carley, and to members of my dissertation committee, David Krackhardt and Jim Herbsleb, for their time and insight. In addition, I deeply appreciate Lester

Lave for setting an example for all of academia (and beyond) to follow. Many thanks also to Linda Argote, Tridas Mukhopadhyay, and Denise Rousseau for their encouragement and productive conversations. Of course, there are many others who have provided a hand along the way, but I extend special thanks to Jeff Reminga for his help in coding some of the complex computational models that have been integral to the research I describe in this dissertation. I may or may not be good at algorithms, but I am a regrettably slow and inefficient programmer.

Over the past five years, funding for this work has been generously provided by the Alfred P. Sloan Foundation's Industry Studies Program, the National Science Foundation (IGERT grant no. 9972762), Carnegie Mellon University's (CMU) School of Computer Science, CMU's Center for Computational Analysis of Social and Organizational Systems, the William Larimer Mellon Foundation, and the CMU Tepper School of Business.

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INTRODUCTION

Groups remain the dominant structure in organizations, and their performance continues to be a subject of intense study by sociologists, psychologists, and behaviorists. Because of its practical orientation, research on group performance has been traditionally focused on field studies and both experimental and quasi-experimental methods. However, because group performance is dynamic and multi-dimensional, such approaches to research can oftentimes be complemented by computational and simulation techniques. In this dissertation, I explore the state of computational models and then attempt to apply simulation and other computational techniques alongside empirical techniques to demonstrate the power of using such methods in combination.

In classic Carnegie Mellon University fashion, this dissertation is a collection of three papers. Each study has been published or submitted for publication in substantially the same form as presented here. Chapter 2, "Can Tools Help Unify Organization Theory," appeared in volume 13, issue 1 (March, 2007) of *Computational and Mathematical Organization Theory.* In this chapter, I survey 28 computational models created and used in organizational behavior research over the fifteen year period from 1989 to 2003. I link the characteristics of the simulation models to a work team effectiveness framework built on the classic contributions of scholars such Richard Hackman, Jim McGrath, Paul Goodman, and Susan Cohen and attempt to identify theoretical gaps in the present models and possible paths to their improved reconciliation with real group behavior. As empirical and laboratory work continues to add new understanding of group performance mechanisms, computational techniques can likewise instantiate this new knowledge in simulations with unprecedented richness. I explore why and how the complexities and implications of this richness can be investigated in complementary ways using improved computational models.

Chapter 3, "Who You Know vs. What You Know," originally appeared in volume 30, issue 1 (January, 2006) of the *Journal of Mathematical Sociology*. In this chapter, I attempt to put into practice the suggestion of Chapter 2 that empirical methods be combined with simulation to generate and explore the boundaries of theories that are difficult or practically impossible to test in field or laboratory settings. Using both qualitative and quantitative data on a software engineering group, I try to examine just how useful the traditional notions of social network centrality are in helping identify, understand, and even predict individual performance in a group. I compare those socially oriented network attributes – "who you know" – with knowledge and task oriented attributes – or "what you know." Conventional wisdom says that one's contribution to performance is all about "who you know, not what you know." However, my study indicates that knowledge dimensions are at least as important as social dimensions, if not more so, in determining individuals' contributions to group performance. Since knowledge and task capabilities may be more evident to managers when initially structuring teams, using knowledge-based approaches may help improve team performance.

While Chapter 3 focuses on one short-term project team, Chapter 4, "Opening the 'Black Box' of Group Learning" (currently under review for publication), examines effects of knowledge network attributes on performance of 118 ongoing work groups in multiple companies. Similar to Chapter 3, the analysis combines empirical data with network computational measures. However, rather than using simulation, Chapter 4 focuses on using computation in ways that extend the ability and essentially become a part of conventional empirical methods. One limitation to the scientific acceptance of computational methods has been its general restriction to generation of theory rather than testing it. By infusing computational techniques into empirical methods, theory can be tested and not merely generated.

Chapter 4 is somewhat ambitious in attempting to introduce, develop, and test a new theory that seeks to provide one of the first glimpses inside the 'black box' of organizational learning. Organizational learning is an exciting and useful way of thinking about organizations because the learning perspective presents a motion picture of performance rather than the more typical collection of snapshots provided in field and lab studies. "Learning" is simply change that occurs over time in response to collective experience. As such, it captures the essence of organizational adaptation. The same kind of learning behavior has also been found to occur at the group level, but despite impressive evidence of learning across many different types of organizations and groups, the "how" and "why" are still fairly open questions.

One reason that the 'black box' has been so difficult to open is that it is notoriously hard to collect the large amounts of data needed in the requisite longitudinal analyses. To make matters even more difficult, large datasets with minimal missing data are required for conducting any type of social network research. Fortunately, computational methods can help in two ways. First, as in Chapter 4, computational techniques can be blended with conventional statistical methods to ground the analysis in current and proposed theory by testing empirical associations between collective experience, network characteristics, and group performance. Then, as outlined in Chapter 5, "Future Research," empirical analyses can be further extended by using simulation to investigate dynamic interactions of multi-dimensional variables such as experience, network attributes, and performance over time.

In Chapter 4, I theorize that a group's ability to learn – that is, its ability to change its performance in response to its collective experience – depends in part on the level of "transactive memory" in the group. Transactive memory is the relative level of "who knows who knows what" in a group and thus combines elements of group communication and perception of expertise among group members. It is probably the nearest thing to a "group brain" or "group memory" that has been identified in the literature on organizational psychology. There are two parts to my formal theory. The first posits that the amount of transactive memory partially mediates (or explains) the "learning process" – that is, the link between collective group experience and group performance. This element of the theory generalizes ideas first proposed by Liang, Moreland, and Argote (1995) that training of people in groups is more effective than training them individually. Their work found that the effectiveness of *group* training was greater because more transactive memory developed during the training period and carried over to the group task. My theory generalizes this finding by hypothesizing that it is not merely training but *all* collective group experience that results in greater group transactive memory and that these increases in transactive memory partially explain the very existence of resultant adaptations of group performance.

The second part of the theory is that the *network structure* of group transactive memory regulates the extent to which the amount of memory mediates the learning process (the link between collective experience and current performance). In particular, I propose that the strength of the mediating relationship depends on the extent to which group transactive memory is structured as a “small-world” network. The idea behind small-world networks was first hypothesized by social psychologist Stanley Milgram in his 1967 study that suggested that any two random people in the U.S. were connected on average by a chain of only six acquaintances (later popularized as “six degrees of separation”). Subsequent research has found that naturally evolving networks such as those in the human brain exhibit such properties as well.

Small-world networks are remarkably efficient. They are characterized by many small sub-networks in which elements are densely connected. Those sub-networks in turn are connected to other sub-networks through fewer or weaker connections. The dense connections within those small sub-networks form clusters of elements that facilitate promotion or exploitation of particular group attributes (such as friendship, gender, affiliation, etc.) or capabilities (such as knowledge or task proficiency). At the same time, the connections *between* the sub-networks (or clusters), although fewer, enable efficient reachability between sub-networks and help enhance the performance and extend the capability of the entire network. Thus, even as networks explode in size – as in the case of even a small group of people and their perceptions of other group members’ differing degrees of knowledge needed for their group task, the efficiency of the network can remain very high. Small-world transactive memory networks apparently enable groups to maximize effectiveness of organizational memory even as the group grows and accumulates richer bodies of knowledge without the burdensome need for every member to be connected to every other member.

The empirical analysis of "moderated mediation" in Chapter 4 supports both hypotheses suggested by the two-part theory. The amount of group transactive memory mediates the link between collective group experience and current group performance, suggesting that transactive memory is a critical mechanism of group learning. Moreover, when the structure of group transactive memory more closely resembles that of a small-world network, transactive memory's mediation of the group learning process is stronger. The chapter concludes with an extensive discussion of implications of the findings for practical management concerns such as turnover and extensions of the theory to organizational, inter-organizational, and even societal levels.

Finally, in Chapter 5, I present a specific plan of future research designed to extend the results of Chapter 4 using simulation techniques introduced in Chapters 2 and 3. I present a plan for calibrating and validating the requisite simulations, creating simulation-induced longitudinal data, and then using the data in a log-log-regression model of group learning curves. Thus, future scholars will hopefully be able use the proposed approach to build on the implications for theoretical and computational research offered throughout this work.

2

Can Tools Help Unify Organization Theory?
Perspectives on the State of Computational Modeling

2.1 Introduction

Work is central to every aspect of modern life. What we "do for a living" influences not only government policy, community norms, and economic status but also our individual self-esteem, social activities, and even seemingly unrelated decisions such as when to marry and if and when to have children (Hulin, 2002). The usual environment for work is some form of organization, ranging from companies, where people are linked as employees engaged in activities supporting profit or welfare maximizing motives, to an array of other organizational forms, such as families, communities, religious groups, and even nation states, where connections between people are based not only on sustainability or economics but also on genetics, social identity, or concern for promoting the welfare of its members. However, despite the pervasiveness and critical importance of organizations to society and individuals, organization science remains a relatively low-consensus field with multifarious and yet less unified paradigms than other scientific disciplines (Hartman, 1988; Aldrich, 1992; Mone and McKinley, 1993; Donaldson, 1995; Pfeffer, 1993, 1995; Van Maanen, 1995a, 1995b; McKelvey, 1997). Economists have a coherent body of theory underlying their understanding of the market transactions or contractual mechanisms that motivate organizations, but management scientists still struggle to provide an integrated theoretical rationale for the complex behavioral, cognitive, and attitudinal aspects of those same organizations (Simon, 1991). To understand why this is so, we must look to the core of the types of organizations considered in this study – human beings.

Notwithstanding the existence of automata, avatars, and agents, organizations are principally comprised of human agents who contract tacitly or explicitly for an exchange of some degree of authority or autonomy for compensation, social identity, preservation, or other objectives of enlightened self-interest. Comprised thusly of *human* agents, organizations, from the simplest of partnerships to the most intricate of international corporations, reflect not only the richness, complexity, variation, chaos, and beauty of human behavior but also its seeming defiance of theoretical conformity. We should not be astonished then why predicting or even understanding organizational behavior is indeed daunting. Nor should we be astonished by the multitude of partial theories of group and organizational behavior, which, although insightful and stimulating, fall well short of theoretical unity or even harmony in many instances (Miner, 2002).

It is precisely this state of affairs that motivates my review of computational organizational models. In the domain of computational modeling, ideally any number of theories can be fused and tested using the touchstone of simulation modeling, enabling researchers to represent the reality of human complexities to the extent necessary to establish robustness. Ultimately, as empirical and simulation findings continue to feed a growing foundation of complementary constructs, such computational modeling capability offers the promise of linking desultory theories of behavior of individuals, groups, organizations, and groups of organizations into a more unified body of theory of organizational behavior (Masuch and LaPotin, 1989). In this review, I examine twenty-eight organizational simulation models developed over the past fifteen years. I first introduce a framework for organizational simulation modeling that will guide the analysis of the reviewed models. Then, based on the resultant nomological construct, I discuss the models and their contributions to understanding organizations and their effectiveness. Finally, I suggest a research agenda for extending the application of computational modeling toward the goal of integrating and ultimately unifying theories of organizational behavior.

2.2 Model Selection Process

Simulation models included in this review span the period from 1989 to 2003. To select models, I first searched general, business, psychology, interdisciplinary, social science, and dissertation abstract databases using the primary terms *simulation*, *model,* and *expert system*, in conjunction with numerous antecedent and secondary terms such as *computer*, *computer-based*, *computational*, *system dynamics, agent-based,* and *multi-agent*. This initial sweep yielded several hundred abstracts, from which I ultimately chose models introduced in twenty-nine peer-reviewed journal articles. The selection rules specifically required that models (1) focus on *human* organizations and networks (i.e., no robotic or avatar-based interactions except as part of overall human systems), (2) inculcate theory at a level at least as aggregate as individual behavior (i.e., no biological or chemical level models), (3) enable investigation of multiple aspects of individual, group, and inter-group behavior (i.e., models that extend beyond a single-purpose use for testing an existing theory, as in the case of Repenning's (2002) exemplary yet limited application of system dynamics to the investigation of innovation adoption). An additional condition I applied for inclusion is that the code for the models be publicly available or identifiable based on publicly available information. Despite the rigorous identification methodology, the twenty-eight models reviewed are not necessarily intended to be "exhaustive." I nevertheless believe the selected models are widely representative of organizationally oriented simulation systems introduced over the 1989-2003 period and will thus form a reasonable basis for providing perspectives on the present and future states of computational modeling.

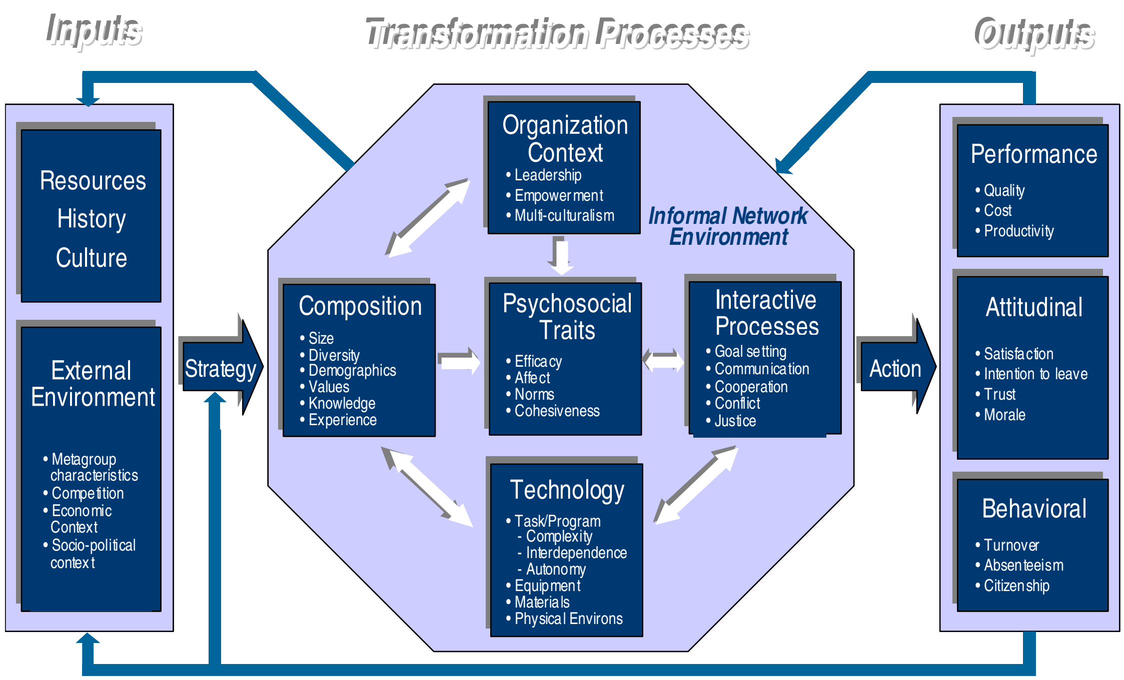
2.3 Definitions

Organizational Simulation Model. I define an organizational simulation model as a type of Turing machine in which the discrete-state machine represents performance of a group of two or more individuals interacting to achieve a common goal. Inputs and outputs are combinations of physical, behavioral, and cognitive characteristics of the individuals and groups comprising the organization. State transitions are described by empirically based associations or mathematical relations founded on existing and proposed theory.

Organizational Simulation Framework. Rather than simply reporting on models and their capabilities, one of my aims is to understand the state of computational organization modeling in the context of theories of organization and organizational behavior. To do so, I require a framework for modeling organizational behavior against which I can measure the coverage of respective models reviewed in the study. I take this approach in recognition that the scientific standards applicable to a good mathematical model also apply to simulation. Such standards dictate that a sound model (1) provide categories of assumptions so that insights and intuitions can be transferred from one context to another and cross-checked between different contexts, (2) allow insights and intuitions to be subjected to tests of logical consistency, and (3) establish the ability to trace back from observations to underlying assumptions to see which assumptions are really at the heart of particular models (Kreps, 1990). Thus, the review is organized around components of a heuristic model of organizational effectiveness that integrates and extends earlier effectiveness frameworks introduced by Hackman and Morris (1975), Nieva, Fleishman, and Rieck (1978), Nadler and Tushman (1980), Hackman (1983), McGrath (1984), Gladstein (1984), Goodman (1986), Sundstrom, DeMeuse, and Futrell (1990), Cohen and Bailey (1997), Marks, Mathieu, and Zaccaro (2001), and Ashworth (2005).

As shown in Figure 2.1, the framework has fifteen constructs, categorized as "Inputs" (Resources, History, Culture, and External Environment), "Transformation Processes" (Composition, Organization Context, Psychosocial Traits, Technology, Informal Networks, and Interactive Processes), "Outputs" (Performance, Attitudinal, Behavioral), and "Linkages" (Strategy and Action). The framework embeds individual characteristics, described by "Composition" attributes, within the group or organization-level transformation processes. Transformation processes represent the means by which strategy translates organizational inputs into meaningful action resulting in performance, attitudinal, and behavioral outputs. Results of both transformation processes and outputs have feedback impacts on inputs and the processes themselves. Performance outcomes range from *objective* measures – such as efficiency, cost, productivity, quality, safety, errors, or customer service – to *perceived* measures of those same dimensions. "Perceived" performance outcomes measure how organizations and organizational units appear to work together, including the perceived level of integration of social identity groups (by gender, age cohort, or role, for example) and the perception of overall team functioning. Examples of attitudinal outcomes are job satisfaction, worker morale, turnover intentions, change resistance, and commitment. Behavioral outcomes range from absenteeism and turnover to communication patterns, innovation, and learning.

Figure 2.1. Organizational Simulation Framework.



I represent organizational design elements in a multi-dimensional construct encompassing technology, composition, and organizational context. I further break down each construct into specific sub-categories in order to surface more explicit distinguishing factors of organizations (Kozlowksi and Bell, 2003). For example, I disaggregate technology design into variables representing task (complexity, interdependence, and autonomy) and non-task technology (equipment, materials, and physical environment). The composition construct is disaggregated into sub-categories that include individual characteristics such as personality, values, knowledge, experience, and tenure, and group and organization level characteristics such as size, demography, and diversity. Similarly, organizational context includes representations of leadership, empowerment, and multi-cultural influences.

With respect to group and unit-level processes, I define categories for cooperation and communication variables in both internal and external contexts as well as separate group goal-setting and organizational justice variables. Cooperation encompasses processes such as conflict resolution, collaborative decision making, and reflexivity. Communication broadly includes processes that facilitate social and cognitive information sharing. Following Cohen and Bailey (1997), I differentiate psychosocial variables as group and division-level constructs such as efficacy, affect, norms, cohesiveness, and cognition. Collective efficacy is an expression of a group's confidence in working together in general, while group affect is a measure of consistent or homogeneous affective reactions in a group (George, 1990). Norms are tacit understandings or implied agreements of how group members should behave under certain conditions, and cohesiveness reflects the level of shared identity in a group or the extent to which members of a group view themselves as a group. Group cognition encompasses group learning processes, shared mental models, and group transactive memory (Wegner, 1986). Finally, the framework incorporates environmental factors as a distinct construct that broadly encompasses industry characteristics, competition, and economic context.

2.4 Analysis

The analysis approach consisted of first identifying factors that could be used to characterize the capabilities of each model surveyed. I distinguished 245 such "capability evaluation factors" representing the following categories:

- *Range of permissible organization designs*. This category distinguishes models that represent one or more forms of organization design. *Hierarchies* are defined as pyramidal arrangements of formal authority with relations descending stepwise from the top to the bottom of an organization (March & Simon, 1958). *Networks* are non-hierarchical forms of organization that evolve as interconnections of individuals engaged in reciprocal, preferential, mutually supportive actions (Powell, 1990). A *team* is a set of two or more individuals working in an interdependent fashion toward a shared and meaningful goal (Urban *et al*., 1996). Any organizational form in which personnel may be assigned both to a functional role and a product or project-specific role is a *matrix* form of organization (Galbraith, 1977). Other distinctive types include more specific forms of teams (such as autonomous or self-directed teams) and bureaucracies, which combine hierarchy with codified rules of conduct, labor specialization, and impersonal cultures (Weber, 1968).

- *Range of permissible entities*. An entity is something that is known or perceived to have its own distinct existence, whether animate or inanimate, physical or conceptual. Agents are animate entities that include people and groups of people (teams, companies, units, etc.) as well as inanimate entities such as robots, avatars, intelligent agents, and web-bots. Conceptual entities include knowledge, physical and financial resources, and tasks.

- *Range of Actions*. Actions are results of transformation processes and represent how entities engage, such as moving, lifting, thinking, or achieving a group goal. Actions have effects measured as performance, behavioral, and attitudinal outcomes.

- *Organizational performance measures*. Performance measures are defined in the same way as the simulation framework in Figure 2.1.

- *Entity and environment characteristics*. This group of evaluation factors distinguishes models by the maximum numbers of entities that can be simulated simultaneously. In addition, this category examines the extent to which characteristics of the organization's environment can be reflected in each model. This includes determining whether models instantiate the organization's strategic objectives, internal and external cooperation, environmental complexity, and socio-political contextual factors.

- *Agent characteristics*. Agent characteristics focus on demographic, psychographic, and cognitive capabilities of agents.

- *Agent behavioral attributes*. Behavioral attributes encompass psychosocial traits such as efficacy, task-orientation, and affect as well as outcomes such as citizenship behavior and absenteeism.

- *Agent cognitive attributes*. Cognitive attributes include capabilities, skills, knowledge, memory (including "forgetting"), and ability to plan ahead. In addition, this category examines the extent to which models incorporate learning from experience (including training, task repetition, and knowledge transfer).

- *Task characteristics*. Task characteristics describe whether tasks are assigned by managers, self-assigned, or "fixed" (pre-programmed, as in the case of an avatar). In addition, other task attributes incorporated in some models include interdependence, complexity, and physical layout.

- *Informal and formal network representation*. Network representation factors indicate the extent to which models represent connections and relationships between entities. This includes social and communication networks (agent-to-agent), knowledge networks (agent-to-knowledge), task assignment networks (agent-to-task), and networks of relationships between other types of entities.

- *Network evolution functions*. These capability evaluation factors indicate the dynamic capability of a model to evolve informal and formal networks over time.

- *Internal processes*. Other interactive processes not included in previous categories are indicated in this set of capability evaluation factors. These include processes of enculturation, innovation, recruitment, dismissal, and goal/reward determination.

- *Communication characteristics*. Lastly, the communication category indicates whether models explicitly distinguish between various forms of communication, such as personal (one-on-one) communication, email, avatars, or telephone.

Table 2.1. Simulation Models Included in Review.

Model	**Reference**
Double-AISS	Masuch & LaPotin (1989)
Construct	Carley (1990a, 1991a)
ELM	Carley (1990b, 1991b, 1992)
OrgCon	Baligh, Burton & Obel (1990, 1994)
Cultural Transmission	Harrison & Carroll (1991)
Social Exchange	Macy (1991)
HITOP-A	Majchzrak & Gasser (1992)
Plural-SOAR	Carley, Kjaer-Hansen, Newell & Prietula (1992)
CORP	Carley & Lin (1993, 1995)
SimVision	Levitt *et al*. (1994)
TASCCS	Versagen & Masuch (1994)
Action	Majchrzak & Finley (1995)
DYCORP	Lin & Carley (1995)
Radar-SOAR	Ye & Carley (1995)
TacAir-SOAR	Tambe *et al*. (1995)
Orgahead	Carley & Svoboda (1996)
Sugarscape	Epstein & Axtell (1996)
TAEMS	Decker (1996, 1998)
STEAM	Tambe (1997a, 1997b)
Blanche	Hyatt, Contractor & Jones (1997)
CASCON 4	Bloomfield & Moulton (1997)
Brahms	Clancey, Sachs, Sierhuis & van Hoof (1998)
Team-SOAR	Kang, Waisel & Wallace (1998); Kang (2001)
Trust Me	Prietula (2001)
Construct-O	Carley & Hill (2001)
NK Fitness	Levinthal (2001)
Construct-TM	Carley (2002)
VISTA	Diedrich *et al.* (2003)

As summarized in Appendix A, each capability evaluation factor was then mapped to one of the fifteen constructs in the organization simulation framework (Figure 2.1). Based on publicly available information, the capabilities of each of the twenty-eight models (Table 2.1) was coded according to the models' coverage of the theoretical constructs in the framework. For all models, I then calculated simple indices representing the proportion of actual capability evaluation factors covered to the total possible. Group indices for input, process, and output-related constructs are depicted in Figures 2.3 and 2.4. To obtain the estimated coverage indices reported in Figure 2.5, I averaged the values across all models for each construct.

Evolution of Simulation Types. Simulation models in the review are grouped into three broad categories according to simulation type: agent-based models, expert systems, and mathematical models. As shown in Figures 2.2a, 2.2b, and 2.2c, while there has been a similar pattern of growth between model types, agent-based models now outnumber other types and are growing at a faster rate; in addition, agent-based simulations have the greatest representation of network structures. Networks are used to characterize not only social relationships but also organizational roles, communication linkages, advice relationships, tasks, knowledge, and resources. Among the models surveyed, a wide range of organizational structures is represented, from hierarchies and bureaucracies to networks and nation-states. The most prevalent type of structure is team-based, with fairly even focus on both traditionally managed and autonomous teams.

Evolution of Dynamic and Cross-Level Capabilities. Models are generally limited to focusing on one level of analysis. However, some models simulate two or more levels (e.g., ELM, TASCCS, DYCORP, STEAM), with linkages defined as one or more performance or decision making outcomes communicated from one level to another. One model, OrgCon, theoretically permits investigation of the effects of an unlimited number of levels; however, the measure is incorporated, as are other measures in such rule-based systems, as a set of ranges reflecting varying levels of influence of complexity or hierarchy on other organizational design variables. Time is generally defined in the form of generic Markovian "time steps," with linkages to normative or positive scientific interpretation completely dependent on the time frame of the inputs provided by the modeler. Thus, most models offer a means of construing time on a relative basis between simulations in a given study rather than on an absolute basis for making time-based predictions.

Figures 2.2a-c. Growth in Simulation Models by Type. (Lightly-shaded region represents percentage that is network-based.)

Figure 2.2a. Multi-Agent Models.

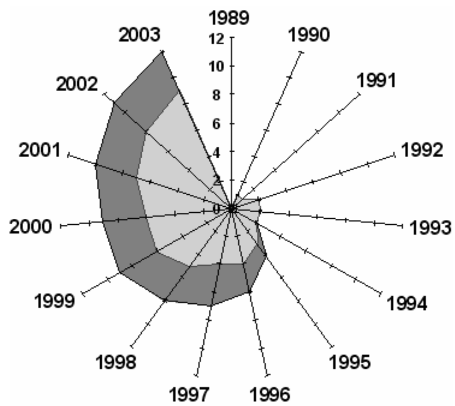


Figure 2.2b. Expert Systems.

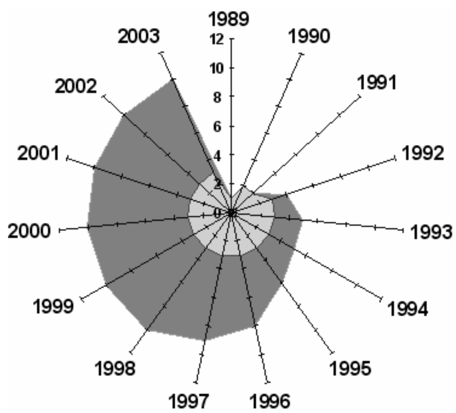
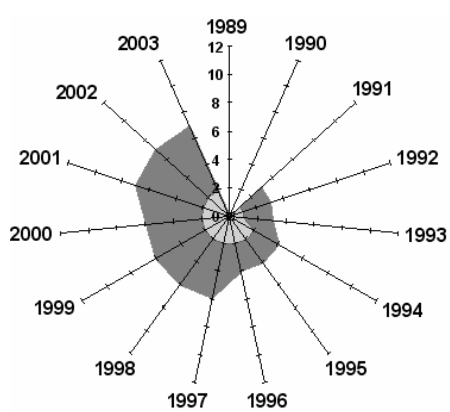


Figure 2.2c. Mathematical/System Dynamics.



Evolution of Multi-Theoretic Designs. While all models instantiate one or more bodies of theory as an analytical foundation, applications of models generally fall into two broad categories – theory-building and situational simulation. Theory-building models (e.g., Table 2.2) pose and test new theory based on results that emerge based on interactions of existing theory. Situational simulations (e.g., Table 2.3) apply existing theory to situations typically unsuited to empirical investigation to validate theory under those conditions. Both theory-building and situational simulations are useful for examining robustness of propositions under scenarios in which some or all key independent variables are changed.

Table 2.2. Examples of Theory-building Models.

Theory Domain	Representative Models
Organization Design	Double-AISS CORP SimVision Orgahead NK Fitness
Organization Change	Construct
Enculturation	Cultural Transmission SugarScape
Cooperation	Social Exchange
Gossip	Trust Me

Table 2.3. Examples of Situational Models.

Situational Domain	Representative Models
Tailor Shop	Construct
Airlines	OrgCon
Manufacturing	ACTION
Warehouse Order Picking	Plural-SOAR
Petroleum Refining	SimVision
Radar Detection	Team-SOAR
Air Combat	TacAir-SOAR
Hospital Scheduling	TAEMS
Border Hostility	CASCON 4
Urban Threats	VISTA

As shown in Table 2.4, the range of theory encompassed by the surveyed models is dominated by socio-technical (Emery and Trist, 1960) and structuration (Giddens, 1986) theories, although the focus of such models is on simulating the *interaction* of people, task, and technology rather than on *optimization* of their social and technological outcomes. Not surprisingly, most of the socio-technical models also incorporate social network representations of actors. Closely aligned with socio-technical approaches are models incorporating contingency theory. These models are concerned less with agent-specific behavior and more with aspects of design that are predicated on factors such as differing levels of formalization, centralization versus decentralization, and proactive versus reactive planning time horizons.

Table 2.4. Underlying Theories of Reviewed Models.

Underlying Theory	**Representative Models**	
Socio-Technical Theory Structuration Theory	Double-AISS Construct ELM Brahms HITOP-A	CORP ACTION Orgahead DYCORP VISTA
Artificial Intelligence Theory	Double-AISS Plural-SOAR TASCCS	Radar-SOAR STEAM Team-SOAR
Organizational Information Processing Theory	SimVision Trust Me Brahms	Orgahead Construct
Contingency Theory	OrgCon CASCON 4	NK Fitness
Evolutionary Theory/Population Ecology	Cultural Transmission Sugarscape	NK Fitness
Joint Intentions Theory	STEAM	
Dynamic Phase Conflict Model	CASCON 4	
Social Learning Theory	Social Exchange Model Trust Me	STEAM

Models based on socio-technical systems approaches are cybernetic and constructivist in nature, seeking to balance technology and task in a context of socially shared meaning. In contrast, models based on artificial intelligence (AI) theory presume that knowledge alone, rather than having a social dimension, is a commodity and that the application of such knowledge is in fact the true expression of intelligence (Minsky, 1967). Thus, models such as TASCCS (Verhagen and Masuch, 1994) and STEAM (Tambe, 1997a, 1997b) instantiate agents with decision logic oriented around agents' respective skills, assigned tasks, memory, and mental models of other agents, enabling them to act and interact based on pre-programmed rules. The "task" of learning thus becomes a pre-programmed routine of reinforcing the agent's stock of knowledge based on responses the agent keeps in memory. AI models are particularly useful for exploring the actions of both human and technological agents engaged in highly standardized processes with protocols defined for as near to all conceivable situations as possible.

Still other models are based on evolutionary designs and population ecology, enabling simple agents to explore complex organizational search spaces based on genetic algorithms or relatively simple sets of rules for death and regeneration. These models tend to be more intellective in nature and are thus powerful for theory-building but less useful for situational emulation. Models incorporating more specific theories, such as joint intentions theory and social learning theory, tend to represent their premises in combination with broader theories such as contingency theory and general artificial intelligence. These models' unique additions extend the detail with which models can address goal and outcome interdependence as opposed to simple task interdependence.

2.5 Discussion

While I recognize that the idea of a unified body of theory of organizations is epistemological in nature, and that establishing the capability to simulate the behaviors of organizations in increasing detail may no more lead to such unification than the present panoply of partial theories, I nevertheless believe that such ideas and attempts to model those ideas are worthy goals (Hulin and Ilgen, 2000). Hence, the calculations of indices of coverage of the simulation framework (Figure 2.1) are intended less as absolute measures than as indicators of the richness and vastness of organizational behavior yet to be integrated. Based on these calculations, as Figure 2.3 indicates, there is a discernible if variable trend upward in the coverage of inputs, processes, and outputs in the framework. The coverage indices of most models cluster in the 5 to 15 percent range, with a few reaching the 25 to 35 percent levels.

Figure 2.3. Coverage indices of models in chronological order, 1989-2003.

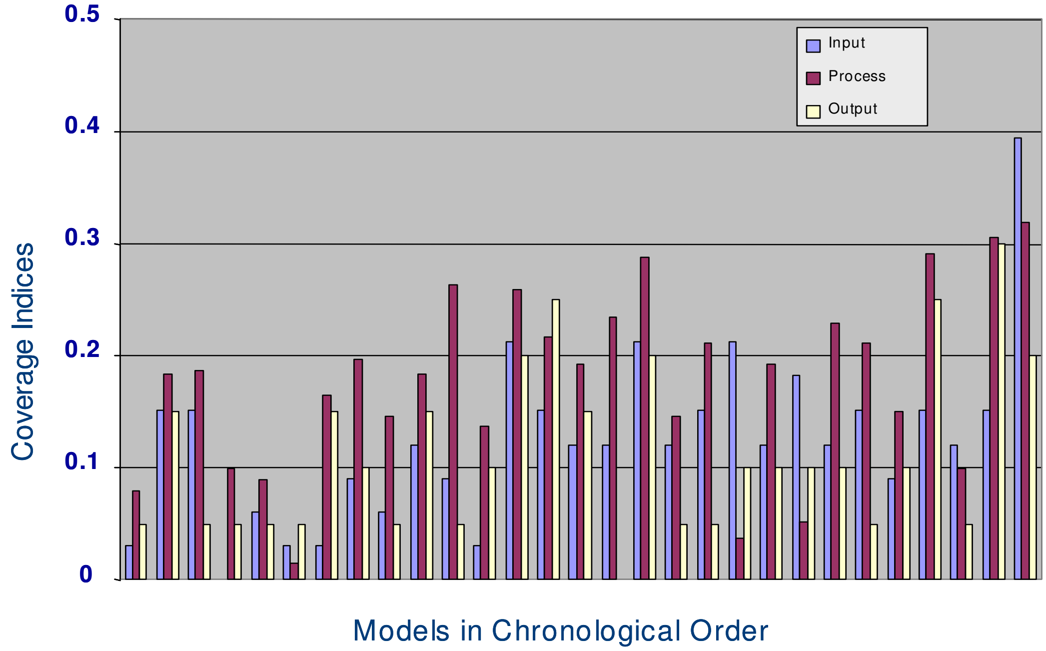
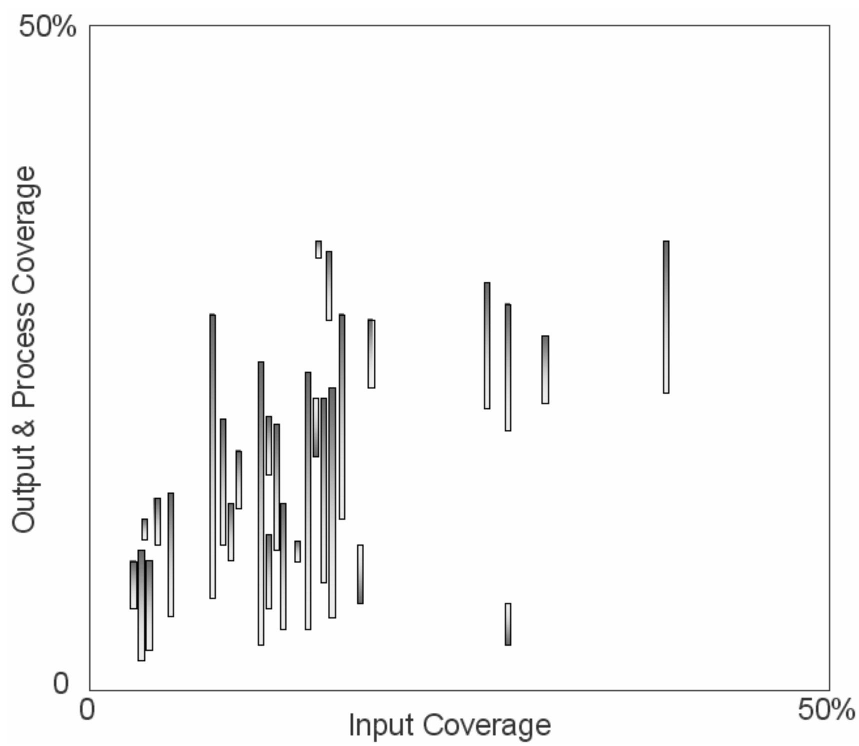


Figure 2.4. Input versus Process (dark spectrum) and Output (light spectrum).



As Figure 2.4 shows, the richness of simulation models has increased over the review period. Representation of processes tends to dominate input and output coverage, indicating that existing simulations focus primarily on transformation factors such as group composition, technology, communication, and cooperation. Somewhat surprisingly, output coverage is generally superseded by both input and process representation. Most models focus on some aspect of performance or productivity, with little or no attention to behavioral and attitudinal measures. Future research should increase the incorporation of attitudinal and behavioral outcomes in models, along with dynamic feedback of those outcomes to input and process variables.

Figure 2.5. Simulation Framework Scorecard (0-100 scale).

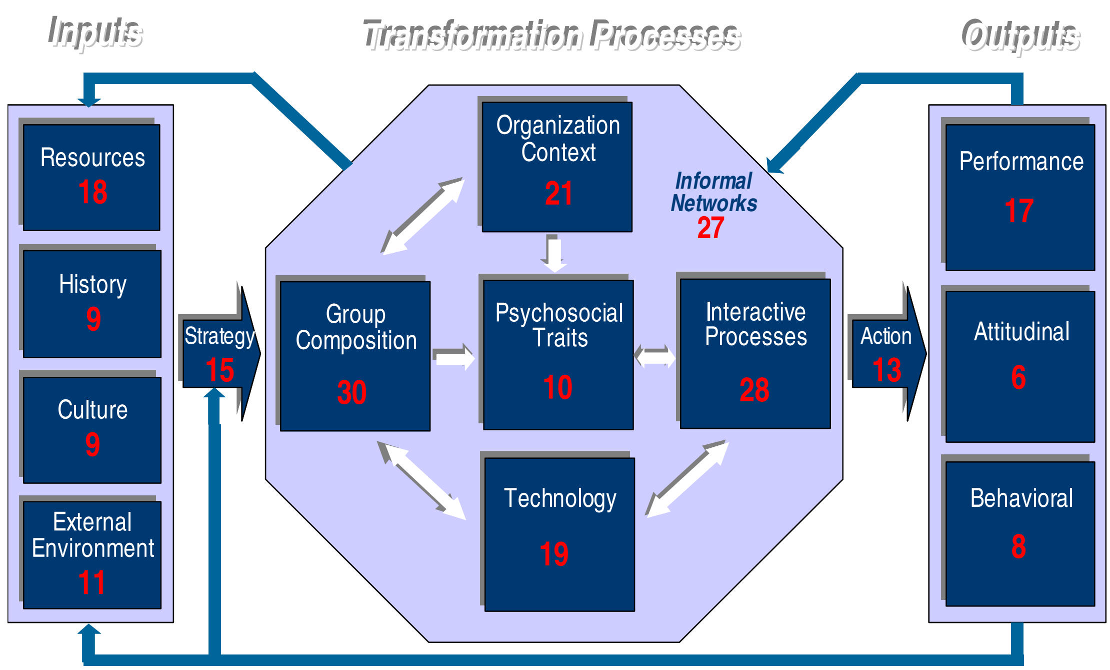


Figure 2.5 summarizes average coverage of the simulation framework across all surveyed models and provides a scorecard value for each construct in the framework. Given that despite its theoretical grounding the framework is arguably much less than 100 percent representative of organization theory, the coverage estimates are clearly biased on the high side. Thus, the analysis reveals there is much ground to cover in

integrating existing theory using computational approaches. While most models exhibit fairly low coverage of the simulation framework, even models with richer feature sets tend to have similar underlying theories and cover many of the same types of factors in the simulation framework. Thus, if there is a road to "unification of theory," it clearly is not one of merely adding or integrating multiple models together. Rather, the range of underlying theory must expand beyond the fractional and mechanistic to the holistic and emergent. Just as understanding biological evolution requires less about what atoms themselves are made of and more about how they behave in chemical and physical networks, discovering more unified laws of organizational behavior will only result from understanding how sundry partial theories of organization interplay at each level in complex networks of people, resources, tasks, knowledge, and technology. Future research should examine the appropriate range of theories further, refining the unified simulation framework ultimately with a level of dependent, independent, and control variables that fosters the study of both integrative and emergent organizational behavior irrespective of the specific goals of the simulation.

2.6 Conclusion

As far back as 1978, Chris Argyris identified "the principal challenge to present-day organization theory is to invent a productive synthesis of fragmentary approaches" (Argyris, 1978, p. 331). Over 25 years later, theories of organization behavior seem to have become *more* rather than less fragmentary (Miner, 2002, 1982). Somewhat disappointingly, the state of organizational simulation modeling has not helped create such synthesis, instead continuing to reflect classical approaches to empirical studies. Mere automation of classical approaches, while enabling organization scientists an additional tool for corroborating and testing relationships between restrictive sets of variables, leads to the same partial theories that result from very empirical and experimental methods underlying those approaches. Although this result is not a poor one, it is certainly one that deprives researchers of the broader capability of computational modeling to integrate bodies of theory that would be impossible to combine otherwise, enabling exploration of unforeseen emergence and identification of new, more unified theory. Thus we must persist in widening the boundaries of simulation modeling beyond the present state of mirroring empirical limitations. Yet, to do this, simulation models themselves must adopt improved theories of computation and applications of existing computer science to enable them to take full advantage of their ability to process complex interactions of increasingly human-like agents. In addition, simulations must widen their boundaries with respect to organizational behavior by incorporating broader empirical grounding synthesized with computational approaches such as network algorithms, structural equation methods, system dynamics, and constraint satisfaction modeling. Consequently, as computer science and simulation methods alike continue to advance, computational organization science may very well have opportunities for making lasting contributions to the development of a unified body of organization theory.

3

WHO YOU KNOW VS. WHAT YOU KNOW
SOCIAL POSITION, KNOWLEDGE, AND PERFORMANCE

3.1 Introduction

Teams require the right combination of personalities, capabilities, and knowledge to achieve maximum effectiveness, but organization charts and personnel evaluations notwithstanding, critical contributors to a team's performance are far from obvious (Prietula and Simon, 1989). This situation arises because work groups are comprised not only of people and their individual behaviors but also of the cultural backgrounds, skills, education, financial and physical resources, and other distinctive traits these "human capital endowments" bring to the organization (Becker, 1975; Mincer, 1970; Stewart, 2001). Social network theories suggest that the types and degrees of an individual's relationships in social and communication networks are key impactors of group performance, while resource dependency theory suggests that non-social factors such as knowledge and skill figure at least as prominently as social dimensions in determining such performance. My objective in this study is to investigate the relative ability of social network theory versus resource-based views to explain the criticality and performance of human capital at a team level in an organization.

In the following sections, I draw on some of the relevant research to provide my motivation and show how omy conjectures extend existing theories of individual productivity, group performance, and social networks. I then describe my theoretical propositions, propose a research methodology, introduce empirical data, and present specific results of the analysis. I conclude with a wider discussion of contributions, limitations, and opportunities for further research. Results provide the first empirical evidence that the extent of an actor's contribution to group performance is more related to the individual's knowledge and tasks than to the individual's position in the team's social network. From a practical standpoint, since objective evaluations of skills and knowledge can be conducted prior to team formation, as opposed to evaluations of social network positions well after teams are established, the measures and methodology offer useful approaches to structuring teams and predicting their performance.

3.2 Motivation

Several areas of organizational behavior literature stress the importance of human capital, including theories of power (Emerson, 1962), complexity (Perrow, 1984, 1986), resource dependency (Hickson, Hinings, Lee, Schneck, and Pennings, 1971; Wernerfelt, 1984), leadership (Graen, 1976), knowledge and learning (Carley and Hill, 2001; Hollenbeck, Ilgen, Phillips, and Hedlund, 1994; Hollenbeck *et al.*, 1995), and social and human capital (Coleman, 1988). While all of these perspectives are related, power and leadership in particular are clearly linked to knowledge and learning due to the fact that such power rests primarily on the control of resources possessing appropriate knowledge and skill (Leavitt, 1996; Mintzberg, 1983), but it is not clear whether social or knowledge factors matter more in determining individual contributions to team performance. Recent work by Ahuja, Galletta, and Carley (2003) found that individual centrality is a strong predictor of individual performance and plays a mediating role with respect to other performance factors such as functional and communication roles, but their study only indirectly incorporates knowledge. Kline and McGrath (1998) suggest that meeting objectives with high quality (accuracy) is the most important evaluative criterion for team performance, but their model fails to link team performance to social position or knowledge of individual actors. Other studies have established the importance of task-related knowledge and group familiarity (Hinds, Carley, Krackhardt, and Wholey, 2000; Littlepage, Robison, and Reddington, 1997), while still others have linked group performance to cognitive structures such as group experience and transactive memory (Carley, Kiesler, and Wholey, 1993; Liang, Moreland, and Argote, 1995), shared mental models (Espinosa *et al.*, 2002), and group "meta-knowledge" (Larsen and Christenson, 1993). Fleishman and Zaccaro (1992) offer a taxonomy that includes team resource distribution as a variable but do not extend their topology to a detailed assessment of team members' knowledge, skill, and task-based capabilities. Kiesler, Wholey, and Carley (1994) discuss the importance of coordination, structure, and communication in determining individual contributions to software team performance, but their work stops short of offering guidance on the relative importance of knowledge versus other factors (although the authors do suggest – as this paper attempts to illustrate – that such research should encompass both the social and the efficiency effects of team coordination). Literature on organizational learning shows the clear relationship of knowledge to organizational productivity (Argote, 1999; Levitt and March, 1988). In the work of Herriott, Levinthal, and March (1985) and Pisano, Bohmer, and Edmondson (2001), for example, differences in productivity across firms are linked to cumulative experience and initial competences of individual actors. Although these inquiries confirm that knowledge is a major determinant of team performance, they do not focus objectively on each individual's *ex ante* knowledge relative to social position.

In contrast to the literature on organizational learning, theories of social networks suggest that, while skills are one of many elements affecting team performance, such performance may be primarily dependent on the power and influence structure of the group's social network (Burt, 1992; Brass, 1984; Everett and Borgatti, 1999; Freeman, 1979; Jones, Hesterly, Fladmoe-Lindquist, and Borgatti, 1998; Krackhardt, 1999). The social network view posits that the contributions of individual actors within a team framework depend fundamentally on the relations between actors as opposed to actors' resources or knowledge (Burt, 1992). Indeed, in this paradigm, the relations themselves are productive resources (Coleman, 1988). The structural character of actors' social linkages with other actors, hence their social network positions, influence the extent to which they are economic producers (Granovetter, 1985; Lin, 2001). While individually and collectively insightful, such theoretic approaches subsume knowledge as a mediating factor while primarily emphasizing social, friendship, communication, and advice networks, thus failing to incorporate a more comprehensive and analytical view of other critical aspects of group performance such as education, skill, and experience.

Although existing literature does not explicitly compare the impact of social position and knowledge on team performance, research in both industrial-organizational psychology and organization strategy has established connections between individual and collective intellectual capital, firm strategic advantage, and organizational performance (Coff, 1997; Coff, 1999; Wernerfelt, 1984). For example, Goodman, Lerch, and Mukhopadhyay (1994) offer Thompson's (1967) framework as a means of explaining potential variation in the levels of individual contributions to organizational productivity, but their final analysis calls for more detailed empirical work to investigate facilitators and inhibitors of individual performance contributions.

Other research offers the notion of task criticality as a partial explanation of the link between individual actors' productivity and organizational effectiveness. Notably, Brass (1984) and Hinings *et. al* (1974) evaluate task criticality in terms of an actor's "non-substitutability" and the number of connections the actor has to other actors for inputs and outputs related to her or his task. Similar recognition of the importance of task and knowledge attributes in organization networks can be traced to Pfeffer (1981) and Mechanic (1962), with their concept of "irreplaceability," and to Crozier (1964), who emphasized task criticality in his analysis of an engineering group's performance in a French tobacco-processing plant.

The primary motivation for this paper is to build on these resource-based views by advancing theory at a finer-grained level on the contributions of individual knowledge to team performance. My motivation is predicated on the post-Weberian recognition that teams are comprised of individuals as opposed to mere placeholders (Goodman, 1998), the growing importance of skill and knowledge elements in modern organizations (Fullerton and Toossi, 2001), and the need to incorporate a dynamic understanding of those elements when seeking to fully understand and manage critical human assets (Senge, 1990).

To explore these facets more formally, I developed three propositions based on the implications of social network and resource dependency theories. Because social network theory does not explicitly incorporate task and knowledge dimensions except in a descriptive sense, following Brass's logic (1984) the theory may not always reliably link all critical actors to team performance. If such theory alone is relied upon to investigate employee contributions to performance, it may accurately identify actors who are key in terms of social connections but not necessarily key in terms of greatest performance impact. Conversely, the application of social network theory as a sole basis for linking individuals to group performance may lead to the identification of actors as critical when they may not be critical in terms of group performance impact. These types of errors are analogous in many ways to "false negative" and "false positive" statistical errors, and for convenience I shall refer to them as such throughout the remainder of the paper.[1] Thus, my first proposition is as follows:

> Proposition P1a: Social network theory alone does not reliably predict all critical human actors on a team as determined by their performance impact;
>
> Proposition P1b: Social network theory alone has an unacceptably high tendency to identify human assets as critical when they may not be.

The reliability and acceptability criteria for evaluation purposes are based on the area under the corresponding receiver operating characteristic (ROC) curve being greater than 0.80, which is generally considered to indicate good to excellent performance of a measurement test construct (Swets, 1995; Tape, 2002).

One of the primary corollaries of the central theme in this study is that resource-based views of knowledge and task relations in organizations are more reliable predictors of individuals' contributions to performance than those provided by social network theory alone. Accordingly, I further posit that

> Proposition P2: Knowledge elements of resource dependency theory can be used to identify critical human assets without unacceptably high levels of false negatives and positives.

[1] We use the analogy of Type I and Type II errors strictly for convenience in describing the efficacy of measures used to evaluate the hypotheses. We do not imply that existing theories are invalid because they exhibit false negatives. Instead, we are suggesting that while theories of organization science may reflect Popper's falsifiability criterion, those theories which can be shown to be consistently less falsifiable (viz., exhibiting consistently fewer false negatives or false positives) are arguably more robust.

Finally, I believe that it will be useful to examine whether both theories acting together can be relied upon to more accurately connect individual actors' contributions to overall group performance. Based on this premise, I propose the following:

> Proposition P3: A combined application of resource dependency and social network theories enables the reliable identification of critical human assets on a team.

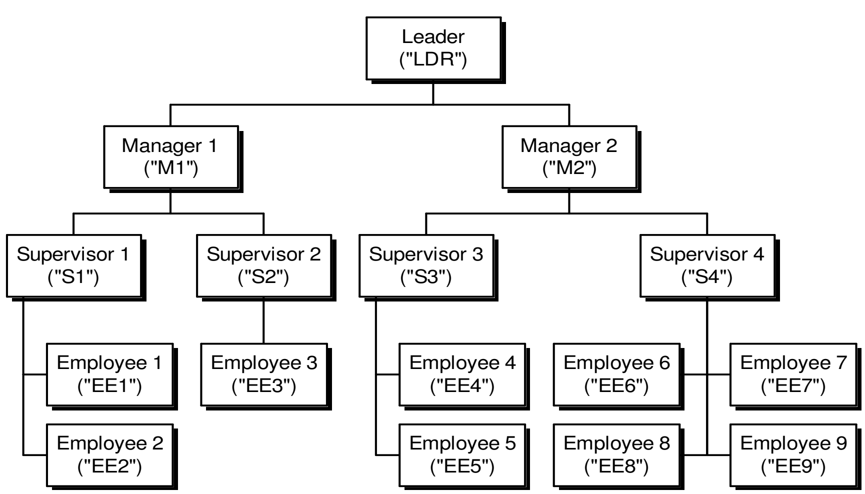
3.3 Method

To provide a realistic framework in which to evaluate these propositions, I first introduce data obtained from a high-tech firm focused on software development. Software development teams in general exhibit high levels of knowledge intensity (Kiesler *et al.*, 1994), making this data selection particularly relevant to my analysis. After describing the data set, I introduce the theoretical model and describe the steps in my research methodology.

Description of Data Set

The data I use for the study relates to a team of 16 information technology (IT) professionals responsible for the programming and implementation phases of a multi-phase IT development project. The team members' specific roles are summarized in

Figure 3.1. Software team organization.



Appendix B (“Actor Vector”) and Figure 3.1.

As shown in the organization chart, there is a leader (project manager), two assisting managers, four supervisors and nine employees, all with skills ranging from artistic design to specialized programming expertise. Since the company would not permit me to access private employee communication records or to conduct a formal social network survey, I faced a potentially vexing primary data problem in developing the social network matrix required for calculating traditional centrality measures. To address this problem, I applied a triangulation approach used successfully in a number of research disciplines (Benbasat, Goldstein, and Mead, 1987; Bonoma, 1985; Bredo and Feinberg, 1982; Jick, 1983; Maxwell, Bashook, and Sandlow, 1986; for more general treatments, see also Cook and Reichardt, 1979; Glaser and Strauss, 1967; Van Maanen, 1983; Yin, 1984), combining qualitative methods – including observation, interviews, and iterative data collection – with quantitative methods. Deriving the social network with such an approach both meets my present methodological requirements and offers a useful pedagogic tactic to the typical organization seeking to perform similar analyses but finding itself (whether for practical or policy reasons) in the similar position of not being able to conduct a more standard social network survey.

Hence, as the first step in modeling the social network, I conducted iterative interviews with key team leaders regarding task–oriented interaction patterns and asked them to provide their view of the team’s network of social interaction with an unvalued, bi-directional tie between actors A and B being defined as “A and B are observed communicating regularly throughout the day.” While “regularly” was subject to some interpretation, the distinction rested on the managers’ assessments of average frequency and duration of communications, with estimates tending to be relatively bi-polar (i.e., communications between two given actors were either comparatively high or low, with a “high” level indicating that a tie exists and a “low” level indicating that no tie exists between the actors). Given both the constant proximity of managers to team members and the open, low-divider work space design, such observations were easily made throughout the project, and, according to Krackhardt (1987), the social network view of actors with high betweenness but low in-degree values (such as project leaders with nonoperational roles) is a reasonable predictor of the true underlying cognitive social structure. To validate the managers' subjective assessment, we then collected data from project management and human resources department records and developed matrices associating actors by interdependent task assignment, team authority and community structures, and actor work station locations (proximity). According to theories of structural action (Burt, 1982) and physical proximity (Festinger, Schachter, and Back, 1950; Korzenny and Bauer, 1981; Monge *et al.*, 1985; Oldham, Cummings, and Zhou, 1995; Olson and Olson, 2000; Kiesler and Cummings, 2002; Monge and Contractor, 2003), these matrices should have significant correlation with the observed social network. Irrespective of the correlation values (as long as they are non-trivial), the correlations of the independent matrices to the social network matrix must be among those with the highest possible levels of correlation in order to be considered "significant." To test the null hypothesis that there is no correlation between the affiliation/proximity matrices and the underlying social network, I used the quadratic assignment procedure (Hubert and Schultz, 1976; Krackhardt, 1987) based on 10,000 Monte Carlo simulations. To avoid potential multicollinearity, I use the semi-partialling extension to the QAP method developed by Dekker, Krackhardt, and Snijders (2003).

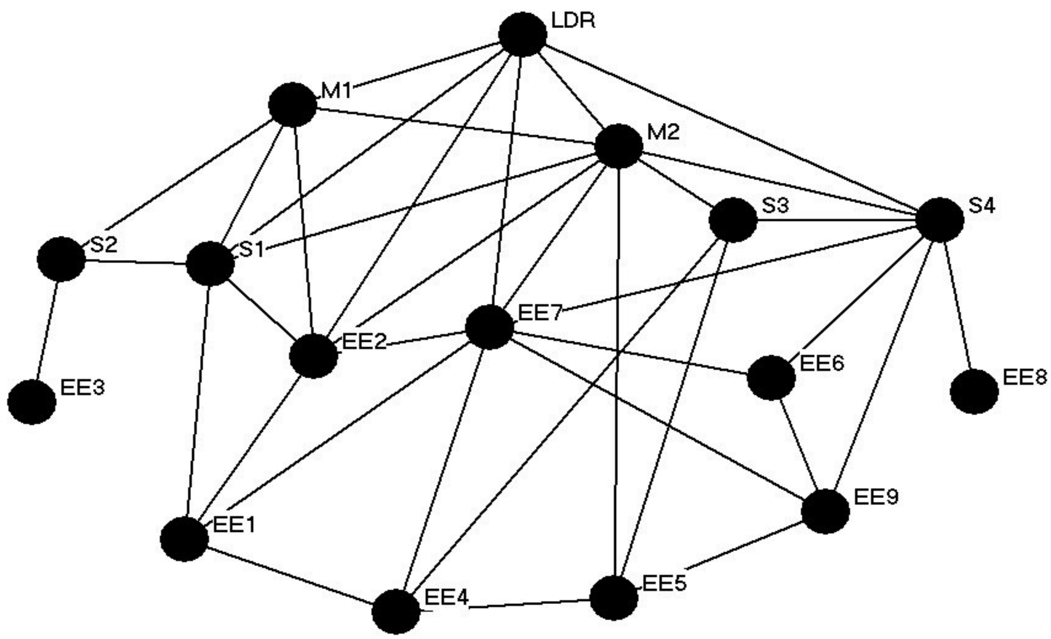
As Table 3.1 shows, the QAP p-values for the proximity, authority/community, and task assignment matrix predictors (Models 1 – 3) are statistically significant, with p values of 0.0023 and 0.0004, and 0.0140, respectively. When the social network is

Table 3.1. QAP Results and Significance Values.

Independent Variable (Predictor) Model	Pearson's r	% Higher (p value)
1. Proximity	0.296	0.0023
2. Authority/Community Structure	0.656	0.0004
3. Interdependent Task Assignment	0.221	0.0140
4. Proximity, Authority/ Community, Task Assignment	0.670	0.0001

regressed on all three predictor variables (Table 3.1, Model 4), the model is strongly statistically significant[2] and exhibits a reasonably high Pearson's *r*. Thus, I reject the null hypothesis that the observed social network identified by the managers is not significantly correlated to the independent predictor matrices. This conclusion provides reasonable assurance that the social network observed by the managers is free from significant random or systematic error. The team's resultant network of social ties is depicted in Figure 3.2.

Figure 3.2. Team social network.



After defining the social network, I identified skills, knowledge elements, and tasks of team members based on information provided by the company's human resources department and cross-validated by the technical division's knowledge management database and the team's formal project management plan (see Appendixes C and D).

[2] In the multiple QAP regression (Model 4), the coefficients of the proximity and authority/community matrices were significant at p=0.05 and p=0.001, respectively. The task assignment matrix, however, did not have a statistically significant coefficient (p=0.20) in the multiple regression. Since task assignment was significantly correlated with the social network matrix when considered standalone (Table 1, Model 3), the reduced significance in the combined regression indicates non-linearity in the multiple regression model.

Theoretical Model

After obtaining data on the software team, I developed a framework in which the data could be organized and evaluated computationally with respect to my investigation of individual actors' impacts on team performance. Building on the organizational meta-network concept (Carley, 2002b; Carley and Hill, 2001; Krackhardt and Carley, 1998), I defined the context of the analysis in terms of a linear algebraic meta-matrix relating the following primitives as depicted in Figure 3.3: people (actors), skills (including knowledge, experience and expertise), resources (physical or financial), and tasks. For purposes of this paper, I only use sub-matrices N, S_N, and T_N, all of which are assumed to represent fully connected, non-directional and dichotomous graphs (see Appendixes E, F, and G).

Figure 3.3. Generalized organization meta-matrix.

	People $n \in \{1, 2\ldots, \hat{n}\}$	Skill (Knowledge) $s \in \{1, 2 \ldots \hat{s}\}$	Resources $r \in \{1, 2 \ldots \hat{r}\}$	Tasks $t \in \{1, 2 \ldots \hat{t}\}$
People $n \in \{1, 2\ldots, \hat{n}\}$	**Social Network** $= N \equiv N_{\hat{n} \times \hat{n}}$ *Who reports to whom (authority network), who communicates with whom (communication network)*	**Skill (Knowledge) Network** $= S_N \equiv S_{\hat{n} \times \hat{s}}$ *Who knows what or has what skills*	**Resource Access Network** $= R_N \equiv R_{\hat{n} \times \hat{r}}$ *Who has what (physical or financial) resource*	**Assignment Network** $= T_N \equiv T_{\hat{n} \times \hat{t}}$ *Who does what*
Skill (Knowledge) $s \in \{1, 2 \ldots \hat{s}\}$		**Information Network** $= S \equiv S_{\hat{s} \times \hat{s}}$ *What informs what (what knowledge/skill is linked to other knowledge/skills)*	**Resource Adequacy Network** $= R_S \equiv R_{\hat{s} \times \hat{r}}$ *What knowledge requires what resource*	**Needs Network** $= T_S \equiv T_{\hat{s} \times \hat{t}}$ *What knowledge is needed to do that task*
Resources $r \in \{1, 2 \ldots \hat{r}\}$			**Substitution Network** $= R \equiv R_{\hat{r} \times \hat{r}}$ *What resources can be substituted for which*	**Requirements Network** $= T_R \equiv T_{\hat{r} \times \hat{t}}$ *What (physical and financial) resources are needed to do task*
Tasks $t \in \{1, 2 \ldots \hat{t}\}$				**Precedence Network** $= T \equiv T_{\hat{t} \times \hat{t}}$ *Which tasks must be done before which*

Social Position Measures

As proxies for comparing social network theory predictions of individual performance, I used traditional measures of degree centrality and betweenness centrality. Although the two indices may be correlated for some individuals (Bienenstock and Bonacich, 2002), they were selected because of their now canonical status (Bavelas, 1948; Freeman, 1979), their familiarity and accepted use (Ahuja *et al*. 2003), and their relative ease of computation for the software team used in our analysis. Accordingly, I introduce a Degree Centrality Index $CI_D(n)$ based on classical definitions of degree centrality (Proctor and Loomis, 1951; Freeman, 1979) as follows:

$$CI_D(n) = \left(\frac{1}{CI_D^{\max}}\right)\frac{\sum_{j=1}^{\hat{n}} N_{nj}}{\hat{n}-1} \tag{3.1}$$

Equation 3.1 states that the Degree Centrality Index $CI_D(n)$ for any actor n is the sum of 1's across row n of the social network matrix N (actor n's raw "degree" measure), divided by $\hat{n}$-1 and normalized by $1/CI_D^{\max}$ (the maximum value of $CI_D(n)$ $\forall$ n).

I similarly define a Betweenness Centrality Index $CI_B(n)$ (Anthonisse, 1971; Freeman, 1977; Wasserman and Faust, 1994) as follows:

$$CI_B(n) = \left(\frac{1}{CI_B^{\max}}\right)\frac{\sum_{j<n<k} g(j,n,k)/g(j,k)}{[(\hat{n}-1)(\hat{n}-2)/2]} \tag{3.2}$$

In Equation 3.2, the numerator represents the betweenness of actor n (that is, the number of geodesics, or "shortest paths," between j and k containing n, divided by the total number of geodesics between j and k), which is then divided by the total number of pairs not including n (to compute a raw betweenness value) and normalized by multiplying the raw value by $1/CI_B^{\max}$.

Knowledge-Based Measures

As proxies for comparison of knowledge and resource-based theories with social network theory, I extended and operationalized theories introduced by Mechanic (1962), and Dubin (1957) by defining three knowledge-based measures. The first, building on concepts of Brass (1984), Hinings *et al*. (1974), and Dubin (1963), is the Task Exclusivity Index (TEI), defined as

$$TEI_n = \frac{1}{TEI^{\max}} \sum_{t=1}^{\hat{t}} \alpha_t T_{N_{nt}} e^{(1-\overline{T}_{N_t})} \tag{3.3}$$

where $\overline{T}_{N_t} = \sum_{n=1}^{\hat{n}} \frac{1}{\beta_n} T_{N_{nt}}$ and $TEI^{\max}$ is the largest observed value of TEI_i. Parameters α_t and β_n are weighting factors for each task *t* and individual *n*, respectively, where $\alpha_t >$ 0 and $0 < \beta_n \leq 1$.

Brass (1984) recognized the importance of workflow criticality and proposed his conceptually similar "Transaction Alternatives" metric, which computes the number of different actors who can perform precedent and post-hoc tasks for each reciprocal task. Actors who exclusively perform such tasks are deemed more critical. Other than the fact that Brass's measure derives from survey and interview data, the main difference between my proposed task measure and Brass's is that his focuses primarily on such reciprocal tasks while mine generalizes to the entire set of task interdependencies as defined by Thompson (1967) and incorporates the inverse proportionality relationship between task uniqueness and task criticality (Dubin, 1963).

The TEI in Equation 3.3 essentially measures the extent to which each actor is the only one who can do certain tasks. The TEI is weighted toward unity for individuals who have one or more unique task assignments, with values associated with individuals with fewer unique tasks declining exponentially. A potential drawback of the TEI approach could arise if the task assignment matrix T_N is defined at such a granular level that every task is assigned to only one person, essentially reducing T_N to a unit matrix. Here, grouping of similar tasks may be necessary to obtain a meaningful assignment matrix.

Consistent with human capital measurement theory (Boudreau, 1997), my second measure, the Knowledge Exclusivity Index (KEI), builds similarly on the knowledge dimension:

$$KEI_n = \frac{1}{KEI^{\max}} \sum_{s=1}^{\hat{s}} \alpha_s S_{N_{ns}} e^{(1-\bar{S}_{N_s})} \tag{3.4}$$

where $\bar{S}_{N_s} = \sum_{n=1}^{\hat{n}} \frac{1}{\beta_n} S_{N_{ns}}$; $KEI^{\max}$ is the largest observed value of KEI_n; and α_s is a weighting factor for skill *s*. As in the TEI (equation 3), the KEI measures the extent to which each actor is the only one who possesses certain skills, knowledge, or expertise. Also similar to the TEI, the KEI is weighted toward unity for individuals who possess one or more unique skill or knowledge elements, with values associated with individuals with fewer unique skills declining exponentially. To avoid issues of granularity similar to those of the TEI, grouping of similar skills may be necessary to obtain a meaningful knowledge matrix S_N.

Extending Brass's (1984) and Hickson *et al.*'s (1971) notion of access exclusivity and Blau and Alba's (1982) suggestion that "communication access" to key individuals increases actor criticality, my next proposed measure is the Knowledge Access Index (KAI). Unlike the TEI and KEI, which range between 0 and 1, the KAI is binary and is defined as follows:

Definition: KAI_n = 1 iff ∃ skill *s* for individual *n* | $\bar{S}_{N_s}$ = 1 and $\bar{N}_n = \sum_{j=1}^{\hat{n}} N_{nj}$ = 1; KAI_i = 0 otherwise. Furthermore, if KAI_n = 1, then KAI_j = 1 for the value of *j* where N_{nj} = 1.

The KAI calculation first identifies an actor who is the only actor possessing certain knowledge. If this actor is tied to only one other actor in the social network matrix *N*, then both the person with the unique knowledge (or skill or expertise) and the actor to whom this person is uniquely tied are considered potentially critical employees and are assigned KAI values of 1.

As a proxy for synthesizing social network and resource dependency theories, my final proposed measure is a Composite Criticality Measure (CCM), defined as

$$CCM_n \equiv f(CI_D(n)) + f(CI_B(n)) + f(TEI_n) + f(KEI_n) + f(KAI_n) \tag{3.5}$$

where $f(Index_n) = 1$ iff $Index_n$ is in the critical cluster of *Index*, and 0 otherwise. I determine critical clusters based on conventional hierarchical clustering analysis.

Consistent with social network and resource dependency theories, I assume that a higher value for any index indicates an actor with a higher level of criticality with respect to that index. In addition, without loss of generality, I set all α and β parameters equal to 1.

Simulation Model

In addition to the meta-matrix framework and the measures of social position and knowledge, another important component of my approach involves establishing a benchmark for comparing actors' criticality based on the proposed measures. The benchmark I apply is *performance impact* as defined through successive simulations of the software development team with and without each actor. Accordingly, I define a *critical human capital asset* as an individual whose absence or loss will result in a greater decrease in team performance relative to other individuals on the same team. Since it is virtually impossible to obtain empirical data examining team performance with and without each actor, simulation proves to be an excellent means of estimating baseline performance values for each individual on the team.

The computer simulation model I employ is an adaptation of the multi-agent Construct model originally developed by Carley and Kaufer (Carley, 1990c, 1991; Carley, Lee, and Krackhardt, 2001; Kaufer and Carley, 1993) and validated in studies by Carley and Krackhardt (1996), Carley and Hill (2001), and Schreiber and Carley (2004). The current version of Construct[3] simulates organizations in terms of tasks, knowledge, and interactions associated with multiple groups and agents. The proposed extended version permits the selective removal of any specific actor at any time in the simulation horizon, enabling researchers to evaluate team performance with and without one or more actors. The team's performance in Construct is determined by each agent's participation in a binary-choice task in which the team must decide for a binary string whether there

[3] Complete executable shareware available publicly at *http://www.casos.cs.cmu.edu/projects/construct/*.

are more 1's or 0's in the string. The task is distributed in such a way that no individual actor or sub-group can "see" and act on the entire string, with the parts of the task that an actor sees being dependent on what pieces of task knowledge and skills the actor has. Thus, in my simulations, such decisions act as proxies for team objectives, which, in the case of the software team, represent stylized sub-tasks in IT project management and implementation. Performance is calculated as "team accuracy," or the fraction of tasks on which the team correctly acts with respect to the full binary-choice task presented. The size of the binary-choice task is the same as the total number of skills/tasks in the knowledge matrix S_N, and in each time period of the simulation, the organization is presented with 25 such stylized tasks. Thus, in terms of the software team simulated in this study, every actor participates in the team's activity each period to the extent of the actor's task knowledge and skill. I make no attempt to represent details of "software coding" in the model, since the task, knowledge, and skill links capture each actor's incremental contribution to team performance.

In addition to defining the communication and knowledge networks, I modeled the team's structure and roles, dividing the software team into three hierarchical levels of three "managers" (a "Project Leader" plus two "managers"), four "supervisors," and nine "employees." Construct enables actors to incorporate transactive memory ("TM") (Liang *et al*., 1995), and although I assumed an average TM level of 50%, I found the simulations to be insensitive to TM levels (varying from 0% to 100%), suggesting that the team was small enough and task-dependent actors were connected well enough to minimize the significance of transactive memory influences over the short duration of the project. Another multi-agent parameter of Construct allows actors to interact with varying degrees of homophilistic (relative similarity) versus information seeking behavior. Although I assumed an equal balance of each type of interaction (50% homophily-based and 50% information seeking-based) for our base case, I found no sensitivity to variations ranging from complete homophily to complete information seeking, suggesting that both homophilistic and information seeking behaviors of team members were primarily aligned with tasks for which they or others similarly tasked were trained and had experience (Hinds *et al*., 2000). I additionally assumed (realistically in the case of the software team analyzed in this study) that all agents were fully engaged in their respective tasks at all times, thus there were no slack resources.

Research Methodology

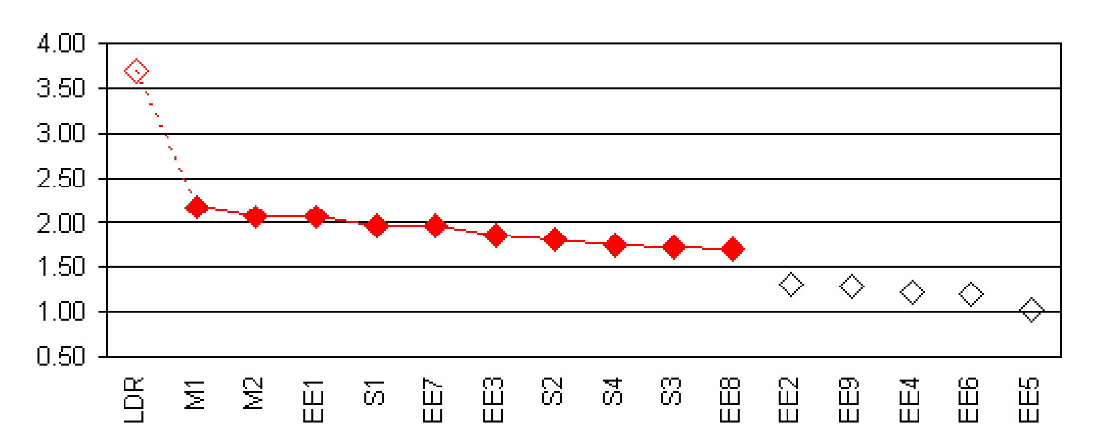
As the first step in the research approach, I determined which members of the software team were critical employees based on their performance impact. I accomplished this by running a base case simulation with all employees and then deleting each actor in turn in 16 subsequent simulations. Based on the incremental difference in performance associated with the removal of each actor, I defined a benchmark measure of each actor's relative criticality as the absolute value of the mean percentage decrease in team performance resulting from the deletion of that actor, *ceteris paribus*. This experimental approach is consistent with Price's (1977) and Argote's (1999) suggestion that organizational effectiveness is positively related to the performance levels of individuals in the organization. I thus theorized, and results confirmed, that performance will always decline upon removal of any non-slack actor. To confirm effect sizes, I conducted statistical testing on the performance differences to examine significance of actor impacts and performed clustering analysis to identify the baseline group of "critical" actors. As an interim check of face validity, I interviewed the project manager of the software team to confirm that the model's resultant identification of critical actors was consistent with management intuition and direct knowledge. Then, for all actors on the team, I calculated the traditional and knowledge-based measures and compared them to the base case estimates using hierarchical clustering. Finally, I evaluated the study's propositions based on receiver operating characteristic (ROC) curve analysis.

3.4 Results

Determination of Critical Human Asset Group

For the base case (that is, for the complete team of 16 people) and for each of the 16 cases representing incremental removal of an actor on the software team, I executed 100 Monte Carlo simulations. Besides establishing a baseline for further comparison, this result confirmed Kiesler *et al.*'s (1994) suggestion that each actor on a well-designed team will have measurable positive impact on the team's overall performance. Each simulation spanned 250 time periods, with a two-period lag at the beginning of each run before removal of any particular actor. The removed actor was not included on the team for the remaining 248 time periods.

Figure 3.4. Results of multi-agent simulation and cluster analysis showing cluster of eleven "critical" employees."



In Figure 3.4, I rank the actors by performance impact and group them into two clusters based on a hierarchical similarity analysis that minimizes average Euclidian distance differences between clusters (Sokal and Michener, 1958).[4] As might be expected given the relatively high performance impact shown for the Leader, the initial clustering analysis placed this actor in a distinct cluster. Since using that cluster alone as a definition of the baseline "critical employees" is trivial, I include the Leader and all employees in the second cluster as the "critical" group. Although specifying 11 out of 16 people on a team as "critical employees" may seem high, it is consistent with the proposed definition of criticality and is intuitively acceptable given the small size of the test team and the typically high degree of specialization on software engineering teams (Carley *et al*., 1993). An interim interview with the project manager also confirmed face validity of the results.

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[4] The hierarchical clustering technique used throughout the paper is based on average linkage updating of distance between clusters (Sokal and Michener, 1958). The distance between the coordinates of each actor (as determined by actors' x and y values of the metric being clustered, such as x=degree centrality with y=performance index) is calculated as Euclidean distance. Then, the distance D_{ck} between clusters c and k is computed as

$$D_{ck} = T_{ck} / (n_c * n_k)$$

where T_{ck} equals the sum of all pairwise distances between actors in cluster c and cluster k, and n_c and n_k are the sizes of clusters c and k respectively. At each stage of clustering algorithm, the clusters for which D_{ck} is the minimum are merged.

Table 3.2 and Figure 3.4 indicate that different individuals have different impacts on the team's performance, contradicting Bienenstock and Bonacich's (2002) contention that removal of any single individual results in the same impact on team performance and affirming theories that such removals are actually deleterious (Price, 1977; Mowday, Porter, and Steers, 1982).

As Table 3.3 reveals, the differences in impacts are generally significant. The average effect size *d* (defined as M_{Base}-M_n/SD) is 0.74, with a range from 0.39 to 2.32, all with moderate to high levels of statistical power (Cohen, 1988), indicating that all performance decrements are significant. The *z* values for a hierarchical, two-tailed Wilcoxon signed rank test of the difference in performance distributions between each actor and the next-lower ranked actor show significance at $p<0.05$ for 11 out of the 15 differences (see Table 3.3). Moreover, the values exhibiting the least significance ($0.0910<p<0.7114$) are consistent with the results of the clustering analysis (Figure 3.4).

Computation and Comparison of Measures

Table 3.4 summarizes raw calculations of all social position and knowledge-based indexes, and Figure 3.5 shows a relative comparison of normalized values for each actor on the software team.

Figure 3.5 reveals results that are non-linear across measures but consistent in many respects with expectations based on traditional social network analysis. Despite a few exceptions (e.g., LDR, S3, and EE2), degree and betweenness measures appear to be correlated. In addition, the leaders of the team (LDR, M1, M2, and S1 through S4) have generally higher degree and betweenness centrality measures compared to the employee group (EE1 through EE9). Notable exceptions are employees EE7 and EE9, both of whom exhibit centrality measures similar to the leadership group. Upon further

Table 3.2. Performance Results and Significance Based on 10,000 Simulations (df=494, *p<.001).

	M	SD	$M_{Base} - M_n$	t-value	% Impact
LDR	63.800	1.056	2.455	17.651*	3.705
M1	64.817	1.649	1.438	8.952*	2.170
M2	64.880	1.683	1.375	8.483*	2.075
S1	64.954	1.791	1.301	7.804*	1.963
S2	65.054	1.725	1.201	7.331*	1.813
S3	65.123	1.807	1.132	6.761*	1.708
S4	65.109	1.790	1.146	6.878*	1.730
EE1	64.891	1.769	1.364	8.228*	2.058
EE2	65.397	1.736	0.858	5.221*	1.295
EE3	65.038	1.712	1.217	7.456*	1.838
EE4	65.443	1.793	0.812	4.870*	1.226
EE5	65.583	1.730	0.672	4.099*	1.015
EE6	65.458	1.797	0.797	4.776*	1.203
EE7	64.963	1.725	1.292	7.884*	1.949
EE8	65.126	1.788	1.129	6.780*	1.704
EE9	65.407	1.733	0.848	5.163*	1.279

Table 3.3. Results of Wilcoxon test showing significance of differences between actors' Performance Impacts (df=248).

Rank	Actor	% Impact	Wilcoxon z	p
1	LDR	3.705	-	-
2	M1	2.170	-13.330	<.0001
3	M2	2.075	-5.999	<.0001
4	EE1	2.058	-0.370	<.7114
5	S1	1.963	-5.210	<.0001
6	EE7	1.949	-1.600	<.1096
7	EE3	1.838	-9.610	<.0001
8	S2	1.813	-2.040	<.0414
9	S4	1.730	-5.370	<.0001
10	S3	1.708	-2.930	<.0034
11	EE8	1.704	-0.590	<.5552
12	EE2	1.295	-13.490	<.0001
13	EE9	1.279	-1.690	<.0910
14	EE4	1.226	-3.000	<.0027
15	EE6	1.203	-2.110	<.0349
16	EE5	1.015	-7.760	<.0001

Table 3.4. Computations of Measures.

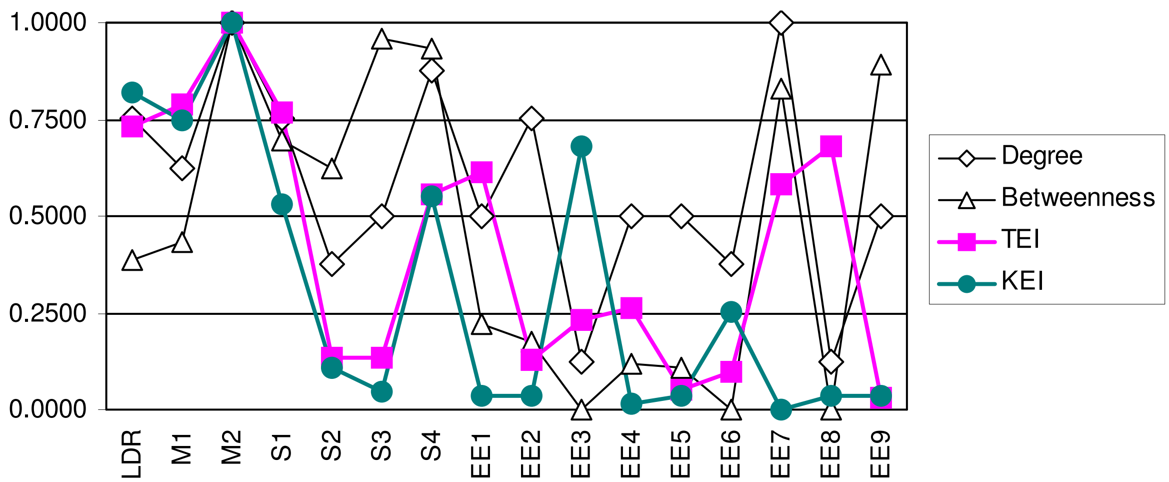
	$CI_D(n)$	$CI_B(n)$	TEI_n	KEI_n	KAI_n	CCM_n
LDR	0.750	0.387	0.730	0.817	0	3
M1	0.625	0.433	0.789	0.747	0	4
M2	1.000	1.000	1.000	1.000	0	4
S1	0.750	0.697	0.769	0.532	0	4
S2	0.375	0.625	0.136	0.110	1	2
S3	0.500	0.957	0.136	0.044	0	1
S4	0.875	0.932	0.558	0.554	0	4
EE1	0.500	0.222	0.616	0.036	0	1
EE2	0.750	0.177	0.127	0.034	0	1
EE3	0.125	0.000	0.232	0.682	1	2
EE4	0.500	0.119	0.260	0.015	0	0
EE5	0.500	0.108	0.050	0.034	0	0
EE6	0.375	0.000	0.096	0.252	0	0
EE7	1.000	0.831	0.585	0.001	0	3
EE8	0.125	0.000	0.679	0.034	0	1
EE9	0.500	0.893	0.029	0.036	0	1

Table 3.5. Critical Employee Groups as Determined by Clustering Analysis of Index Results (- or + indicates false negative/positive).

	Base Case	$CI_D(n)$	$CI_B(n)$	TEI_n	KEI_n	KAI_n	CCM_n	Social Position Heuristic	Knowledge-based Heuristic
LDR	C	C	-	C	C	-	C	C	C
M1	C	C	-	C	C	-	C	C	C
M2	C	C	C	C	C	-	C	C	C
S1	C	C	C	C	C	-	C	C	C
S2	C	-	C	-	-	C	C	C	C
S3	C	-	C	-	-	-	-	C	-
S4	C	C	C	C	C	-	C	C	C
EE1	C	-	-	C	-	-	-	-	C
EE2		C+						C+	
EE3	C	-	-	-	C	C	C	-	C
EE4									
EE5									
EE6									
EE7	C	C	C	C	-	-	C	C	C
EE8	C	-	-	C	-	-	-	-	C
EE9			C+					C+	

inspection, however, Figure 3.5 indicates clear inconsistencies between social position and knowledge-based measures. For example, while employees EE1, EE3, and EE8 have relatively low degree and betweenness centrality measures, they score among the highest in terms of task exclusivity for EE1 and EE8 and in terms of knowledge exclusivity for EE3. While not always the case, actors with low centrality measures may be more introverted "experts" (Burt, 1992; Prietula and Simon, 1989), so the fact that EE3 and EE8 are near-isolates (see Figure 3.2) is not inconsistent with such tendencies.

Figure 3.5. Measures results for all team members.



Evaluation of Propositions

Figures 6a through 6d reveal graphically the results of agglomerative hierarchical clustering analysis performed on the degree, betweenness, TEI_n, and KEI_n measures. I do not include graphs for the KAI_n and CCM_n measures, but their clustering results are summarized in Table 3.5 along with all other measures tested. These graphs indicate that there is a "core" of three critical actors – M2, S1, and S4 – identified by all four indexes. However, as hypothesized, the traditional social position measures of degree and betweenness identify certain actors as critical who are *not* deemed critical in the simulation benchmark. For example, while the social position measures correctly identify actor S3 as critical (even when the knowledge-based measures do not), the social position measures ascribe criticality erroneously in other cases (e.g., EE2 and EE9).

In Table 3.5, rather than using numerical values, I indicate criticality of an actor for any given index with the letter “C.” In the “Social Position Heuristic” and “Knowledge-Based Heuristic” columns, I provide heuristic measures denoting an individual as critical (“C”) if the union of the respective social position (degree and betweenness centrality) or knowledge-based (task, knowledge, and knowledge access exclusivity) measures yields a “C.” False negatives and false positives versus the base case for each index are flagged with a “-” or “+” sign, respectively. For example, the “C+” for employee EE2’s degree index, $CI_D(n)$, indicates that the degree index measure

Figures 3.6a-d. Results of clustering analysis for (a) degree, (b) betweenness, (c) TEI and (d) KEI. Critical actors are shaded (+ or – indicates false positive/negative).

Figure 3.6a. Degree critical actors.

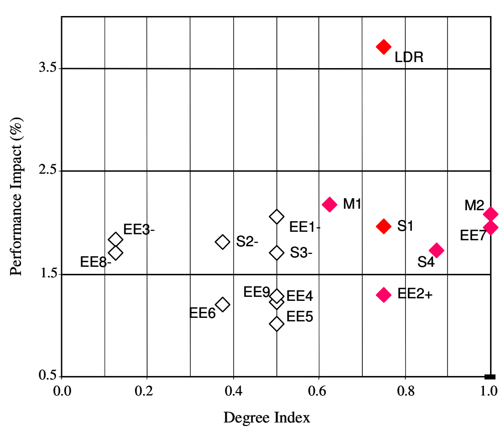


Figure 6a

Figure 3.6b. Betweenness critical actors

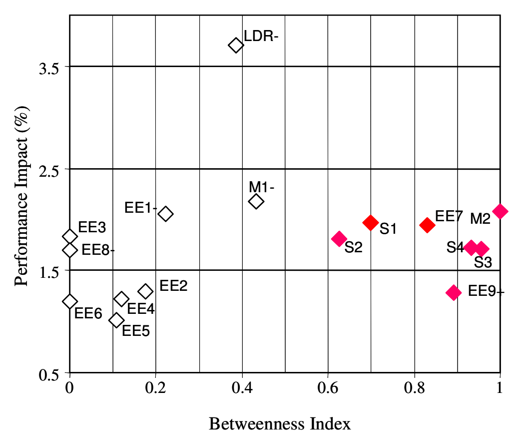


Figure 6b

Figure 3.6c. TEI critical actors.

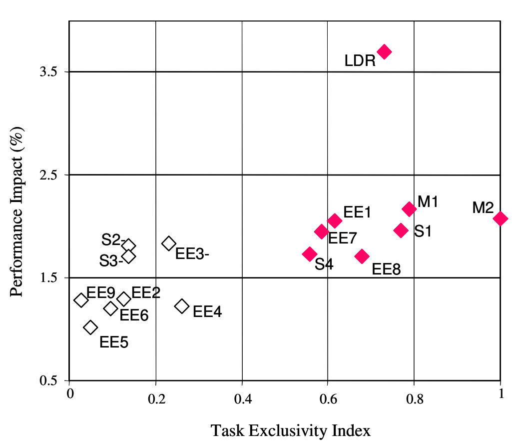


Figure 6c

Figure 3.6d. KEI critical actors.

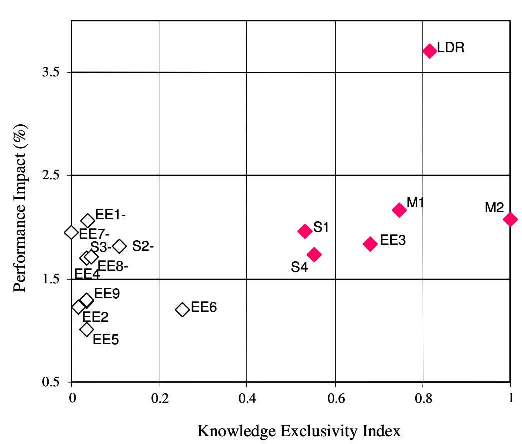


Figure 6d

identified EE2 as critical, but the "+" indicates that this result was a false positive. Likewise, the "-" shown for employee M1's betweenness index, $CI_B(n)$, indicates that M1 was *not* identified as critical according to the cluster analysis of betweenness results, but the "-" means this is a false negative (i.e., M1 should have been identified as critical).

Based on these results, I can now examine in detail the research propositions. With respect to P1a and P1b, it is clear they cannot be rejected, as indexes $CI_D(n)$ and $CI_B(n)$ as well as the $CI_D(n) \cup CI_B(n)$ relation ("Social Position Heuristic") all display significant instances of false negatives (affirming P1a) and false positives (affirming P1b). As shown in Figures 3.7a and 3.7b, the area under the ROC curves for the degree (area=0.44), betweenness (area=0.44), and social position heuristics (area=0.43) are all unacceptably low. Thus, I accept propositions P1a and P1b.

With respect to P2, Figure 3.7a shows that the ROC results for task exclusivity (area under TEI_n ROC curve=0.73) and knowledge exclusivity (area under KEI_n ROC curve=0.55) fare appreciably better than those of social network measures, but these measures still do not exhibit acceptably robust ROC levels (i.e., area under curve>0.80) when used alone. However, when used in combination, the TEI_n, KEI_n, and KAI_n identify EE1, EE3, and EE8 as critical, and those instances alone are enough to prove non-constructively that knowledge elements, particularly as represented by task and knowledge exclusivity, can be used to identify critical human assets that social network theory applied in isolation may overlook. As the ROC curve analysis shows in Figure 3.7b, the "knowledge-based heuristic" measure, where an individual is assigned "critical" status if $TEI_n \cup KEI_n \cup KAI_n$ = "C", exhibited the highest degree of discriminatory power and provides support for proposition 2.

Finally, I do not find support for the proposition that a synthesis of theories, represented by the composite measure, CCM_n, can be used to reliably identify all critical human assets, since I find unacceptable levels of false negatives (S3, EE1 and EE8) and only a fair rating with respect to the ROC curves in Figure 7b (area under CCM_n ROC curve=0.73). This result is not altogether unexpected, since the composite measure

Figure 3.7a. ROC curves comparing degree, betweenness, TEI and KEI measures.

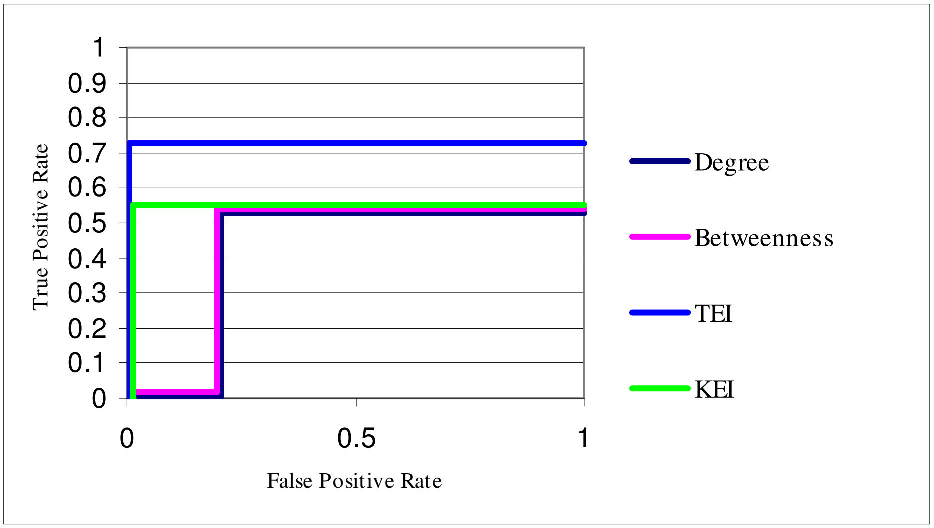
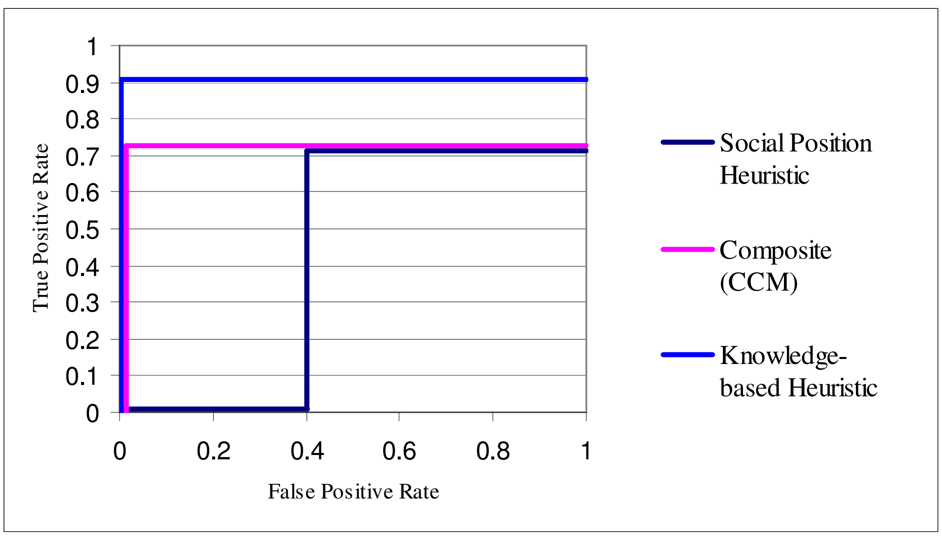


Figure 3.7b. ROC curves comparing composite, social position and knowledge-based heuristic measures.



results reflect the unfortunately high number of false negatives indicated by the social network measures.

3.5 Discussion and Contributions

Results confirm that social network theory is reasonably robust in predicting human capital performance but may present deficiencies when task assignment and knowledge are taken into account. I posited that resource dependency theory may satisfy those deficiencies and used task- and knowledge-based measures to show how a resource-based view substantially improves the robustness of predicting criticality of human assets based on their relative impact on team performance. Notwithstanding the improvements offered by knowledge-based theories, I find that no single measure or class of measures identifies *all* critical human capital, but that a heuristic application of knowledge-based measures results in the highest overall accuracy. As Figure 3.7 shows, the “Knowledge-Based Heuristic” approach using our task- and knowledge-based measures alone results in a significantly more satisfactory ROC curve than any of the other measures (area under curve = .91, compared with other values ranging from 0.43 to 0.73).

Hence I believe the major contribution of this work is in providing empirical evidence that the impact of individuals on team performance is more closely associated with knowledge and task dimensions than with social network structure. This work also strengthens the tenets of resource dependency theory by providing new motivation for increased attention on the value of managing the knowledge and skill bases of individuals in organizations.

Finally, this work contributes to the growing body of literature on social network theory, human capital measurement theory, and dynamic organization network theory. Traditional social network theory is limited not only in its focus primarily on socio-metric aspects of organizations, but also in its lack of practical ability to incorporate the dynamic nature of those aspects. The survey-based data employed in social network analyses are difficult to obtain and even more difficult or perhaps impossible to maintain longitudinally. The methods proposed in this paper can operationalize theory using data that may be more easily obtained dynamically, longitudinally, and non-invasively from existing organization information systems such as ERP systems, human resource information systems, project management databases, and knowledge databases.

With respect to potential shortcomings of social network theory, it bears emphasizing that even though the social position measures used in the study fared less convincingly compared to knowledge-based measures, I do not believe this means that centrality measures are not useful or valid. Traditional social network analysis focuses on limited type of linkages (such as friendship and advice) between actors at only one point in time (Carley, 2004). Moreover, such analyses assume perfect or near perfect information. Despite their limitations as revealed in the present analysis, such traditional centrality-based approaches can clearly be richer in social dimensions that may have important organizational implications in their own right, suggesting that a synthesis of social network measures, such as information centrality (Stephenson and Zelen, 1989) and continuing flow (Bolland, 1988), with resource-based approaches may provide a stronger combination of qualitative and quantitative insight on criticality of team actors. The implications are consistent with Wasserman and Faust's (1994) observation that "one should not use any single centrality measure [since] each has its virtues and utility." I extend this admonition to knowledge-based measures as well.

Although the proposed integration of theory has intuitive and empirical appeal, I also recognize potential limitations to its wider application. For example, the accuracy of knowledge-based predictions is based on the premise that key tasks and related knowledge elements are well understood for all actors in the organization. In reality, these factors may not be understood at all, and, depending on each individual's knowledge-sharing characteristics and the presence of socially connected versus isolated members, certain knowledge elements may not become diffused in the group over time (Thomas-Hunt *et al.*, 2003). Even though I believe the task and knowledge elements of the meta-matrix framework contribute to improving such understanding, assembling such data could be just as daunting and costly as social network analysis.

Another issue that may limit application of my findings is scalability to teams that are larger or more diverse than the software team analyzed in the study. In particular, use of a single team as the central source of empirical data constrains generalizability. However, the study incorporated essentially 17 teams by using simulation to analyze the base case view of the full 16-member team along with 16 "experimental" teams, each with one of the 16 original members missing. Scalability is affected not only by the size and number of teams but also by the intensity of ties, level of decentralization, and number of generalists versus specialists in the organization. Additional research should explore just how "complete" the information needs to be before results can be accepted with reasonable confidence. With respect to accuracy of the measures, I believe that more research is also needed on the effects of the α and β parameters, since they may provide a means of increasing sensitivity. I suspect, however, that any increase in sensitivity may come only at the expense of specificity if the parameters are set *a priori* based on traditional social network analysis or management intuition.

3.6 Conclusion

In summary, many dynamic facets of human capital – ranging from power and social relations to task, knowledge, and resources – are crucial in understanding the relative contribution of individuals to team performance. Findings of this study indicate that a resource-based view focusing on knowledge provides the most robust link between individual performance and team performance. My knowledge and task-based perspectives confirm empirically that key contributors may not always be obvious actors such as leaders and managers, but rather those "everyday actors who offer something absolutely unique, with a special history in every respect" (Barnard, 1938). In understanding and managing team performance, the knowledge and skill possessed by those "everyday actors" may just represent the most critical human capital of all.

4

OPENING THE 'BLACK BOX' OF GROUP LEARNING
TRANSACTIVE MEMORY AND ITS SMALL-WORLD STRUCTURE

"Learning is not compulsory… neither is survival."
-- W. Edwards Deming

4.1 Introduction

To *learn*, according to Merriam-Webster (2005), is to *gain knowledge or understanding of or skill in by study, instruction, or experience*. Research on organizations has found that such capacity is not restricted to individuals. Indeed, organizations, much like individuals, "learn" new behaviors in response to their collective experience (Argote, 1999; Huber, 1991; Levitt and March, 1988). Within organizational units, similar adaptation results in "group-level learning" (Edmondson, 1999; London, Polzer, and Omoregie, 2005). Although organizational learning research provides a useful framework for examining cross-firm performance and strategic innovation, one of its practical limitations has been its predominant focus on macro-level outcomes with comparatively less consideration given to the actual mechanisms of learning. Thus, while prior literature provides substantial evidence that organizations do in fact learn, reasons how and why they learn or even issues related to more existential questions such as why organizations should learn at all have received less attention. My objective in this study is to open up the "black box" of learning at the group level and to propose and test the theory that a significant portion of such group learning behavior is associated with the network characteristics of what Wegner (1986) called "transactive memory," or the extent to which group members are familiar with other members' knowledge. Groups may be able to enhance their productivity by shaping such network characteristics in ways that positively affect learning (Cyert and March, 1992) as well as other organizational outcomes (Krackhardt and Stern, 1988). Therefore, identifying transactive memory and its network structure as mechanisms of group learning can help practicing managers foster group environments that are conducive to promoting the positive outcomes generally associated with organizational learning across many types of industries, firms, and processes (Argote, 1999; Yelle, 1979).

As pointed out by Huber (1991), for a work group to actually make use of its collective experience, learning must encompass not only knowledge creation and management but also knowledge *retention*. Just as in the case of an individual person, a group cannot apply knowledge that it cannot "remember" (de Holan and Phillips, 2004). Thus, retention of knowledge is often aided by procedures and standards stored in written or electronic form (Anand, Manz, and Glick, 1998). In addition to such physical or process-related storage, cognitive structures and shared mental models are also critical to "organizational remembering" (Espinosa et al., 2002; Larson and Christensen, 1993; Liang, Moreland, and Argote, 1995; Reagans, Argote, and Brooks, 2005). In particular, the cognitive structure known as transactive memory has been found to positively influence group performance (Austin, 2003; Lewis, 2004; Moreland, Argote, and Krishnan, 1996; Stasser, Stewart, and Wittenbaum, 1995; Waller, Gupta, and Giambatista, 2004). Transactive memory, according to Wegner's (1986) original definition, is a shared system for encoding, storing, and retrieving information used by two individuals. The key word in his definition is "shared." Conceptually, the only difference between an individual person's memory and "transactive memory" is that transactive memory is *shared* so that the burden of storing and recalling knowledge is shouldered reciprocally by each individual. Wegner's original theory concentrated on dyadic relationships, but subsequent work has found evidence of transactive memory at the level of groups (Austin, 2003; Lewis, 2004; Ren, Carley, and Argote, 2006) and organizations (Monge and Contractor, 2001; Palazzolo, 2005). Whether referring to dyads, groups, or organizations, transactive memory is analogous to distributed computer memory in which information is stored on several different computers but potentially accessible by each of the computers as long as linkages exist between them;

linkages to memory on other computers expand a single computer's memory without requiring the computer to have additional storage capacity (Wegner, 1995). In a similar way, members of a group of workers with a well-developed "group transactive memory" have access to a greater and richer level of task-related knowledge and information than would be available in single group member's memory (Brandon and Hollingshead, 2004; Hollingshead and Brandon, 2003; Wegner, Erber, and Raymond, 1991). For example, if group member *A* knows that group member *B* is an expert in knowledge area *K*, then the necessity for *A* to acquire or maintain *B*'s level of knowledge concerning *K* may be reduced. In addition, if a communication path exists between *A* and *B*, even other group members connected to *A* by other communication paths may similarly end up relying on *B* for the needed expertise about knowledge area *K*.

This paper theorizes that the level of such transactive memory in a work group partially accounts for the relationship between collective group experience and current period performance, thereby explaining a significant portion of a group's learning behavior. The study takes an important first step in testing this theory by using data obtained from 1,456 employees and 87 managers in 118 electricity industry work groups to analyze the mediating characteristics of transactive memory networks. Results of empirical tests show not only how transactive memory helps explain group learning but also how its small-world structure moderates the memory's mediating effect. Finally, discuss the study's findings and describe practical implications and limitations as well as how the findings may extend to inter-group, organization, inter-organizational, and even societal levels.

4.2 Networks and Transactive Memory

Networks contain a wealth of information about the content and configuration of various types of relationships between organizational actors and between actors and their resources (Wellman and Berkowitz, 1988). A network is simply a set of *nodes* (also called "vertices" or "points") along with the set of *connections* (also interchangeably called "ties," "edges," or "links") that exist between pairs of those nodes (Diestel, 2005; Harary, 1969; Wassermann and Faust, 1994). In applying the network concept to organization theory, nodes can represent virtually any factor or attribute of production, including people, roles, knowledge, tasks, and resources. In similar fashion, a connection between two nodes can represent any relationship or interaction particular to the entities contained in the network.[5] Thus, networks can reveal informal aspects of performance that may not be obvious from organization charts or management reports (Krackhardt and Stern, 1988; Prietula and Simon, 1989).

Although increased attention has been focused on such networks in the past decade, their existence and importance was clearly recognized by the early twentieth century. For example, Follet's (1924) prophetic work on leadership and conflict resolution depended heavily on the informal structure of communication networks and homophily[6] in groups and emphasized the intrinsically dynamic nature of these relationships in psychological and social science settings. Barnard (1938: 114-123) dedicated an entire chapter to informal organizational networks in his seminal work on management leadership, averring that such networks are both necessary antecedents and natural consequences of formal organization. More recently, in their epilogue to the second edition of *A Behavioral Theory of the Firm*, Cyert and March (1992: 233-234) described network conceptualizations as richer, more accurate portrayals of organizational structure than traditional hierarchies and stressed the need to understand how interactions within those structures lead to organizational outcomes.

Despite the rich history of networks in the strategy, leadership, and sociology literatures, surprisingly little research has examined their relationship to transactive memory development. Although prior research on sociotechnical systems (Trist and Murray, 1993) suggests that the extent to which organizations learn is influenced by complex interactions between explicit structural attributes of organizations and the social and knowledge-seeking relationships between organizational members, only one relevant work combined learning with the network perspective. A simulation study by Carley (1992) examined network structures over a virtual time horizon and found that

[5] Some social network perspectives use the term *network* interchangeably with *simple graph*. Diestel's (2005) notion of a network as a directed, valued graph defaults to a simple graph if the connections between nodes are bi-directional and weights of all connections are equal. Diestel's more precise, graph-theoretic definition of a network is used as a foundation for the discussion of transactive memory networks later in the paper.
[6] Homophily refers to the tendency for interaction to be based on similarity between agents, such as same gender, same age cohort, same ethnicity, etc. (Lazarsfeld & Merton, 1954).

“hierarchical” (or centralized decision-making) structures were generally better able to withstand impacts of turnover than “team” (or distributed decision-making) structures. However, conclusions with respect to network effects on learning were limited because learning resulted only from homophily or information-seeking interactions rather than as a result of equally important individual and collective task-related experience.

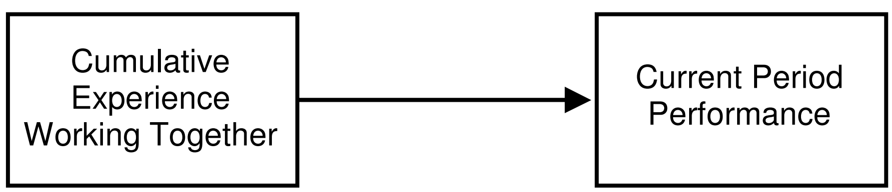
While the specific links between network structure and transactive memory have remained relatively unexplored, recent research on knowledge transfer and distribution suggests that networks indeed play an important role in organizational performance outcomes. For instance, Rulke and Galaskiewicz (2000) found support for the connection between social network composition and knowledge distribution in their survey of thirty-nine teams of MBA students. In their study, group structure was found to be unrelated to performance when groups were dominated by generalists, but decentralized groups were associated with higher performance than centralized groups when the groups were composed predominantly of specialists. A similar field study examining only the leadership and operational structure of organizations found that hierarchical structures as well as configurations with highly connected “cores” and sparsely connected “peripheries” were negatively related to performance (Cummings and Cross, 2003). Such “core-periphery” networks are generally lower in communication density, leading to lower group productivity (Reagans and Zuckerman, 2001). Communication also interacts with knowledge distribution in organizations to regulate the exchange of knowledge. In organizations where individuals who were members of cohesive “knowledge pools” were also weakly connected via communication ties to members in other knowledge pools, knowledge transfer occurred more easily (Reagans and McEvily, 2003).

Although most studies of networks and performance outcomes have found positive relationships, at least one study suggests that not all network effects are significant. In Sparrowe, Liden, Wayne, and Kraimer’s (2001) field study encompassing teams in several different organizations, for example, the density, or the proportion of the actual number to the maximum number of ties, of advice-sharing networks did not significantly affect manager-rated performance of the teams. This suggests that the level of advice sharing alone may not capture the workings of group transactive memory. Without some form of knowledge organization, mere increases in density may in fact result in decreases in performance due to higher levels of coordination and transaction costs.

4.3 A Small-World Model of Transactive Memory

The general model of organizational (Womer, 1979; Yelle, 1979) or group-level (Liang et al., 1995) learning posits that the current effort required to produce a unit of output is a function of the cumulative amount of output produced over a period of time, implying that current performance is a function of cumulative previous experience (Figure 4.1). "Cumulative previous experience" acts as a proxy for a work group's knowledge built up over time and stored in the group's "memory" – that is, in explicit routines, standards and technologies along with the collective memories of the individuals in the group. Prior studies have shown that when collective group experience is associated with changes in productivity (Argote, 1999) or quality (Lapre, Mukherjee, and Van Wassenhove, 2000) in the current period the group is leveraging its knowledge gained from experience in order to improve current performance – that is, the group is *learning*.

Figure 4.1. General Model of Group and Organizational Learning

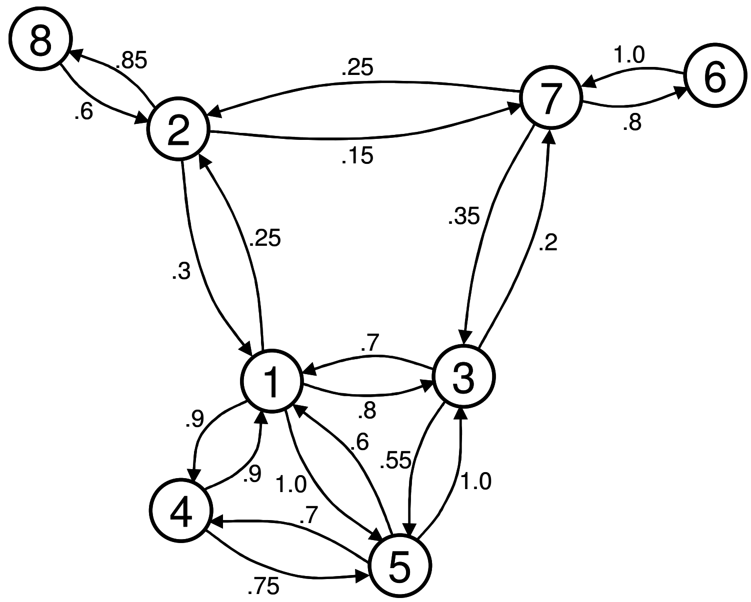


Learning is thus an evolutionary process that converts group knowledge (as represented by cumulative group experience) into contributions to current performance. But while critical for performance, knowledge alone, particularly knowledge possessed individually by members of the group, is not sufficient for group performance. Members must be aware of other members' knowledge and sufficiently connected to them to access the knowledge in a timely manner (Borgatti and Cross, 2003). This "network" view holds that the performance contributions of individuals comprising the group depend not only on members' knowledge, resources, and experience but also on the network relations between the group members (Brown and Duguid, 2000; Burt, 1992; Cross, Borgatti, and Parker, 2001; Davenport and Prusak, 1998; Doreian and Stokman, 1997). Indeed, in the network paradigm, the relations themselves are productive resources and influence the extent to which team members contribute to economic production (Coleman, 1988; Cummings and Cross, 2003; Granovetter, 1985; Lin, 2001) and innovation (Burt 2004; Kratzer, Leenders, and van Engelen, 2004). Thus, the requirement of shared awareness of members' knowledge combined with the network aspect of group knowledge distribution suggests that group transactive memory is also organized as a network.

In addition to knowledge awareness, another essential component of transactive memory systems is communication between group members. Transactive memory tends to be greater in groups with stronger communication ties based on shared responsibility, joint decision making, and conversations that are both work and non-work-related (Hollingshead, 1998). Thus, for transactive memory to exist in a work group, two networks must exist and operate simultaneously – (1) a communication network linking individuals in a social context and (2) a "cognitive knowledge network" (Monge and Contractor, 2003) linking individuals with other individuals' knowledge required for the group's tasks. The first type of network describing actor-to-actor communication linkages is well known in social network research (Harary, 1969; Wassermann and Faust, 1994; Wellman and Berkowitz, 1988). These networks evolve for a variety of reasons, including friendly chat as well as task-oriented dialogue, and oftentimes enable knowledge transfer socially (Friedkin and Johnsen, 1999) or even "serendipitously" (Kilduff and Tsai, 2003). The structure of the communication network affects members' access to information and hence their level of control of relevant resources within the network (Burt, 1992; Everett and Borgatti, 2002; Freeman, 1979; Mechanic, 1962).

The communication network is defined as a valued digraph containing a node for each group member along with ties between the nodes representing the extent to which communication channels exist between group members. Communication between individuals may or may not be perceived as reciprocal, thus values between nodes may not be symmetric. As shown in the example in Figure 4.2, values for network relations are based on representations of tie strength between individuals.

Figure 4.2 Example of a Communication Network[a]

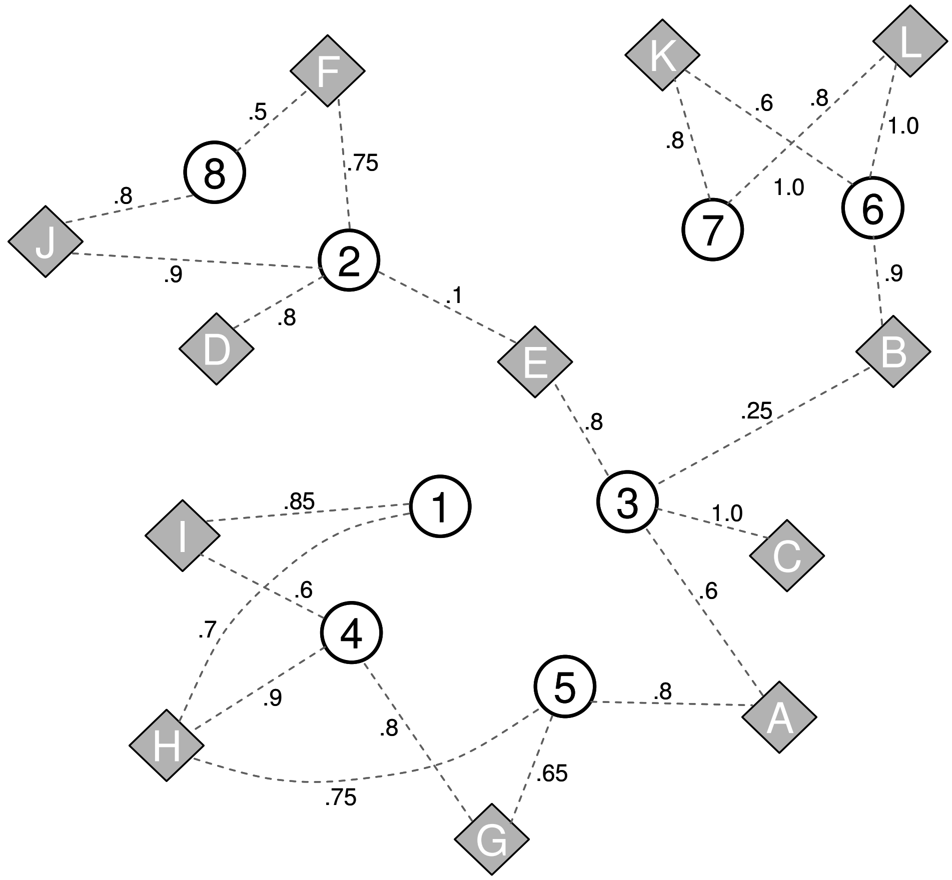


[a] The network has 8 nodes (representing the individuals in the organization) connected by 20 directed, valued ties (representing the relative strength of the ties between the individuals).

Depending on the level of individual task interdependence in the group, the location of individuals within these communication networks can affect task performance (Brass, 1984). With greater social interaction between members, barriers to information access and knowledge resources are lower and explicit knowledge transfer is greater (Cummings and Cross, 2003; Nonaka, 1994). Although in a recent study by Shaw, Duffy, Johnson, and Lockhart (2005) the impact of social capital losses on performance was found to be the same regardless of communication network density, data for their study were collected from a restaurant chain with 92 percent annual turnover, indicative of an environment providing very little opportunity for communication networks to evolve. In less volatile contexts, groups with higher numbers of communication gaps generally have been found to have lower performance (Rosenthal, 1997), inferring that stable networks with a higher percentage of communication connections perform better. Supporting this contention, Reagans and Zuckerman (2001) found that intra-group communication levels were positively associated with the productivity of corporate R&D teams. Even over relatively short periods of time, simply working or training together on similar tasks enables work group members to develop an awareness of other members' expertise that is critical to performance (Bottger, 1984; Liang et al., 1995; Littlepage, Robison, and Reddington, 1997). Hence, the ability of groups to enhance performance over time depends in part on the relative social connectedness of its members.

In contrast to a communication network, which links individuals, the second type of network required for transactive memory to exist is a "cognitive knowledge network" (Monge and Contractor, 2003) linking individuals with other individuals' knowledge. A cognitive knowledge network is essentially the set of all actors' views of the levels of knowledge possessed by other actors in the network. Even though cognitive knowledge networks are perceptual, for the construct to have comparative meaning across members a "true" knowledge network is presumed to exist comprised of all members connected with their respective levels of each knowledge area relevant to completing group objectives, tasks, or activities. The amount, structure, accuracy, and consensus of the cognitive knowledge networks can then be assessed relative to the "true" knowledge network. Typically, "true" knowledge networks are heterogeneous in their distributions of expertise levels across individuals but may exhibit clustering around task assignments (Reagans and McEvily, 2003; Shafer, Nembhard and Uzumeri, 2001; Uzumeri and Nembhard, 1998). Such knowledge networks are comprised of ties from members to knowledge areas representing the levels of knowledge that individuals have concerning focal knowledge areas. For example, "experts" in a particular area would have the highest value on the tie between themselves and the knowledge area for their area of expertise, while individuals with little or no knowledge in that area would have ties with correspondingly lower values. Figure 4.3 graphically depicts a "true" knowledge network for the hypothetical group introduced in Figure 4.2.

Figure 4.3. Example of a "True" Knowledge Network[a]



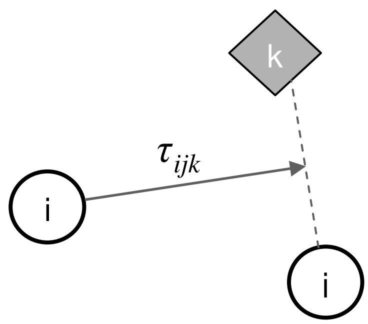
[a] The knowledge network is depicted for an organization of 8 individuals (see Figure 2) who collectively possess 12 different areas of knowledge. The network has a total of 20 nodes (representing the individuals and knowledge areas in the organization) connected by 23 undirected, valued ties (representing the relative levels of the knowledge possessed by each individual)

Cognitive knowledge networks are not traditional social network structures linking nodes with other nodes (whether or not the nodes are of the same type or in distinct node groups). Rather, cognitive knowledge networks are comprised of "hybrid" linkages that connect nodes with ties between other nodes. To represent such hybrid linkages graphically, a generalized graph concept called an *iterad*[7] is thus introduced as a valued, directed path, τ_{ijk}, between node *i* and the link, if it exists, between node *j* and

[7] The iterad neologism builds on an anatomical analogy to an *iter*, or a type of passageway connecting different areas of the brain. The pronunciation is "EYE-ter-ad."

node k (see Figure 4.4). An iterad therefore represents the value assigned by node i to a particular relation between nodes j and k. In the context of cognitive knowledge networks, an iterad corresponds to the level of knowledge that actor i believes actor j possesses about knowledge area k. Iterads are conceptually similar to relations described by Krackhardt's (1987) cognitive social structures but generalize his idea to any combination of complex multi-modal relations. In addition, iterads enable efficient graphical representation of complex perceptual networks.

Figure 4.4. Example of an Iterad[a]

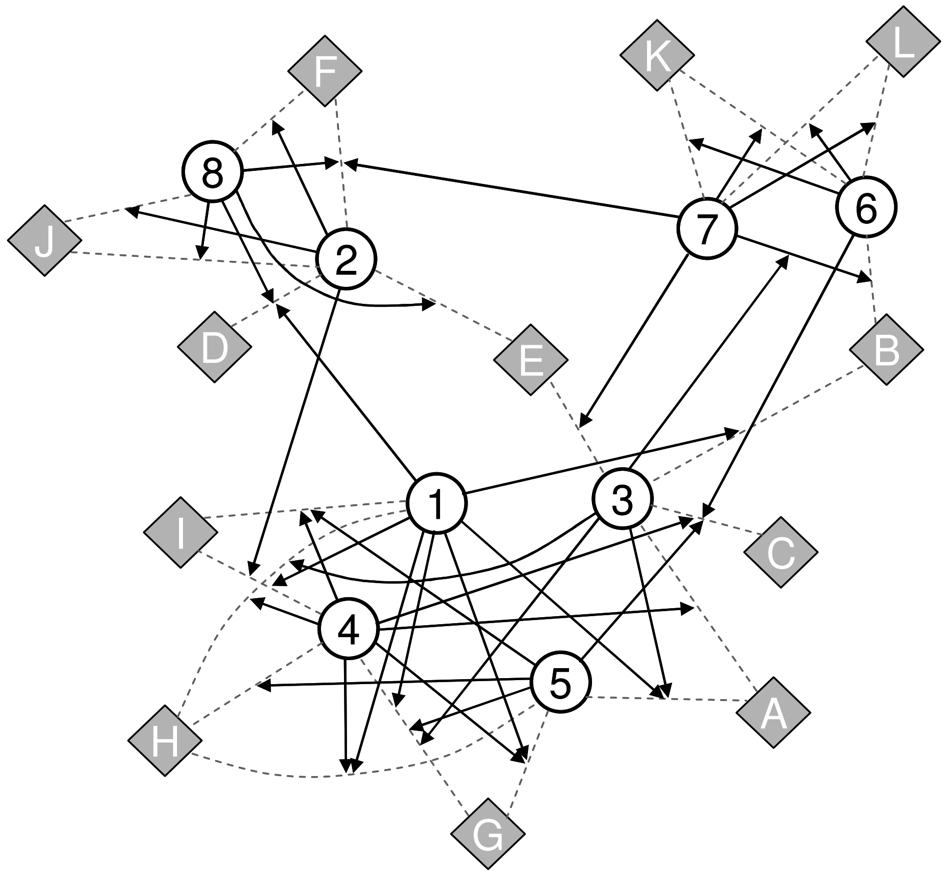


[a] Iterad τ_{ijk} is the directed link between node i and the connection between node j and k.

Iterads are thus useful for visualizing a cognitive knowledge network for a group of N actors with K possible knowledge areas as the graph induced by the iterads τ_{ijk} that exist between all actors $i \in \{1 \ldots N\}$ and knowledge areas $k \in \{1 \ldots K\}$ possessed by actors $j \in \{1 \ldots N\}$, where $i \neq j$. Figure 4.5 shows a cognitive knowledge network for the actors in Figure 4.2 and the knowledge areas possessed by those actors shown in Figure 4.3.

Then, building on the communication network and cognitive knowledge network concepts, a *transactive memory network* is defined by combining linkages in the communication network with linkages in the cognitive knowledge network to create a new network representing *who knows who knows what*. More precisely, a transactive memory network is represented by the graph obtained by the concatenation (or union) of the nodes and ties in the communication network with the nodes and iterads in the

Figure 4.5. Graphical Depiction of a Cognitive knowledge network[a]

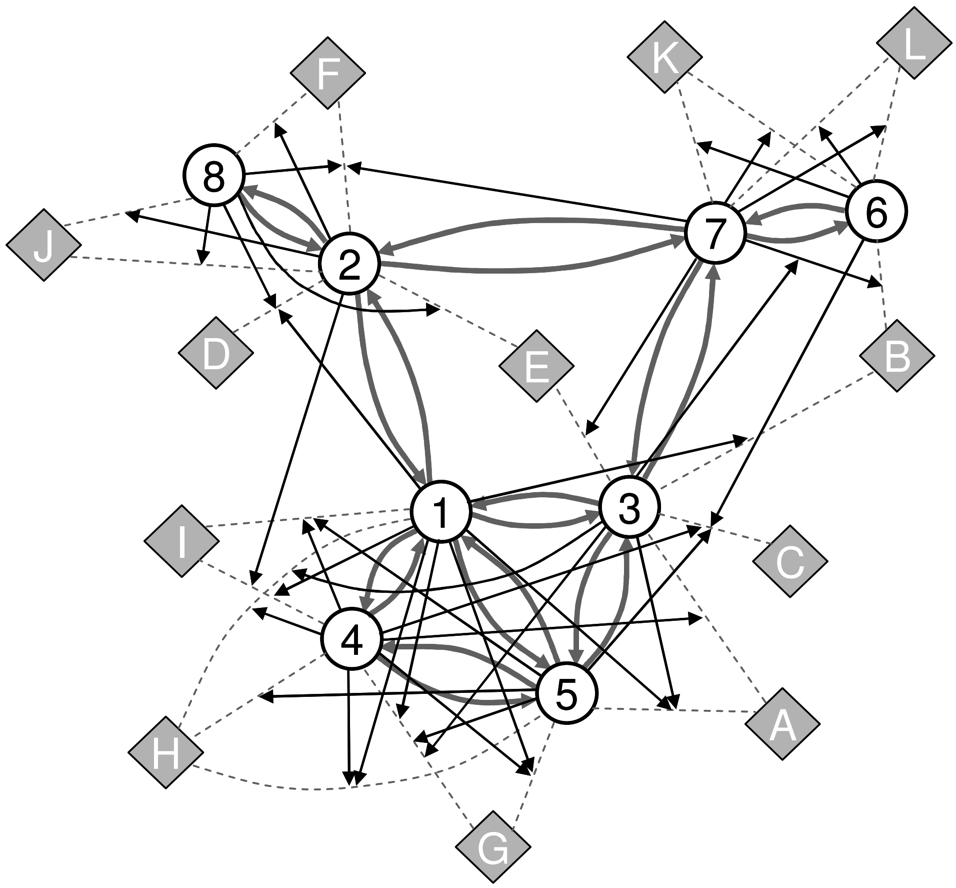


[a] The network depicts 34 iterads linking each of the 8 individuals in Figure 2 with the respective knowledge areas possessed by other individuals (see Figure 3). For clarity, values of each iterad are not shown

cognitive knowledge network. As depicted in Figure 4.6, the set of ties between group members simply represents the communication network (i.e., the value of the communication linkages between any two actors). The set of iterads between group members and knowledge areas possessed by other members represents the cognitive knowledge network.

At a group level, the formation of transactive memory can be characterized as the collective outcome of the encoding of episodic memory of individuals comprising the group. Episodic memory is the form of explicit or declarative long-term memory

Figure 4.6. Graphical Depiction of a Transactive Memory Network[a]



[a] The network combines the communication network from Figure 2 with the cognitive knowledge network from Figure 5. For clarity, values of each iterad and each directed communication tie are not shown.

associated with an individual's ability to recall events (and their contexts) experienced at a specific time and place (Squire, 1992; Tulving, 1983). For example, in a work group setting, being introduced to a team member with a different role, observing another member's response to a task-related operation, or learning about another member's expertise based on some type of referral (e.g., from another person or a database) are types of episodic memory events. Common features of experiences stored in episodic memory are gradually stored in *semantic* memory, the other form of explicit long-term memory associated with an individual's ability to access a broader base of knowledge, rules, concepts, and mental representations quickly and effortlessly (Squire, 1992;

Yonelinas, 2002). In this process, episodic memory reduces its sensitivity to particular events so that the information about them can be generalized. Actors' familiarity with the knowledge of other actors in the same task-situated social cluster occurs quickly and is high and relatively accurate due to the higher frequency of episodic memory events within such clusters and hence the greater opportunity for episodic memory to transition to semantic long-term memory before forgetting sets in. Conversely, the existence of fewer episodic memory events among actors in *different* task-situated knowledge structures results in lower levels of semantic memory concerning the knowledge that respective actors in one task-situated social cluster have about the knowledge of actors in the other task-situated social cluster. The lower the level of a cluster's semantic memory about and hence awareness of the knowledge of actors in other task-situated social clusters, the weaker the ties between those clusters.

Thus the episodic-semantic memory model suggests that as team members work together on common tasks, regular and more frequent episodic memory events combined with social interaction in the context of those events results in the formation of task-situated clusters of actors. As actors from different clusters interact in less frequent social or task situations, ties *between* clusters emerge, providing clusters with weak (Granovetter, 1973) but low cost (Robins, Pattison, and Woolcock, 2005) access to knowledge from other clusters.

Prior research has shown that the accuracy of actors' perceptions of other actors' knowledge can influence how much impact an organization's transactive memory will have on performance (Austin, 2003). Higher performance has been associated with work groups whose members accurately discern and incorporate task-relevant knowledge of other members (Henry, 1995; Littlepage et al., 1997; Waller et al., 2004), but no studies have specifically addressed the impact of transactive memory on the ability of a group to improve performance based on cumulative experience, that is, based on learning. Research suggests that, over time, communication and advice network linkages are updated based on what members need or desire to know for given tasks, their awareness or belief concerning who has the requisite knowledge, their access to those presumably knowledgeable members, and the costs associated with asking those members for the relevant advice (Borgatti and Cross, 2003). The episodic-semantic memory model infers that the "awareness" dimension forms through repeated episodic updates of task-related communication and advice channels, ultimately leading to the broad and accurate understanding of the roles and expertise of other members, lower transaction costs associated with knowledge transfer, and clearer accountability for member productivity suggested by Wegner (1995). Groups with higher levels of transactive memory, other things equal, are able to access task-related information and apply a wider range of experience to problem solving more quickly than other groups (Liang et al., 1995). Thus, a group's level of transactive memory should not only be associated with higher performance at a single point in time but also be partially responsible for a group's ability to learn from experience.

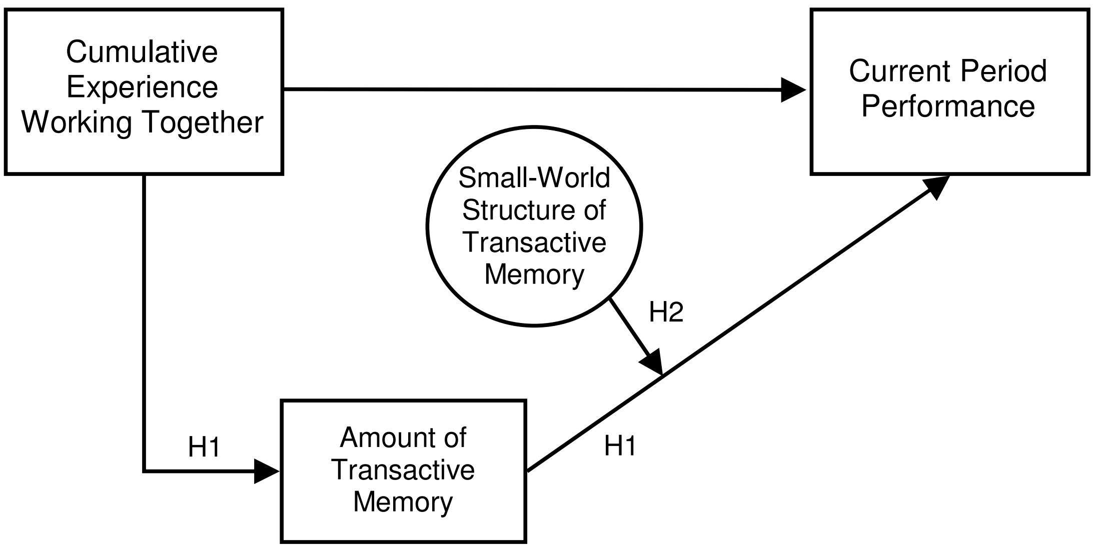
Of course, transactive memory can only partially explain group learning because other group psychological, contextual, and structural factors such as trust (Levin and Cross, 2004), cognitions (Fiol and Lyles, 1985), routines (Cohen and Bacdayan, 1994; Levitt and March, 1988; Nelson and Winter, 1982), and information technology (Tippins and Sohi, 2003), as well as individual learning characteristics (Mazur and Hastie, 1978; Shafer et al., 2001) and knowledge transferred from other groups (Darr, Epple, and Argote, 1995), all may account for variations in levels of learning. Thus, transactive memory is expected to partially explain group learning, leading to my first hypothesis (see "H1" in Figure 4.7) that

> Hypothesis 1: The relationship between a group's collective experience and its performance is partially mediated by the amount of the group's transactive memory.

As mentioned previously, the episodic-semantic memory model suggests not only that the *amount* of transactive memory changes over time but also that the perceptions that individual group members have about other members' knowledge tend to "cluster" according to social relationships maintained in the repeated performance of a task. This clustering is consistent with empirical evidence of "knowledge pools" (Reagans and McEvily, 2003; Singh, 2005) in work teams. Reagans and McEvily

(2003) found that when such knowledge pools were connected to each other through socially connected members of the respective pools, knowledge transferred more easily within the network. Thus, the way knowledge is concentrated in task-centered clusters keeps it embedded in the work group while making it potentially accessible through extant communication links outside those clusters.

Figure 4.7. Small-World Theory of Transactive Memory and Learning



The clustered *structure* of transactive memory is distinct from the *amount* of transactive memory in a group. Assuming the conditions are met for the existence of transactive memory (i.e., the presence of both a communication network and a cognitive knowledge network), it is proposed that the extent to which transactive memory actually bears upon the effectiveness of the work group depends on whether such memory is structured to enable efficient access to knowledge distributed throughout the group. Thus, the efficiency of a group's transactive memory depends not only on how quickly and accurately team members can access knowledge of group members in their own knowledge clusters but also on how easily they can access knowledge of members in other clusters. That is, efficiency rests on the network of social ties and iterads within such knowledge clusters along with ties and iterads between the clusters themselves.

The model that is proposed to maximize transactive memory efficiency is the "small-world network" model (Kochen, 1989; Milgram, 1967; Watts and Strogatz, 1998). Small-world networks are composed of clusters of nodes connected to other node clusters throughout the network. Within clusters, nodes are more highly connected to each other than to nodes outside of the cluster. However, the path between any two random nodes remains relatively short because typically at least one node in each cluster is connected to a node in another cluster. Thus even as the size of the network increases, the efficiency with which one node can access another node anywhere in the network is virtually the same.

Such structures have been found to characterize a variety of complex physical, biological, and social phenomena (Albert and Barabási, 2002; Strogatz, 2001). For example, the efficient functioning of memory in humans depends on distributed functionality yet high connectivity between various physical memory areas in the brain via neural shortcuts (Mountcastle, 1997; Roxin, Riecke, and Solla, 2004). Other examples include the network of hyperlinks in the Internet and the network of social relations in the spread of infectious diseases (Bar-Yam, 1997). Watts and Strogatz (1998) demonstrated that the neural network of the worm *Caenorhabditis elegans*, the power grid of the western United States, and the collaboration graph of Hollywood film actors are all similarly structured as small-world networks. The authors further suggested that such networks are generic for many networks found in nature. Small-world networks have even been popularized by the concept of "six degrees of separation" (Guare, 1990) and the "Kevin Bacon Game" (University of Virginia, 2005).

The structure of group transactive memory implied by the episodic-semantic memory model – that is, a network comprised of densely connected clusters (or sub-groups) that also have easy access to other densely connected clusters – is also consistent with the small-world network model. In small-world networks, *clustering* promotes efficient local information sharing, while connections between clusters promote *reachability* between any two nodes throughout the network. The extension of small-world network characteristics to transactive memory is similarly dependent on these twin concepts. Within knowledge-centric clusters of work group members, communication links arising from knowledge-seeking, homophily, or proximity create rich channels (Adler and Kwon, 2002) through which members can opportunistically or intentionally transfer knowledge (Ancona and Caldwell, 1992a; Kilduff and Tsai, 2003; Nonaka, 1994; O'Reilly, Caldwell, and Barnett, 1989) and thus improve group performance (Oh, Chung, and Labianca, 2004). As group members spend more time working together, stronger communication networks promote reachability that enables the group's experience working together to enhance productivity (Reagans et al., 2005).[8] Moreover, the evolution of stronger ties *within* knowledge clusters results in higher levels of transfer of tacit and complex knowledge, while the development of ties *between* clusters, although possibly weaker, is sufficient to account for transfer of less complex explicit knowledge between various network regions (Hansen, 1999). Such patterns are weaker or non-existent in groups with underdeveloped communication networks, where higher percentages of more socially isolated members may potentially constrain the positive effect of knowledge sharing on productivity (Thomas-Hunt, Ogden, and Neale, 2003).

While the inference that transactive memory is structured as a small-world network may be appealing upon first glance, it is not immediately apparent that group or even organization-level transactive memory networks are large enough to exhibit small-world characteristics. This would be arguably true were the transactive memory network only composed of communication linkages between members. However, given that transactive memory networks are comprised of group member communication links as well as each member's iterads indicating perceptions of every other member's level of knowledge, the maximum number of nodes and iterads in the transactive memory network is on the order of N^2K. Thus, even for the relatively small group of eight members in the example introduced in Figure 2, the size of the transactive memory network is on the order of $8^2 \cdot 12$, or 768. For more practical sizes of knowledge networks, the size of a transactive memory network for a team with only eight members

[8] Katz (1982) found that teams comprised of members who largely had been together for more than five years exhibited significantly less frequent intra-team communication than teams with lower average tenures, leading to reduced team performance. However, his study measured communication in terms of overall frequency as opposed to potential for communication as represented by changes in the density of network linkages. Hence, declines in gross intra-team communication frequency may arguably be explained by reductions in longer-tenured groups' needs for communication due to changes in knowledge stocks and group efficacies without concomitant reductions in network density. The network view holds that the richness of the communication interconnections can persist and grow irrespective of gross communication frequencies.

would be 1,200 or higher.

Thus, the implication of small-world network theory is that the most efficient group transactive memory is characterized by highly connected, knowledge-centric communication clusters connected by relatively few communication links between clusters. When social connections between team members are clustered around task-related knowledge areas of team members, their learning is embedded in knowledge pools that evolve as members work together. In "small world" transactive memory networks, at least one member of such knowledge clusters is also connected with at least one member of another knowledge cluster, shortening the geodesic distance between members needing task-related advice or knowledge. It is anticipated, then, that the extent to which transactive memory affects group learning is dependent on the "small-worldliness" of the transactive memory network, engendering my second hypothesis (see "H2" in Figure 7) that

> Hypothesis 2: The magnitude of the partial mediation effect of transactive memory on the relationship between cumulative group experience and group performance depends on the degree to which the transactive memory network is structured as a small-world network.

The example of a transactive memory network shown in Figure 6 displays such small-world properties in its arrangement in three distinct clusters. Nodes 2 and 8 comprise one cluster around knowledge areas *D*, *F*, and *J*. Similarly, nodes 6 and 7 form a second cluster around knowledge areas *B*, *L*, and *K* despite the relatively weak tie between node 3 and knowledge area *B*. The third and largest cluster is composed of nodes 1, 3, 4, and 5 combined with knowledge areas *A*, *C*, *E*, *G*, *H*, and *I*. Each cluster is characterized by relatively strong and dense social ties and iterads within the cluster itself. Connections between clusters are provided by somewhat weaker ties between nodes 1 and 2, nodes 2 and 7, and nodes 3 and 7 (see Figure 2 for tie weights). In addition, the example shows how quickly a transactive memory network even in a small work group can become very complex. Despite the complexity, however, efficiency remains high because even the most distant nodes are separated by a path going through only three other nodes. For example, although actor 3 is an expert in knowledge area *C*, her expertise is accessible by node 8 (who apparently has little or no expertise in knowledge area *C*) through node 8's (strong) connection to node 2, node 2's (weak) connection to node 1, node 1's (strong) connection to node 5, and node 5's strong social tie and iterad connected to knowledge area *C*. Node 1's strong social connection to node 3 could also prove beneficial in future exchanges as node 1 increases awareness of node 3's knowledge about *C*. Thus, task-centric and socially-situated knowledge in each cluster reinforces the strength of the social connections as well as the levels of intra-cluster knowledge awareness. Ties between clusters are weaker, thus lowering transaction costs while guaranteeing reachability between nodes in different clusters.

4.4 Method

Data

The study population is comprised of four U.S. companies engaged in the production and sale of electricity to industrial, commercial and residential consumers. Because of concerns in the electricity industry about knowledge retention due to anticipated high levels of retirement (Greene, 2005), the companies volunteered access to their workforces in return for insight from the study that they believed could be useful in their human resource strategies. Participants were also assured in writing that no information would be published that could be traceable by competitors to their respective organizations, thus I report no identifying information, including size and geographic information. Other than access to employees (which represented a substantial contribution), no direct financial support was provided by participating companies, and no financial inducements were provided to participating employees in return for their completing the surveys. While a field study is clearly not a random sample, I believe the commitment of the companies to the research objectives enabled a high level of access to managers and groups for initial and follow-up access as needed and helped promote the high level of participation crucial to reliable empirical network studies (Stork and Richards, 1992).

Within the participating companies, 120 groups representing five distinct areas – plant operations, distribution system maintenance, installation services, and customer call center services – agreed to complete the extensive network survey. In addition, two to four managers per group were separately surveyed and interviewed with regard to performance of teams about which they were knowledgeable. In all, 1,503 employees and 87 managers participated in the study. Fifteen surveys (from nine employees on one team of 18 and six employees on another team of 15) could not be used because the level of missing data at the group level exceeded the 15 percent threshold discussed below. Out of a total of 1,488 employees on the remaining 118 teams, 1,456 provided usable surveys, representing a net participation rate of 97.8 percent. Of the 32 employees who did not complete surveys, most were unavailable due to training or illness; four refused to complete the survey and, in accordance with survey guidelines, their refusals were not documented or reported to managers in any way. Data collection began in December, 2004 and continued until August, 2006.

I administered printed surveys of knowledge, social, and transactive memory networks in person to all participants at their work sites during work hours. The surveys took each group approximately 30 to 45 minutes to complete. Employees participated voluntarily and without separate pay. Because of the importance of high response rates for network-oriented studies, repeat visits were scheduled usually within one week as needed to survey group members unavailable during the initial survey meetings. Twenty teams were surveyed in a pilot phase to validate survey construction and administration procedures. Meetings with team managers confirmed the survey instrument validity with only cosmetic changes in the instrument at each group and company. In limited cases, I conducted some manager follow-up conversations by phone.

In cases where the overall survey participation rate for a group was below 85 percent, all surveys for that group were rejected. Omitted data for employees on work groups with low levels of missing data were be imputed using dyadic reconstruction, which has been shown to provide acceptable results when non-response levels do not exceed 15 percent (Robins, Pattison, and Woolcock, 2004; Stork and Richards, 1992). Dyadic reconstruction is based on presumed transitivity with other team member responses where possible or with the median team response otherwise.

In addition to survey data and manager interviews, archival data was obtained where feasible to help validate performance ratings. Such data have limited value in a cross-sectional group study because the standards and measures of performance across groups vary widely. However, the data were useful in corroborating the relative rankings of groups with common managers.

Measures

Dependent Variable

Manager-rated Team Performance. Manager ratings of group performance have been found to be reasonable predictors of actual team performance (Heilman, Bock, and Lucas, 1992) and were assessed by external leaders using three items adapted from Roe, Dienes, Ten Horn, and Zinovieva (1995) and Schippers, Den Hartog, Koopman, and Wienk (2003). The three items are: "This team's performance exceeds the performance of other teams," "This team meets or exceeds performance targets," and "There are no or few complaints about the quality of this team's work" (1=Strongly Agree, 5=Strongly Disagree). The average of Cronbach's alpha computed across sets of common managers was 0.88, indicating strong internal validity of the survey questions. The responses were reverse coded and averaged to compute manager-rated team performance for each work group.

Although not used in the formal statistical analyses, employee versions of the same three questions were also asked of each group member as a means of providing a modest measure of consistency. The three items are: "Our team's performance exceeds the performance of other teams," "Our team meets or exceeds our performance targets," and "There are no or few complaints about the quality of our team's work" (1=Strongly Agree, 5=Strongly Disagree). The items were reverse coded and averaged for each work group. The average Cronbach's alpha (weighted by group size) across all 118 groups is 0.85. Average group member self-ratings, while predictably systematically higher (by an average of 7.9 percent, significant at $p<0.01$) due to well-documented biases in self-assessment (Dunning, Heath, and Suls, 2004), they correlated very highly with manager ratings (*r*=0.89).

While both cross-sectional and self-ratings raise the possibility of common method bias, they do permit comparison of performance across teams with tasks of varying complexity and generally incompatible performance criteria. In addition, Evans' (1985) study of correlated error in interaction models found that common method bias does not induce artifactual interaction and that true interactions can in fact be attenuated, suggesting that if anything such bias might result in understatement of observed interactions.

Independent Variables

Average Group Tenure. Each type of work group in the sample measured output differently, and even output measures for groups of the same type across different companies varied considerably. Thus, average group tenure – or the average number of years that members have been part of their current work group – is used as a proxy for collective group experience. At the group level, tasks of work groups included in the study are uniform with respect to group type. For example, a plant team's task is to maintain production facilities and reliably produce electricity when called upon to do so. As group members focus on such shared group tasks over time, better coordination and communication along with the development of shared knowledge structures lead to improved performance (Klimoski and Mohammed, 1994; Liang, Moreland, and Argote, 1995). Thus, the amount of time members have spent working as an intact group captures the nature of specific occurrences shared by team or group members such as engaging in group training, dealing with emergency conditions, or overcoming widespread outages. While the measure is quantitative, its purpose is also to capture qualitative elements of experience, which according to Tesluk and Jacobs (1998) adds another important but often neglected dimension to the robustness of group experience measures.

Transactive Memory Network Density. The amount of transactive memory in a work group is represented by the density of the group's transactive memory network, or the proportion of actual transactive memory compared to the maximum possible transactive memory. As introduced earlier (see Figure 6), a transactive memory network is comprised of the union of a communication network and a cognitive knowledge network. Thus, transactive memory network density is a combination of the density of the underlying communication and knowledge networks.

The first component of group transactive memory network density is the density of the communication network (see Figure 2). A group's communication network is formally defined as a valued graph represented by the square, asymmetric matrix C[i, j], with $i \in \{1 \ldots N\}$ rows, one for each of N team members, and $j \in \{1 \ldots N\}$ columns, also one for each team member. Each cell in C[i, j] represents the level of communication between individual i and individual j.

Values for network relations in the communication networks of the groups in this study were based on responses to the question "Please indicate approximately how often you communicate with your team members for any reason." Communication levels were measured on a Likert scale from 1 to 5 (1=Once per Month (or less), 5=More than Once per Day). Although individual reports of connections with others are not perfect reflections of their actual interactions (Bernard, Killworth, and Sailer, 1982), group members are quite good at remembering long-term or typical patterns of interaction with other members (Freeman, Romney, and Freeman, 1987). Respondents report frequently contacted, close, core network ties with those whom they have many types of relationships more reliably than they do more distant, simple relations (Kogovšek and Ferligoj, 2004), and those close ties are also more accessible in memory (Brewer, 1995; Burt, 1986; Verbrugge, 1977). Thus, even though respondents' answers on the survey reflect their typical interpersonal environment rather than a mathematically accurate representation of communication, it is argued that the survey instrument is acceptable for identifying the key communication patterns needed in this study.

Communication Network Density, D_C, is then defined as the proportion of actual communication compared to maximum possible communication. Since diagonals (which would represent self-communication) are not considered, the maximum level of communication would be 5N(N-1). Thus, D_C is calculated as:

$$D_C = \frac{\sum_{i=1}^{N} \sum_{j=1}^{N} \mathrm{C}[\mathrm{i}, \mathrm{j}]}{5N(N-1)} \tag{4.1}$$

The second component of group transactive memory network density is the density of the cognitive knowledge network. Introduced earlier (see Figure 5), a cognitive knowledge network K[i,j,k] for a group of N actors with K possible knowledge areas is now formally defined as the graph induced by the iterads τ_{ijk} that exist between all actors $i \in \{1 \ldots N\}$ and knowledge areas $k \in \{1 \ldots K\}$ possessed by actors $j \in \{1 \ldots N\}$, where $i \neq j$. Because team members were generally limited to thirty minutes to complete the survey, it was not possible to survey team members on their detailed perceptions of values of other members' knowledge over all knowledge areas. Similar limitations have been documented in previous network research (Krackhardt, 1987). Thus, this study used a simplified form of cognitive knowledge network, focusing on whether team members perceive others to be experts in each knowledge area for the group's task. In the cognitive knowledge network represented by the matrix K[i,j,k], the iterad τ_{ijk} in each cell is thus set to a value of 1 if team member i perceives team member j to be an expert about knowledge area k, otherwise the cell value is 0. Values of entries in the cognitive knowledge matrix were based on responses to the following survey question:

> "For each knowledge area, please indicate the team member or members (including yourself) whom you believe are experts in that particular knowledge area. If you cannot identify anyone for a certain area, leave it blank. If there is more than one, list them all."

Knowledge areas were elicited based on task-related training materials, personnel descriptions, and interviews with managers and subject-matter experts. Knowledge awareness as revealed by survey responses was assumed to be a "true" representation of knowledge awareness. Variables for transactive memory accuracy and consensus (introduced in the "Control Variables" section below) control for variance of the actual group transactive memory networks from the ideal (for example, due to incorrectly identifying someone as an expert). Since self-ratings of expertise are subject to overconfidence bias (Dunning, Heath, and Suls, 2004), those self-nominations were excluded from consideration in calculating transactive memory network density (future studies will examine the effects of these "reflexive iterads").

Cognitive knowledge network density, D_K, is obtained by finding the proportion of a group's actual cognitive knowledge compared to its maximum possible cognitive knowledge. The actual cognitive knowledge for a group is sum of all the cells in the matrix K[i,j,k]. The maximum possible cognitive knowledge for a given group depends on the number of distinct experts (excluding self-nominations) identified for each knowledge area. Summing the number of distinct knowledge experts in each knowledge area over all knowledge areas and multiplying that value by N-1 yields the maximum possible cognitive knowledge, K_{max}, for that group. Thus, D_K is calculated as:

$$\frac{\sum_{k=1}^{K}\sum_{i=1}^{N}\sum_{j=1}^{N} K[i,j,k]}{K_{\max}} \qquad (4.2)$$

Transactive memory network density, D_T, for a group is the weighted combination of the densities of the group's communication and cognitive knowledge networks:

$$D_T = \omega_C D_C + \omega_K D_K \qquad (4.3)$$

where $\omega_C + \omega_K = 0$, and global values of ω_C and ω_K were determined by iterative optimization of the statistical model to minimize the sum of squared errors.

Small-World Quotient. The extent to which group transactive memory exhibits small-world characteristics is captured in the "Small-World Quotient," or *SWQ* (Kogut and Walker, 2001; Davis et al., 2003; Uzzi and Spiro, 2005). As discussed previously, small-world networks are characterized by high clustering accompanied by low average distance between nodes. The "clustered" nature of group transactive memory is measured by calculating a dynamic, multi-dimensional version of the *clustering coefficient* (Watts, 1999) for the transactive memory network. The clustering coefficient reflects the average tendency of group members' transactive memory "neighborhoods" to be relatively highly connected. In calculating the clustering coefficient, the proportion of actual connections in every member's "neighborhood" is compared to total possible connections. Values for each member are then averaged to obtain the group's clustering coefficient. Since the group transactive memory network is a union of two networks – the communication and cognitive knowledge networks, a group member's neighborhood consists of both ties to other members as well as other iterads. Accordingly, I define a group member's "neighborhood" as the collection of:

(1) group members to whom the focal member is connected via communication ties,

(2) ties from the focal member to the knowledge areas in which one or more members in the neighborhood view the focal member as expert (thus, this excludes ties resulting from self-nominations),

(3) agent-to-knowledge ties to which the focal member is connected via his or her iterads,

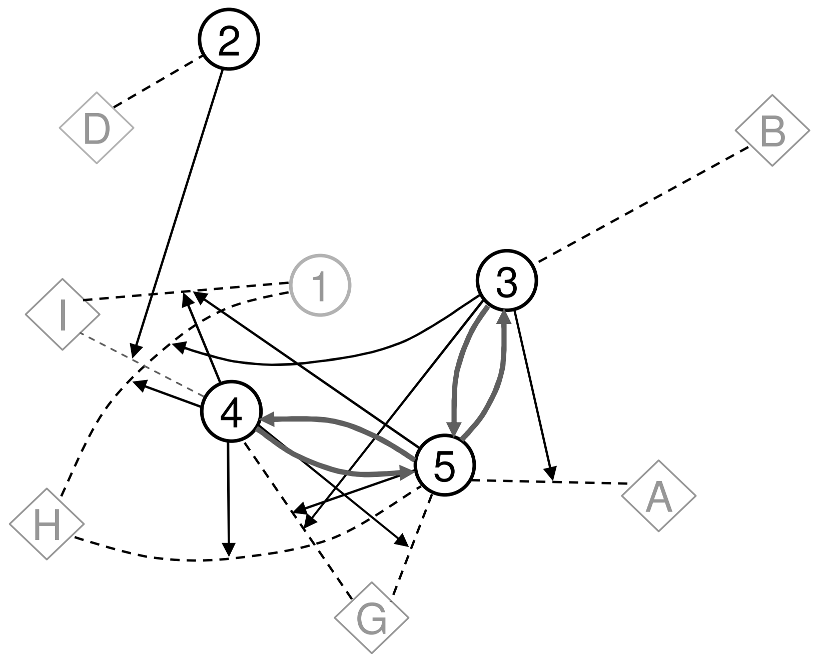
(4) ties between group members defined in (1),

(5) iterads formed between group members in (1) and the ties defined by (2), and

(6) iterads formed between group members in (1) and the ties defined by (3).

For example, Figure 4.8 shows the neighborhood of group member 1 based on the transactive memory network example depicted in Figure 4.6. Group member 1's neighborhood is comprised of members 2, 3, 4, and 5; the ties between member 1 and knowledge areas H and I; the member-to-knowledge ties 2-to-D, 3-to-B, 4-to-G, 4-to-H, 4-to-I, 5-to-A, 5-to-G, and 5-to-H; and the total of twelve ties between these sets of neighborhood elements – specifically, the two connections between member 5 and members 3 and 4, along with the ten iterads $\tau_{3\text{-}1\text{-}H}$, $\tau_{4\text{-}1\text{-}H}$, $\tau_{4\text{-}1\text{-}I}$, $\tau_{5\text{-}1\text{-}I}$, $\tau_{2\text{-}4\text{-}I}$, $\tau_{3\text{-}4\text{-}G}$, $\tau_{3\text{-}5\text{-}A}$, $\tau_{4\text{-}5\text{-}G}$, $\tau_{4\text{-}5\text{-}H}$, and $\tau_{5\text{-}4\text{-}G}$.

Figure 4.8. Transactive memory network "neighborhood" for group member 1



The clustering coefficient, CC_i, for any group member i is the ratio of C_i, the actual number of ties between the elements of i's neighborhood, to $C_i^{\max}$, the maximum number of ties between those elements, where

$C_i^{\max} = C_j^{\max} + C_{jk}^{\max} + C_\tau^{\max}$;

$C_j^{\max} = \dfrac{j_{-i}(j_{-i}-1)}{2}$ = maximum number of ties between group members in i's neighborhood (excluding i);

$C_{jk}^{\max} = j_{-i}k_i$ = maximum number of ties between members of i's neighborhood and the ties between i and i's expert knowledge areas;

$C_{\tau}^{\max}$ = $j_{-i}H_x + \left(j_{-i} - 1\right)\sum_{j=1}^{j_{-i}} H_{\mathrm{J}(j)}$ = maximum number of iterads connecting members of i 's neighborhood with the member-to-knowledge pairs to which member i is connected;

j_{-i} = number of nodes in set J∈ {members to whom i is directly connected};

k_i = number of nodes in set K∈ {knowledge areas in which member i is acknowledged as an expert by one or members of i 's neighborhood};

$H_{\mathrm{J}(j)}$ = number of J(j)-to-knowledge area pairs to which i is connected by an iterad, and

H_x = number of x-to-knowledge area pairs to which i is connected via an iterad, where member x is not part of i's communication neighborhood.

Returning to the example in Figure 4.8, the maximum number of transactive memory connections in member 1's neighborhood is

$$\frac{(4 \cdot 3)}{2} + (4 \cdot 2) + [(4 \cdot 0) + (3 \cdot 7)] = 35 .$$

Thus, the clustering coefficient for group member 1 is 12/35 or 0.34. The clustering coefficient for the entire transactive memory network, or *CC*, is the average of CC_i over all i∈ {1…*N* group members}. This component of the *SWQ* reflects the tendency of team members to cluster around both common connections to one another and knowledge areas related to the shared group tasks.

In addition to high clustering, small-world networks exhibit low average distance between group members. Thus, the *SWQ* incorporates this dimension using a measure of *characteristic path length* (*CPL*) of the communication network. Assuming that the communication network C[i, j] is fully connected (that is, every member is reachable through one or more connections with other members[9]), then the distance between any two members is the shortest length of the possible paths connecting them. The *CPL* is obtained by averaging the shortest distances between every pair of nodes.

Combining the *CC* and *CPL* into a single measure, *SWQ*, requires recognition that small-world networks have clustering coefficients much higher than clustering coefficients of random graphs and characteristic path lengths that are on the same order as characteristic path lengths of random graphs (Watts and Strogatz, 1998). Following Watts and Strogatz, for a random transactive memory network of n members, k knowledge areas, d average number of communication edges per member, and d_k average number of iterads per member, the clustering coefficient CC_{random} is approximated by $(d+d_k)/[n(k+1)]$, and the characteristic path length CPL_{random} between members is approximated by $(\ln n)/(\ln d)$. The *SWQ* is calculated by dividing the ratio of *CC* to CC_{random} by the ratio of CPL to CPL_{random}. Higher *SWQ* values more strongly indicate that the focal network exhibits small-world characteristics.

Control Variables

Average Task Experience. Measures of experience based on both tenure (McDaniel, Schmidt, and Hunter, 1988; Medoff and Abraham, 1981; Schmidt, Hunter, and Outerbridge, 1986) and the number of times a task is performed (Lance, Hedge, and Alley, 1989; Vance, Coovert, MacCallum, and Hedge, 1989) have been shown to have positive yet curvilinear associations with individual performance. However, as suggested by Quiñones *et al*. (1995) and Tesluk and Jacobs (1998), measures that represent both time and task perspectives of experience are more robust. Because of the nature of the group tasks in this study, it is argued that role tenure is also a reasonable measure for task experience (i.e., the number of times various tasks have been performed). For example, the task of a steamfitter in a power plant is generally focused on maintenance and repair work involving piping, valves, and gaskets for transporting high- and low-pressure steam, oil, and air. Routine maintenance frequency, procedures, and job-time allocations are centrally prescribed and thus the number of times a

[9] In this study, the lowest weighting on a communication linkage is 0.20, corresponding to a frequency of communication of less than once per month. Thus, the assumption that the communication network of each group is fully connected is valid.

steamfitter has performed assigned tasks is largely a function of the member's tenure as a steamfitter. Other team members' levels of experience are similarly associated with their role or position tenure. Thus, this measure is calculated at the group level as role tenure averaged over all team members.

Average Organization Tenure. Organizational commitment, which generally has been found to have positive effects on performance (Mowday, Porter, and Steers, 1982), has been found to decay as a function of tenure. New organization members have been found to exhibit high levels of commitment that dissipate with increasing time in the organization (Wright and Bonett, 2002), resulting in lower group performance. Thus, if significant, this measure is expected to have a negative coefficient and is calculated at the group level as the average number of years each member has been in the organization of which the group is a part.

Turnover. Turnover is defined as "the degree of individual movement across the membership boundary of a social system" (Price, 1977). While not all findings regarding turnover have been negative (see Jovanovic, 1979, and Guthrie, 2001), most studies that incorporate turnover as an independent or interactive variable have found deleterious effects. For example, McElroy, Morrow, and Rude (2001) found that turnover adversely affected profitability, productivity, service costs, and customer satisfaction in 31 financial services firms. Huselid's (1995) study of nearly 1,000 firms found that firm-level turnover was associated with lower sales per employee as well as inferior financial performance. Further studies by Batt (2002) and Shaw, Duffy, Johnson, and Lockhart (2005), found similar negative impacts on performance as turnover increased. Experimental research by Argote *et al.* (1995) found that turnover affected groups with complex tasks less than those with simple, non-decomposable tasks. All of these findings suggest that turnover can be a crucial control variable in performance studies. In this study, turnover rates are relatively stable and thus are measured for the twelve months preceding the month in which the survey was administered. It is expected that turnover will have a negative coefficient and is calculated as the number of separations for the year divided by average monthly employment for the year (U.S. Department of Labor, 2006).

Transactive Memory Consensus. Moreland (1999) stressed that the level of agreement among team members concerning how knowledge is distributed is an important dimension of transactive memory. Prior research suggests that communication in group task settings, even over relatively short periods of time, leads to reasonably accurate awareness of other actors' knowledge (Bottger, 1984; Liang, Moreland, and Argote, 1995; Littlepage, Robison, and Reddington, 1997). However, Austin (2003) found that the level of "task transactive memory consensus" is positively associated with group performance. Austin's original measure assumes that each team member recognizes only one other team member as a potential expert in a given knowledge area. This restriction could lead to overstating the level of agreement, since members may believe that multiple members are experts. Thus, to build on Austin's measure yet reflect a more robust level of expertise awareness in groups, transactive memory consensus is defined as the extent to which members agree that any number of members are experts in each knowledge area.

To compute this measure, for each knowledge item k in the cognitive knowledge network, $K[i,j,k]$, I first calculate the average "distance" between each group member's perception of experts and every other member's perception as the average Hamming distance between member i 's perceived experts vector $K[i,j,k]$, and all other agents' perceived experts vectors $K[1,j,k]$, …, $K[i\text{-}1,j,k]$, $K[i+1,j,k]$, …, $KA[N,j,k]$, $i \neq j$. The average Hamming Distance between agents for a given knowledge area is then normalized by dividing by the maximum Hamming distance, N. After this process is repeated for each knowledge area, the k normalized distance values are then averaged to obtain a group average Hamming distance over all knowledge areas. Finally, the value of the group's Transactive Memory Consensus is obtained by subtracting the group average Hamming distance from 1 to indicate that a high score is associated with high transactive memory consensus.

Although knowledge of which team members have useful connections *outside* the work team is also associated with improved team performance (Ancona and Caldwell, 1992b), impacts from these external transactive memory references are outside the scope of this study and will be examined in future research.

Transactive Memory Accuracy. According to Krackhardt (1990), the accuracy of individuals' perceptions of network relationships influences the strengths and patterns of interactions within those networks. With respect to group knowledge, the extent to which perceptions of individuals regarding the knowledge possessed by others are consistent with the knowledge actually possessed by those other team members leads to better group performance on problem-solving tasks (Libby, Trotman, and Zimmer, 1987; Littlepage and Silbiger, 1992). Transactive memory accuracy, or *TMA*, measures the extent to which group members' perceived levels of other members' knowledge are consistent with actual levels of knowledge possessed by those other members. Austin (2003) validated this approach and found that such accuracy was positively associated with self and manager ratings of team performance.

As previously mentioned, members' status as perceived experts in one or more knowledge areas is presumed to be revealed by values in the cognitive knowledge network. In this study, for all knowledge areas *k* where KA[i,j,k]=1 and $i \neq j$, member *i* is considered an expert. However, in addition to asking members about their "awareness" of others as experts, the network survey asked members to rate themselves regarding their relative level of expertise in each knowledge area. As introduced earlier (see Figure 3), the resulting "knowledge network" is defined as a valued graph represented by the bipartite matrix, K[i, k], with $i \in \{1 \ldots N\}$ rows, one for each team member, and $k \in \{1 \ldots K\}$ columns, one for each knowledge area listed on the survey. Each cell in K[i, k] represents the relative level of knowledge that individual *i* has concerning knowledge area *k*. Values for network relations were based on responses to the question,

> "For each knowledge area required for tasks performed by your team, please check the box that corresponds to your evaluation of your ability in that particular area."

Knowledge levels were measured on a Likert scale from 1 to 5 (1=Very Low, 5=Very High), and responses were coded from 1 to 5, with 1 representing little or no knowledge of a particular area and 5 representing expert knowledge.

The *TMA* measure is calculated by averaging the values in a "transactive memory accuracy matrix," TMA[i,k]. This matrix summarizes average values of actual knowledge possessed by members perceived as experts. The value of a cell in TMA[i,k] represents the average of the actual levels of knowledge about k possessed by those group members perceived by member i to be expert in k. Thus, the value for a cell is obtained by first identifying the group members identified by i as expert in knowledge area k – that is, any member j where KA[i,j,k]=1, $j \in \{1, 2, \ldots, N\}$, $i \neq j$. The value of TMA[i,k] is simply the average of the knowledge network values K[j_k,k] for each of the members j where KA[i,j,k]=1. The final TMA measure for a group is the average of the values in every cell of the matrix TMA[i,k], or

$$TMA = \frac{\sum_{i=1}^{N} \sum_{k=1}^{K} \mathrm{TMA}[i,k]}{N \cdot K}. \tag{4.4}$$

For example, in Figure 4.4, member 1 identified group members 4 and 5 as experts on knowledge area G. As shown in Figure 4.3, members 4 and 5 rated their own levels of knowledge of area G as 0.8 and 0.65, respectively. Thus, the value of TMA[1,G] is the average of 0.8 and 0.65, or 0.725. A similar process is repeated for each cell in TMA[i,k]. The values in TMA[i,k] are then averaged over all actors and knowledge areas to compute a group measure of transactive memory accuracy. Although conceptually similar to Austin's (2003) measure, this approach permits members to identify more than one expert in each knowledge area.

Task and Outcome Interdependence. Interdependence is essentially a measure of how much team members depend on one another to perform their jobs (Gully, Incalcaterra, Joshi, and Beaubin, 2002; Wageman, 1995). This perspective has typically been characterized by both a *task* and an *outcome* dimension. According to Thompson (1967), levels of task interdependence can range from low or "pooled" interdependence, in which tasks are performed separately and in any order, to medium or "sequential" interdependence, in which some tasks are required to be completed before others, to high or "reciprocal" interdependence, in which pairs of tasks require outputs from each other before completion. In addition to Thompson's technological perspective, task interdependence can also be viewed as a characteristic of team members' behavior in executing their work (Shea and Guzzo, 1989; Wageman 1995). For example, workers who help one another complete their tasks even though those tasks are not necessarily assigned are more task interdependent than workers who do not. Task interdependence has been positively linked to effectiveness outcomes such as productivity, satisfaction, and manager ratings of performance (Campion, Medsker, and Higgs, 1993; Kiggundu, 1983; Pearce and Gregerson, 1991).

Outcome (or goal) interdependence, on the other hand, reflects the extent to which team members believe their individual goal attainment depends on the successful goal attainment of other team members. Team effectiveness has been shown to be higher when team members share greater degrees of outcome interdependence (Hyatt and Ruddy, 1997). However, impacts are to some extent dependent on demographic and tenure diversity, with teams having lower diversity and higher longevity displaying the greatest impacts of goal interdependence on satisfaction and commitment (Schippers *et al.* 2003).

Both task and outcome interdependence have been found to be positively associated with attitudinal outcomes such as job satisfaction and commitment over and above individual job characteristics (Van Der Vegt, Emans, and Van De Vliert, 2000, 2001). However, job satisfaction appears greatest when teams exhibit high goal interdependence in conjunction with high task interdependence (Van der Vegt, Emans, and Van de Vliert, 2001). Since the structuring and assignment of tasks infers interdependence that can influence the levels of team commitment (Bishop and Scott, 2000) as well as interaction in executing the task (Hackman and Morris, 1975), it is expected that groups with higher task interdependence will show greater impacts of social and knowledge network attributes on organizational learning.

Task interdependence is measured by responses to the following five questions: (1) “I have to obtain information and advice from others on my team to complete my work” (reverse coded), (2) “I depend on the contributions of others on my team for the completion of my work” (reverse coded), (3) “I have a one-person job; I rarely have to check or work with others,” (4) “I have to work closely with others on my team to do my work properly," and (5) "In order to complete their work, other team members have to obtain information and advice from me" (reverse coded). Like other survey questions, responses were on a Likert scale (1=Strongly Agree, 5=Strongly Disagree, weighted average Cronbach's α=0.85).

Outcome interdependence is measured by responses to the following two questions: (1) "Members of our team are informed about the goals we should attain as a unit" and (2) "Members of our team receive feedback on the basis of our collective performance. Responses were on a Likert scale (1=Strongly Agree, 5=Strongly Disagree) with a weighted average Cronbach's alpha of 0.84. Only two questions could be included in the survey because of length limitations.

Group Size. Group size can influence transactive memory by affecting communications within the group and by changing the amount of information needed to maintain a high level of group expertise (Wittenbaum, Vaughan, and Stasser, 1998); larger groups require each group member to remember information about more people.

Number of Knowledge Areas. The number of knowledge areas required for the group task may affect the efficiency of the transactive memory network (Ashworth and Carley, 2006). Similar to larger groups, groups with more knowledge areas have more to "remember" about each agent in the group.

Other Controls. Since the data are cross-sectional, all model specifications included fixed effects of company and group type to control for unobserved heterogeneity across groups (Hausman and Taylor, 1981), including those arising from geographic location and physical layout. In addition, demographic controls are included for age, gender, race, Hispanic origin, and educational level. Group-level "age" was calculated as the average age of the group members. Gender at the group level was calculated as the average of responses coded as "0" for female or "1" for male. Thus, values represented the percentage of the team that is male. Since the only races represented in all survey responses were African-American and Caucasian, the "race" variable was calculated as the average of responses coded "0" for African-American or "1" for Caucasian. Thus, values for "race" simply indicated the percentage of a team that is Caucasian. Consistent with U.S. Census Bureau (2005) norms, the survey included a separate category for Hispanic origin, coded as "0" for non-Hispanic and "1" for Hispanic. Thus, values for Hispanic origin indicated the percentage of a group that is Hispanic. Education level was calculated as the average of the number of years of education reported by each group member.

Empirical Model

In the analysis, I used ordinary least squares (OLS) regression procedures for testing moderated mediation as recommended by Muller, Judd, and Yzerbyt (2005). The following equation was used to test for the relationship between average group experience and performance:

$$Performance_{icg} = \beta_1 AvgGroupExp_{icg} + \gamma_{1-14} Controls_{icg} + C_c + T_g + \varepsilon_{icg} \tag{4.5}$$

As a first step in testing for mediation, the following equation then tests for a significant relationship between the independent variable (average group experience) and the proposed mediating variable (transactive memory network density, or *TMND*):

$$TMND_{icg} = \beta_1 AvgGroupExp_{icg} + \gamma_{1-14} Controls_{icg} + C_c + T_g + \varepsilon_{icg} \tag{4.6}$$

With the following equation I then test for the significance of the effect of the mediator (transactive memory network density) on performance, controlling for average group experience:

$$Performance_{icg} = \beta_1 AvgGroupExp_{icg} + \beta_2 TMND_{icg} + \gamma_{1-14} Controls_{icg} + C_c + T_g + \varepsilon_{icg} \tag{4.7}$$

To establish whether mediation has occurred, the coefficient β_1 in Equation 4.7 (the residual direct effect of average group experience on performance) is then compared to the coefficient β_1 in Equation 4.5. Mediation is said to have occurred if β_1 in Equation 4.7 is significantly smaller in magnitude than β_1 in Equation 4.5.

Finally, Equations 4.8-4.10 test for the moderating effect of the small-world structure on the mediator, transactive memory network density:

$$Performance_{icg} = \beta_1 AvgGroupExp_{icg} + \beta_2 SWQ_{icg} + \beta_3 (AvgGroupExp_{icg} * SWQ_{icg}) + Co_c + Type_g + \varepsilon_{icg} \tag{4.8}$$

$$TMND_{icg} = \beta_1 AvgGroupExp_{icg} + \beta_2 SWQ_{icg} + \beta_3 (AvgGroupExp_{icg} * SWQ_{icg}) + Co_c + Type_g + \varepsilon_{icg} \tag{4.9}$$

$$Performance_{icg} = \beta_1 AvgGroupExp_{icg} + \beta_2 SWQ_{icg} + \beta_3 (AvgGroupExp_{icg} * SWQ_{icg}) + \beta_4 TMND_{icg} + \beta_5 (TMND_{icg} * SWQ_{icg}) + Co_c + Type_g + \varepsilon_{icg} \tag{4.10}$$

According to Muller, Judd, and Yzerbyt (2005), to establish moderated mediation, the overall effect of the independent variable (β_1 in Equation 4.8) must be significant but not dependent on the proposed moderator, *SWQ* (that is, β_3=0 in Equation 4.8). In addition, the following conditions must hold:

- either the effect of the independent variable on the mediator depends on the moderator ($\beta_3 \neq 0$ in Equation 4.9) or the partial effect of the mediator on the dependent variable depends on the moderator ($\beta_5 \neq 0$ in Equation 4.10), or both;

- if $\beta_3 \neq 0$ in Equation 4.9, then there must also be a partial effect of the mediator on the outcome on average (that is, $\beta_4 \neq 0$ in Equation 4.10); and

- if $\beta_5 \neq 0$ in Equation 4.10, there must also be a significant overall effect of the independent variable on the mediator (that is, $\beta_2 \neq 0$ in Equation 4.9).

Based on Cohen's (1988) method of statistical power analysis, assuming anticipated effect sizes in the small to moderate range (2 to 10 percent), the likelihood is greater than 0.99 that the sample of 118 groups will yield a model R^2 that is significant at an alpha level of 0.05. Although Cohen's analysis does not take into account the interaction terms, which can proportionately reduce the effective power, it was assumed that the terms are not perfectly reliable but do not reduce power to an unacceptable level.

4.5 Results

Descriptive statistics and Pearson correlations are provided in Tables 4.1a and

4.1b. Company and group type fixed effects were not significant (at $p<0.10$) in any of the statistical models, indicating an apparent absence of significant systematic effects due to company or group type. In addition, the only control variables that exhibited significance in most models were turnover, transactive memory consensus, outcome interdependence, and group size. The coefficient for gender was positive and significant in the models testing the mediator, transactive memory, as the dependent variable; however, the coefficient is not significant (p values range from 0.33 to 0.73) in tests with group performance as the dependent variable, suggesting that significance in the former case is possibly an artifact of the relatively recent increase to 25 percent female in the electricity industry in the last fifteen years. Although each statistical model included all controls, Tables 4.2 and 4.3 summarize only the results of variables with significant coefficients. Remaining coefficients are reported separately in Table 4.4.

Table 4.1a. Summary Statistics (sample of 118 groups).

	Variable	Mean	Std. Dev.
1	Group Performance	3.05	0.53
2	Average Group Experience	5.04	1.90
3	TM Network Density	0.00	0.13
4	Small World Quotient	0.00	1.60
5	Average Task Experience	9.33	3.78
6	Average Organization Tenure	19.85	5.22
7	Turnover	0.06	0.09
8	TM Consensus	0.90	0.05
9	TM Accuracy	0.66	0.10
10	Task Interdependence	3.20	0.50
11	Outcome Interdependence	3.35	0.64
12	Group Size	12.61	5.63
13	Number of Knowledge Areas	32.08	9.09
14	Gender	0.78	0.27
15	Age	47.60	3.83
16	Race	0.86	0.14
17	Ethnicity	0.09	0.10
18	Years of Education	13.22	0.68

Table 4.1b.
Pearson Correlations.

	Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1	Group Performance																	
2	Average Group Experience	.60***																
3	TM Network Density	.46***	.41***															
4	Small World Quotient	.37***	.18	-.21*														
5	Average Task Experience	.07	.17	-.07	-.11													
6	Average Organization Tenure	.05	.13	-.03	-.17	.63**												
7	Turnover	.53***	-.32***	-.42***	-.23***	.07	.124											
8	TM Consensus	.15	.02	-.28**	.60***	-.07	-.12	-.09										
9	TM Accuracy	.27**	.30***	.10	.55***	-.18	-.12	-.22*	.41***									
10	Task Interdependence	.18*	.20*	.38***	-.07	-.17	-.22*	-.21*	-.13	-.01								
11	Outcome Interdependence	.36***	.19*	.22*	.08	-.24**	-.30**	-.37***	-.01	.03	.29**							
12	Group Size	-.21*	-.21	-.67***	.15	.23*	.06	.40***	-.22*	-.14	-.33***	-.28**						
13	Number of Knowledge Areas	.22*	-.05	.26**	-.08	-.09	-.11	-.22*	-.05	-.22*	.26**	.43***	-.23*					
14	Gender	.18	.13	.07	-.22	.09	.18	-.29**	-.06	-.04	.38	.11	-.31	.39				
15	Age	.04	.18*	.01	-.23*	.57***	.78***	-.16	-.09	-.11	-.09	-.12	.08	-.01	.15*			
16	Race	.08	-.07	.11	.12	.16	.01	-.07	-.08	-.06	-.01	.07	.08	.06	.08	.04		
17	Ethnicity	.09	.13	.06	.11	-.20*	-.08	-.06	.07	.03	-.04	.03	-.12	.08	.07	.10	.01	
18	Years of Education	-.26**	-.21*	-.12	-.05	-.22*	-.19*	.36***	-.04	-.01	-.23	-.07	.04	-.19	-.15	-.14	-.08	.12

N=118 * p<.05, ** p<.01, *** p<.001

Table 4.2 presents results of statistical models testing the hypothesis that the amount of transactive memory mediates the relationship between cumulative group experience and group performance. In column 1 of Table 4.2, the coefficient for average group experience is positive and significant, indicating that average group experience is positively associated with average manager ratings of group total performance. Not surprisingly, this confirms the relationship between the group learning constructs depicted in Figure 1. Column 2 of Table 4.2 reflects the model based on Equation 6, which tests the significance of the independent variable, average group experience, on the hypothesized mediating variable, transactive memory network density. The

Table 4.2. Test of transactive memory density mediation (Hypothesis 1) of relationship between average group experience and group performance.

Variable	1 (DV=Group Performance)	2 (DV=TMND)	3 (DV=Group Performance)
Average Group Experience	0.126*** (0.022)	0.017*** (.005)	0.099*** (0.022)
Transactive Memory Network Density (*TMND*)			1.604*** (0.437)
ω_c	0.237*** (0.040)	0.251*** (0.043)	0.247*** (0.042)
Turnover	-1.832*** (0.522)	-0.210‡ (0.111)	-1.496** (0.501)
Transactive Memory Consensus	1.275‡ (0.756)	-0.392* (0.161)	1.904* (0.734)
Outcome Interdependence	0.122‡ (0.071)	-0.023 (0.132)	0.159* (0.068)
Size	0.008 (0.008)	-0.010*** (0.002)	0.024** (0.009)
Company Fixed Effects?	N.S.	N.S.	N.S.
Group Type Fixed Effects?	N.S.	N.S.	N.S.
Adjusted R^2	0.553	0.646	0.605

N=118 ‡ p<.10, * *p*<.05, ** *p*<.01, *** *p*<.001, N.S. = Not significant. Standard errors are heteroskedasticy robust. Other control variables were generally not significant and are reported separately in Table 4.3.

coefficient in this case is positive and significant, confirming that the level of group transactive memory increases with the amount of time that groups work together. In addition to demonstrating a significant effect of the treatment on the mediator (Baron and Kenny, 1986), Kraemer et al. (2002) point out that the mediator must occur during treatment and be correlated with the treatment variable. While it is possible that transactive memory within a group can be aided by prior knowledge of members (for example, based on the reputation or title of an expert who joins the team), the relative density of the transactive memory network grows predominantly in accordance with the episodic-semantic memory model and thus co-evolves with average group experience. In addition, as shown in Table 4.1b, average group experience is strongly correlated with the proposed transactive memory mediator. Thus, the additional criteria suggested by Kraemer et al. (2002) for qualifying a mediating variable are satisfied. In column 3 of Table 4.2, the coefficient of the mediator, transactive memory network density, is strongly positive and significant. The coefficient of the treatment variable, average group experience, is also strongly positive and significant, except that the coefficient is significantly reduced from 0.126 (at $p<0.001$) in the model without mediation (column 1) to 0.099 (column 3). Thus, results provide support for Hypothesis 1.

Table 4.3 presents the results of statistical tests for the hypothesis that the magnitude of the mediating effect of transactive memory depends on the degree to which the transactive memory is structured as a "small-world" network. The first step in establishing moderated mediation is shown in column 1 of Table 4.3. The coefficient for average group experience, similar to the unmoderated model in Table 4.2, is strongly positive and significant. Moreover, the coefficient of the proposed moderating variable (the small-world quotient, *SWQ*) and the coefficient of the variable representing the interaction between average group experience and *SWQ* (Average Group Experience**SWQ*) are not significant, indicating that *SWQ* does not moderate the effect of the treatment variable on group performance. As shown in column 2 of Table 4.3, the coefficient of the treatment variable (average group experience) is strongly significant (similar to the unmoderated case in Table 4.2, column 2), indicating the treatment's effect on the mediator when controlling for the proposed moderator, *SWQ*. The full model of moderated mediation is provided in column 3 of Table 4.3. In column 3, the coefficient of the variable representing interaction between the mediator (transactive memory network density, or *TMND*) and the theorized moderator (small-world quotient, or SWQ), *TMND*SWQ*, is positive and significant. In accordance with standards of moderated mediation suggested by Muller et al. (2005), coefficients of both the interaction variable, Average Group Experience**SWQ* in Table 4.3, Column 2, and the

Table 4.3 Test of moderating effect of "small-worldness" on mediating variable (Hypothesis 2).

Variable	1 (DV=Group Performance)	2 (DV=TMND)	3 (DV=Group Performance)
Average Group Experience	0.118*** (0.022)	0.018*** (.005)	0.0640** (0.022)
Small-World Quotient (*SWQ*)	0.007 (0.093)	-0.060** (0.020)	0.237** (0.074)
Average Group Experience**SWQ*	0.024 (0.019)	0.009* (0.004)	0.008 (0.018)
Transactive Memory Network Density (*TMND*)			1.389** (0.445)
*TMND*SWQ*			0.842** (0.282)
ω_c	0.242*** (0.040)	0.260*** (0.055)	0.256*** (0.045)
Turnover	-1.815*** (0.513)	-0.272* (0.109)	-1.800*** (0.503)
Transactive Memory Consensus	0.552 (0.769)	-0.316‡ (0.163)	0.754 (0.707)
Outcome Interdependence	0.102 (0.069)	-0.022 (0.015)	0.139* (0.062)
Size	0.007 (0.008)	-0.009*** (0.002)	0.018* (0.008)
Company Fixed Effects?	N.S.	N.S.	N.S.
Group Type Fixed Effects?	N.S.	N.S.	N.S.
Adjusted R^2	0.591	0.677	0.684

N=118 ‡ p<.10, * *p*<.05, ** *p*<.01, *** *p*<.001, N.S. = Not significant. Standard errors are heteroskedasticy robust. Other control variables were generally not significant and are reported separately in Table 3.

Table 4.4.

Coefficients and standard errors of Control Variables not reported in Tables 2 and 3.

	(Continued from Table 2)			(Continued from Table 3)		
	1	2	3	1	2	3
Variable	(DV=Group Performance)	(DV=TMND)	(DV=Group Performance)	(DV=Group Performance)	(DV=TMND)	(DV=Group Performance)
Average Task Experience	0.004	0.001	0.002	0.006	0.001	0.009
	(0.013)	(0.003)	(0.013)	(0.013)	(0.003)	(0.012)
Average Organization Tenure	0.007	-0.004	0.014	0.006	-0.004	0.016
	(0.013)	(0.004)	(0.012)	(0.013)	(0.003)	(0.011)
Transactive Memory Accuracy	0.350	0.065	0.245	0.246	0.067	0.321
	(0.479)	(0.102)	(0.454)	(0.504)	(0.107)	(0.449)
Task Interdependence	-0.001	0.012	-0.021	0.037	0.002	0.044
	(0.085)	(0.018)	(0.081)	(0.084)	(0.018)	(0.075)
Number of Knowledge Areas	0.008	0.001	0.007	0.006	0.001	0.005
	(0.005)	(0.001)	(0.005)	(0.005)	(0.001)	(0.005)
Gender	0.132	0.119**	0.059	0.160	0.111**	0.080
	(0.168)	(0.036)	(0.167)	(0.163)	(0.035)	(0.152)
Age	0.002	0.003	0.003	0.014	0.002	0.012
	(0.015)	(0.003)	(0.014)	(0.015)	(0.003)	(0.013)
Race	-0.196	0.042	-0.264	-0.143	0.044	-0.298
	(0.284)	(0.061)	(0.269)	(0.275)	(0.058)	(0.246)
Hispanic Origin	0.342	0.054	0.255	0.211	0.074	0.062
	(0.393)	(0.084)	(0.372)	(0.382)	(0.081)	(0.341)
Years of Education	0.009	0.011	0.010	0.045	0.010	0.054
	(0.046)	(0.010)	(0.044)	(0.046)	(0.010)	(0.042)

N=118 ‡ p<.10, * p<.05, ** p<.01, *** p<.001

interaction variable, *TMND*SWQ* in Table 4.3, Column 3, are positive and significant. Further, the results satisfy the additional necessary condition (see Muller et al., 2005) that the partial effect of the mediator on group performance in Column 3 be significant. Thus, I also find support for Hypothesis 2.

Since the use of an ordinal dependent variable potentially causes problems for OLS regression which may yield inefficient estimates (McCullagh and Nelder, 1989), the analysis was also conducted using an ordered probit regression model (which is preferential to an ordered logit regression since the standard errors are normally distributed). By including multiple intercepts, this procedure allows for the possibility that respondents potentially did not perceive the hierarchically ordered categories as equally distant. The ordered probit results were very similar in terms of both magnitude and significance of all variables.

To test for robustness of the small-world quotient, following Uzzi & Spiro (2005), I introduced the separate numerator and denominator values comprising the *SWQ,* as well as squared terms for *SWQ* and its components, as controls in additional statistical models. None of these values was significant at $p<0.10$, indicating that models in Table 4.3 incorporating the *SWQ* measure are not affected by potential curvilinearity of *SWQ* or its components.

4.6 Discussion

The work groups in this study exhibited a characteristic positive relationship between cumulative group experience and group performance: as average group tenure increased, manager ratings of combined productivity and quality increased accordingly. The amount of group transactive memory partially mediated this positive relationship, with results suggesting that transactive memory accounts for approximately 21 percent of the impact of cumulative experience on group performance. The magnitude of the mediation was further found to be moderated by the extent to which the transactive memory network was organized as a small-world network. These results suggest that transactive memory plays a crucial role in group learning and that the role is heavily dependent on the small world structure of the transactive memory network. Contrary to findings of Uzzi and Spiro (2005), which suggest that the small-world effect follows an inverted-U-shaped function, the findings of this study suggest that transactive memory cannot be "too" small-world-like. Instead, those groups whose transactive memory structures exhibited the greatest resemblance to "perfectly" small-world networks – that is, networks whose clustering coefficients were much greater than those in random networks coupled with characteristic path lengths nearly identical to those of random networks – had the greatest positive effects from their transactive memory. Thus, while Simon's (1957) principle of bounded rationality infers that the impact of transactive memory has an upper bound beyond which the individual memories of organizational members are saturated with social and knowledge connection, the results regarding the small-world structure of transactive memory seem to indicate that transactive memory can indeed continue to be effective at very high levels. Although members cannot have maximum-strength ties to everyone nor can they possess maximum expertise in every knowledge area (Pavitt, 2003), the small worlds that characterize socially-situated, task-centered interaction in groups may provide an evolutionary compromise enabling deep explicit and tacit knowledge to reside in clustered transactive memory structures that do not exceed the bounds of rationality. Apparently, small-world transactive memory networks enable groups to maximize effectiveness of organizational memory even as the group grows and accumulates richer bodies of knowledge without the burdensome need for every member to be connected to every other member.

Thus, the key implication of small-world transactive memory theory is that the most efficient transactive memory is characterized by highly connected, knowledge-centric communication clusters which in turn are connected by relatively fewer or weaker communication links between clusters. When social connections between team members are clustered around task-related knowledge areas, their learning becomes embedded in task-oriented clusters as the group accumulates time working together. In small-world transactive memory networks, at least one member of each knowledge cluster is also connected with at least one member of another knowledge cluster, reducing the number of connections with other members that a typical member must go through to reach those who possess relevant task-related advice or knowledge. Hence, the most efficient group transactive memory networks more closely resemble "small-world" networks and thus experience higher rates of group learning.

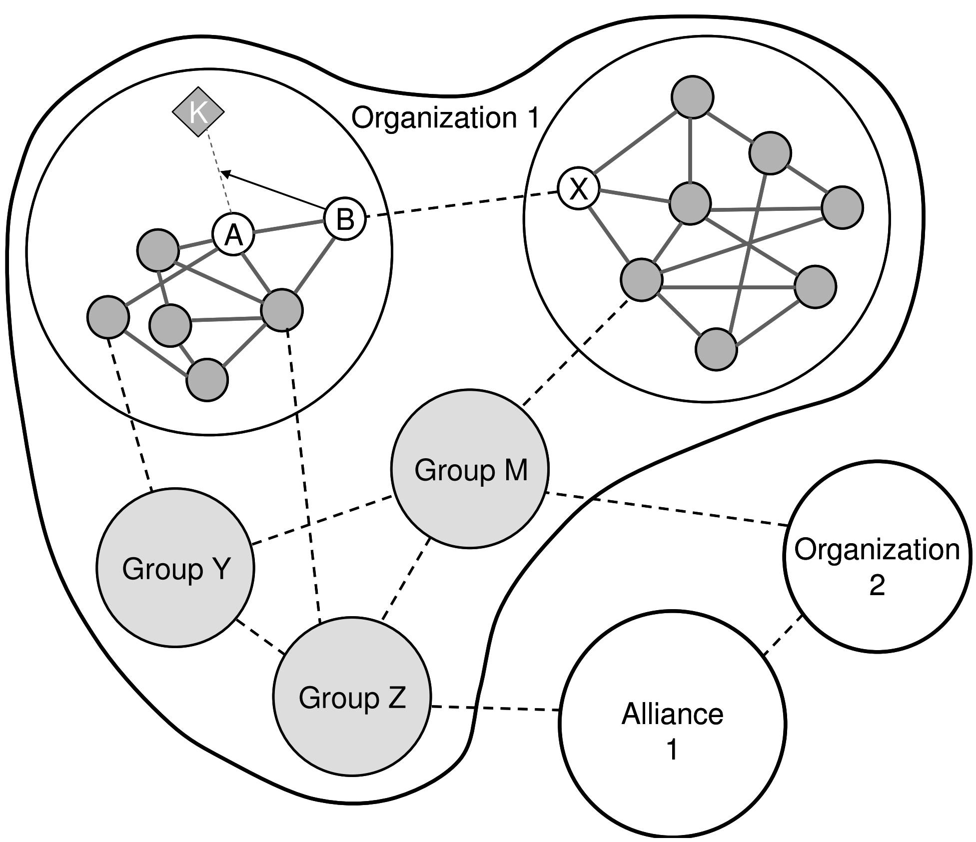
Another potentially useful outcome of the analysis is the coefficient, ω_c, introduced previously in Equation 3. ω_c, equal to approximately 25 percent in each of the six models in Tables 4.2 and 4.3, represents the relative significance of communication in the determination of the mediating effect of transactive memory network density. The complement of ω_c is ω_k, representing the relative weight of the cognitive knowledge network density in the determination of the effect of transactive memory network density. Thus, the importance of the network of perceived expertise appears to be about three times the importance of the communication network. A practical implication of this result could be that the effectiveness of team-building activities may be increased by incorporating task-related activities in addition to social and morale-boosting activities.

While the theory and outcomes presented thus far have focused on the group level, prior research suggests that the small-world model of transactive memory may scale to other levels of organizational structure (Robins et al., 2005), including inter-group (Ancona and Caldwell, 1992b) and inter-organization (Haunschild, 1993; Nooteboom, 1999; Robins and Alexander, 2004; Stuart, 1998) levels. Even though not all behavioral processes are necessarily operative at inter-group and inter-organizational levels, the instances of social or serendipitous interaction between groups and organizations leading to weak ties between socially situated knowledge clusters still result from the episodic-semantic memory mechanism. Building on the group-level example presented earlier, if team member *X* from *another* work group *T* communicates with group member *A* and knows that team member *B* is an expert in knowledge area *K*, the necessity for *X* to acquire *B*'s level of knowledge diminishes while team *T*'s access to the knowledge of *B* increases to the extent that *X* is connected to *A* and others in team *T*.[10] To the extent that the episodic-semantic memory model can be expected to result in

[10] As a practical example, if a "customer service department" team member knows a member of a "human resource department" team who is an expert in developing employee benefits self-service programs, the customer service team member may be able to refer a fellow customer service team member to the human resource team member for advice on development of similar self-service processes being developed for the organization's external customers.

ties between groups whose members socialize extemporaneously (see Kilduff and Tsai's [2003] "serendipitous" connections) or purposefully (in project team, task force, or matrix-organization assignments, for example), *organizational* level transactive memory would be expected to be structured as a small-world network composed of interconnected small-world *group* transactive memory networks. Strong ties between groups with *similar* group tasks (such as product assembly teams) would enable transfer of explicit and tacit knowledge relevant to the group task, while weaker ties between groups with *different* group tasks would facilitate innovation and cross-functional cooperation. Likewise, in inter-organizational settings, boundary-spanning activities of executives sitting on multiple boards of directors, mid-level executives participating in inter-firm alliances, or managers and specialists taking part in industry standards committees all provide mechanisms for development of transactive memory characterized by strong, dense, knowledge-centric ties within organizations connected to

Figure 4.9. Small-World Transactive Memory Networks at the Organizational and Inter-Organizational Levels



other organizations by weaker communication ties and knowledge iterads. Thus, transactive memory networks may similarly evolve at group, organization, inter-organization, and alliance levels (see Figure 4.9), inferring that such networks mirror the theoretical and methodological scaling suggested by Abbott's (2001) "fractal" ontology of sociological development. Fractal structures are created using the same mathematical rules at every level of complexity and thus appear similar at all scales of magnification (Mandelbrot, 1982). While the specific shape of a transactive memory network may not be identical at every level, its configuration as a small world irrespective of dyadic, group, or organizational level is certainly consistent with Abbott's ideas.

Given that the scaling of transactive memory networks depends primarily on the episodic-semantic memory mechanism rather than other individual, group, or organization-level psychological factors, the small-world transactive memory model may actually provide one of the mechanisms supporting Abbott's fractal theory of sociology (2001). For example, Marshall McLuhan (1964: 7-8) theorized that changes in the hidden patterns of interactions within a society's communication network result from the interactions themselves. As intrinsic, dynamic extensions of human interaction, transactive memory networks and their small-world structures may help explain the very existence and variety of learning and performance outcomes not only at group and organizational levels but at societal levels as well. As evolutionary outcomes in their own right, small-world transactive memory networks may also prove to be important measures and predictors of such societal development. Indeed, small-world transactive memory may provide the first evidence that McLuhan was right – the "medium really is the message."

Thus, potentially at many levels, the small-world nature of transactive memory has important implications for organizational learning and performance and suggests several avenues for additional research. For example, in organizations composed of multiple units, connections between members of different groups may facilitate innovation in both similar and dissimilar groups as well as enable exploitation of specialization resident in dissimilar groups. In this case, the theory may help account for March's (1991) exploration and exploitation behaviors in organizational learning, suggesting that exploitation may originate predominantly *within* groups, while exploration originates in search behaviors guided by transactive memory connections *between* groups.

The model also has implications for predicting and managing the effects of turnover on performance. In the early 1980's, Staw (1980) and Mobley (1982) argued convincingly for organizational researchers to examine the consequences of turnover in addition to its antecedents. In particular, Staw (1980) called for greater attention to longitudinal impacts of turnover in both field and experimental studies. During the same time frame, Tichy (1981) and Rogers (1987) suggested that network perspectives be applied to organizational research to look more closely at interactive mechanisms underlying behavioral outcomes such as turnover. But after more than two decades, neither the longitudinal consequences of turnover nor the effect of turnover in different network environments has seen much research progress. Turnover is still treated predominantly as an outcome variable (Glebbeek and Bax 2004), continuing to result in "more and more independent and moderator variables [in] already crowded models predicting turnover" (Krackhardt and Brass, 1994, p. 208). Of those studies that *have* considered the consequences of turnover, only a handful have examined how social and knowledge networks might increase or decrease such consequences (Johns 2001), and very few studies have examined turnover's impact on time dependent outcomes such as organizational learning rates.

The results in Tables in 4.2 and 4.3 suggest that transactive memory has durable effects on performance even in the face of very significant turnover. Moreover, relatively lower effects of turnover in the fully specified transactive memory model of Table 4.2, column 3, further suggests that the amount of group transactive memory may significantly moderate the effect of turnover on performance. When turnover was specified as the independent variable and transactive memory network density was introduced as a moderating variable, results indicated that turnover moderated the effect of turnover to such an extent that turnover itself was no longer statistically significant. Only the transactive memory network density (*TMND*) and the interaction between turnover and *TMND* were significant. Results of Muller et al.'s (2005) test of mediated moderation (not to be confused with the test of 'moderated mediation' conducted in Tables 4.2 and 4.3) showed that the small-world structure of transactive memory partially mediated its moderating influence on the effect of turnover on performance. This outcome suggests that groups with sufficient transactive memory may suffer little to no effects of moderate levels of turnover and that bolstering transactive memory and its small world structure may help insulate groups from the potentially negative effects of knowledge loss due to downsizing or employee retirements. This latter direction could have important implications for current global concerns over losses of knowledge due to "baby-boomer" retirements (DeLong, 2004). Systematic loss of knowledge due to retirement may be reduced by the tendency of new (replacement) members to benefit from the knowledge embedded in the clusters of which the departing members were a part (Moreland and Levine, 1992). Hence, the moderating effects of transactive memory density and structure can help ameliorate the impact of knowledge lost in such departures. Additional research should be conducted to examine the dynamics and limits of transactive memory's interactive effects on turnover.

In addition to turnover, other behavioral phenomena in groups and organizations may be explained at least in part by small-world transactive memory. For example, specialization may not represent simply a choice of individuals or an assignment by managers but rather an outcome of socially-situated learning that induces such specialization as a by-product of the formation of highly efficient transactive memory. Similarly, the small-world model has implications for the formation of structural holes (Burt, 1992). In addition to resulting from self-monitored brokerage of social capital, structural holes may also be the result of the co-evolution of sparse ties linking knowledge-centric clusters and reflecting boundary-spanning behavior within small-world transactive memory networks. Thus, structural holes may partially reflect the social "bridges" between knowledge clusters that evolve in small-world transactive memory networks as means of facilitating innovation and overcoming impediments to the transfer of internal knowledge (Szulanski, 1996). At the inter-firm level, these same bridges upon which firms may depend in part for innovation are difficult to maintain in the face of "incessant external developments," potentially resulting in decreased organizational learning (Sorensen and Stuart, 2000). The small-world transactive memory model suggests that this may be due to the level of external developments exceeding the capacity of the transactive memory network at firm boundaries. The model also suggest that solutions to such “ravages of corporate aging” could lie in reinforcing the transactive memory network possibly by stimulating iterads from multiple levels within the firm to fresh sources of external information concerning competitive changes.

The small-world transactive memory model may also offer scientific insight into how *communities of practice* evolve and operate. A “community of practice” is a group of people who have worked together over a period of time and who share accepted task routines (whether documented or not) that have evolved within the social context of the group members (Wenger, 1998). Group members may be part of many communities of practice both within and external to the group. For example, a company manager may be part of an internal accounting department community focused on compliance with new governmental regulations while at the same time participating in a similar community composed of accountants representing other company divisions, a community of similarly-engaged specialists from a regional professional interest group, and yet another community in an industry-level group focused on the same regulatory requirements. Research on communities of practice indicates that such task-centered and oftentimes overlapping social structures that emerge within and between organizations may facilitate organizational learning (Barley, 1988; Bourdieu, 1977; Brown and Duiguid, 1991; Hutchins, 1991a, 1991b; Lave and Wenger, 1991). The emergence of transactive memory networks patterned as small worlds may provide the blueprint for the evolution of communities of practice within and among groups, organizations, and professional fields. Such “communities” may in effect represent task-centered social structures within a single group or within groups of similar task-centered social structures simultaneously inside and among organizations, and their evolution as small-world networks may be a determinant of their effectiveness as mechanisms of organizational learning.

Even absorptive capacity at the group (Tiwana and McLean, 2001) or organization (Cohen and Levinthal, 1990) level may develop in advance of or in parallel with small-world transactive memory. Small-world transactive memories guarantee that the level of reachability from one member to another will remain high and virtually constant even as the number of organizational members and knowledge areas grows. This high level of reachability of nodes from any point in the network facilitates a key element of absorptive capacity – the identification of relevant knowledge. Simultaneously, the embedding of such knowledge in dense, socially-connected clusters may further facilitate development of absorptive capacity by helping to ensure that the knowledge so identified will actually be assimilated, adapted, and applied to improve organizational performance. The similarity of evolutionary patterns of transactive memory development at a group level suggests that absorptive capacity may be an important group-level performance predictor as well.

Small-world transactive memory networks may also explain the coherence of complex adaptive systems in the face of change (Holland, 1995) and the relative rarity of so-called "complexity catastrophes" (Kauffman, 1993; Perrow, 1999). For example, in an *NK* topology (Kauffman, 1993), an organization's level of fitness and suitability for survival are dependent on combinations of *N* binary attributes (such as the organization's strategy, structure, technology, etc.) along with the interaction of any particular attribute with $K \in \{1 \ldots N\text{-}1\}$ other attributes (Levinthal, 1997). For fixed levels of *N*, the likelihood of a complexity catastrophe increases as *K* increases. Small-world transactive memory viewed as one of the *N* endogenous attributes may inherently limit *K* to levels of interaction substantially below catastrophe levels. On the other hand, even if small-world transactive memory acts exogenously (*i.e.*, it is not one of the *N* attributes), it may account for the selection of other, more optimal combinations of attributes well beyond localized "basins of attraction" (Kauffman, 1993; Levinthal, 1997). Thus, potential performance declines associated with increasing complexity could be averted through the tendency of small-world transactive memory to self-organize densely into social and knowledge clusters within easy reach of one another through relatively weaker and/or sparser social connections, thereby acting as a "governor" to keep network interaction below catastrophic levels.

Beyond the potentially advantageous outcomes suggested by small-world transactive memory, there also may be negative consequences. For instance, the self-regulative aspects of small-world transactive memory may account for deleterious outcomes of entrainment such as competency traps (Levitt and March, 1988). Even though weak ties within the small-world may help identify more optimal combinations of group attributes, those same ties may also constrain groups to established ways of thinking (Uzzi and Spiro, 2005). Thus, while some of those paths might indeed identify better combinations of attributes, being constrained to the same sources of knowledge limits access to even more innovative thinking that may be available elsewhere in the network or external to it.

Despite the promising implications of the findings of this research, as in any one-period study, results must be viewed with caution, especially with respect to inferences of causality. The outcomes of this study, while potentially useful, should be expanded to longitudinal settings so that dynamic aspects can be allowed to change over time and stronger inferences of causality can be examined. In addition, in any network study, endogeneity can bias coefficient estimates and overall model reliability. Because of the inevitable interrelationships in social networks, it is impossible to control for such endogeneity. Thus, this limitation persists despite apparently interesting results.

Another potential threat is simultaneity, particularly between transactive memory network density (*TMND*) and the proposed moderator of *TMND*'s mediating effect, the small-world quotient. Kraemer et al. (2002) stress that a moderator must occur *before* treatment and must not be correlated with the treatment variable. In the case of the tests for moderated mediation (Hypothesis 2), although *SWQ* is not correlated with average group experience and has no significant moderation of the impact of average group experience on group performance, nevertheless *SWQ* is weakly (at $p<0.05$) correlated with *TMND,* the mediating variable it is supposed to moderate. It is also arguable that the "small-worldness" of a transactive memory network does not strictly precede the density of the transactive memory network, potentially confounding the conclusion that *SWQ* moderates *TMND*'s mediating effect. Finally, the fact that the companies in the data sample are all in the same industry clearly limits the study's external validity. The study attempted to minimize the lack of generalizability by encompassing multiple group types in vertical divisions of the companies in an attempt to increase the extent to which the groups in the study could be analogous to similar types of groups in other industries. Moreover, the study results were not sensitive to fixed effects of company or group type, suggesting that transactive memory is a durable and generalizable group construct.

4.7 Conclusion

By observing and understanding how changes occur in small-world transactive memory networks, it may be possible to magnify positive effects of changes in interaction patterns while anticipating and even mitigating negative effects. Transactive memory networks, like other types of informal organizational structures, emerge at every organizational level, and the findings of this study suggest that bolstering their densities and small-world properties can result in improved group performance. The key implication of the small-world transactive memory is that the positive effect of cumulative group experience on group performance is operative at least in part through the group's transactive memory. Further, the mediating effect of transactive memory is strongest in groups whose transactive memory structures more closely resemble small-world networks. The greater challenge may now lie in determining how such small-world transactive memory networks can be successfully induced where they do not exist and repaired when they have become dysfunctional.

5

FUTURE RESEARCH

In extending the work conducted in Chapter 4 to a truly dynamic, longitudinal analysis, the level of data collection would likely prove infeasible. Thus, in this chapter I propose a simulation methodology employing one additional data collection along with a modified version of the computer model used in Chapter 3 ("Construct").

5.1 Extension of Simulation Model

The proposed extension of Construct adds the capability of agents to "learn from experience." The extension requires to new elements. First, "knowledge" areas should have continuous levels of depth along the range [0, 1] that may have starting values specified by the user. Agents can have any starting level but may progress to deeper (higher) levels of knowledge based on learning and experience in addition to social interaction with other agents. For example, in the study in Chapter 4, actors may have 5 starting levels of knowledge for each knowledge area, corresponding to the Likert scale values described in Section 4.4. In the simulation model, an actor's starting knowledge level of "2" for a knowledge area would be represented as 2/5, or 0.4, in Construct. The actor would progress to higher levels if and only if the actor gains enough experience and has enough memory to add the knowledge. Thus, knowledge would not simply diffuse based on homophilistic or information-seeking interactions alone but would also evolve based on "learning from experience" which may or may not include such interactions.

Second, the proposed extension would permit an agent's knowledge in specific areas to be enhanced by training and experience in addition to knowledge transferred from other agents. In the current version of Construct, the same pre-set number of tasks is assigned to be completed by the group for every time period of the simulation. Thus the experience gained by repetition of tasks to which agents are assigned is essentially lost. In a more realistic learning model, if tasks are performed only infrequently, knowledge depreciates and "forgetting" limits the value of the experience. If too many tasks are assigned at once, agents' "bounded rationality" likewise limits the amount of experience that can be converted to actionable knowledge. The extended version of Construct would link the number of tasks completed by the team, as well as the team's task completion accuracy for those tasks, to the agents' knowledge and experience levels in addition to their likely social interactions. Thus, agents represented in the simulation model would be capable of "learning-by-doing" (that is, learning from experience), enabling both the agents themselves and the entire group of agents to perform more tasks per period (representing increased productivity) with the same or even better accuracy (representing improved quality).

The proposed model of experienced-based learning for an individual agent builds on theoretical and empirical work by Mazur and Hastie (1978), Uzumeri and Nembhard (1998), and Shafer, Nembhard, and Uzumeri (2001). In these models, individuals learn both conceptual and motor skills based on the following hyperbolic function:

$$y_{it}(c_{it}) = \pi_{it}\left(\frac{c_{it}\delta_{it} + p_{it}}{c_{it}\delta_{it} + p_{it} + r_{it}}\right) + \varepsilon_{it}\ , \tag{5.1}$$

where

$y_{it}(c_{it})$ = performance of individual i on task t after c_{it} accumulated task completions,

π_{it} = highest possible level of performance of individual i on task t,

p_{it} = prior expertise based on training or similar or past experience,

r_{it} = cumulative number of tasks required to get to ½ of π_{it} ,

δ_{it} = knowledge retention rate of agent i doing task t, and

ε_{it} = error term,

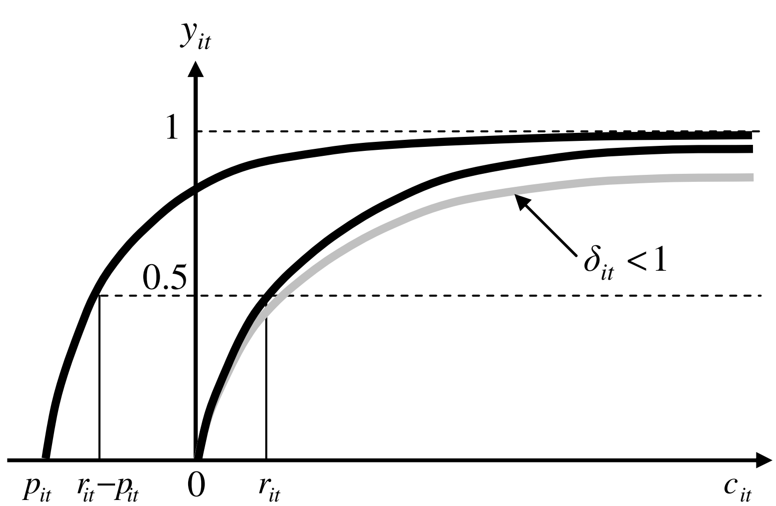
subject to $c_{it} + p_{it} + r_{it} \neq 0$.

Within the current Construct simulation model, performance is measured as accuracy of the entire group (or organization). In the extended version, three new measures of performance are proposed for each simulation time period:

- Accuracy of individual *i* in executing task *t*,
- Productivity of individual *i* in executing task *t*, measured as the number of tasks *t* completed during the time period, and
- Productivity of the group, measured as the total number of all types of tasks completed during the time period.

For simplicity, it can be assumed that $\pi_{it} = 1$ and $r_{it} > 0$ for all agents performing all tasks. Thus, agent-level learning curves will be of the form shown in Figure 5.1. Distributions of the p_{it}, r_{it}, and δ_{it} parameters can be estimated based on empirical literature and data validated in interviews with managers and subject matter experts.

Figure 5.1. Agent-level Learning Curves.



5.2 Revised Regression Model of Group Learning

For analyses of simulation results over multiple time periods, the full regression models in Equations 4.7 and 4.10 should be restated as cross-sectional time series functions. For example, the general form of the re-stated model for Equation 4.7 would be

$$\ln(Performance_{icgt}) = \beta_1 \ln(AvgGroupExp_{icg,t-1}) + \beta_2 \ln(TMND_{icg,t-1}) \\ + \gamma_{1-14} Controls_{icg} + C_c + T_g + \varepsilon_{icgt} \qquad (5.2)$$

while the re-stated model for Equation 4.10 would be

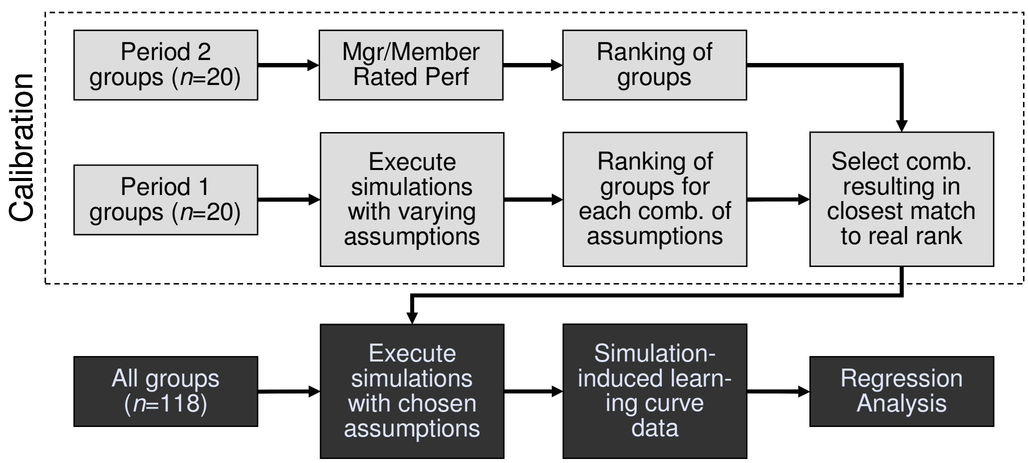
$$\ln(Performance_{icgt}) = \beta_1 \ln(AvgGroupExp_{icg,t-1}) + \beta_2 \ln(SWQ_{icg,t-1}) \\ + \beta_3 \ln(AvgGroupExp_{icg,t-1} * SWQ_{icg,t-1}) \\ + \beta_4 \ln(TMND_{icg,t-1}) + \beta_5 \ln(TMND_{icg,t-1} * SWQ_{icg,t-1}) \\ + Co_c + Type_g + \varepsilon_{icgt} \qquad (5.3)$$

5.3 Combined Empirical and Simulation Methodology

To use a simulation model in a longitudinal empirical analysis, the model must first be calibrated. Calibration requires that empirical data be collected on all or some significant subset of the sample of the groups surveyed in the study. I call this the "second survey administration." The first step in calibration is calculating and recording all measures for the groups in the second survey administration. Then, using data from the *first* survey administration for those same groups, the extended version of Construct outlined in section 5.1 would be executed both with different input assumptions and for different numbers of time periods. For example, input assumptions could be varied as to the relative levels of homophilistic versus information-seeking behavior, and time period assumptions could be varied initially from 50 to 250 time periods in increments of 50. For each combination of input and time period assumptions, groups are ranked based on dependent variable results at the end of each simulation. The simulation-based rankings are then compared to the ranking obtained using empirical performance outcomes from the second survey administration. The set of assumptions shown to best match the empirical results should then be used in simulations of all groups (based on the first survey administration) to create data sets for examining the time series impacts of transactive memory network characteristics on group learning. To calibrate the simulations with calendar time, it can be assumed that the number of simulation time periods associated with the selected set of assumptions equates to the period of time elapsed between the first and second survey administrations.

Once the assumptions have been calibrated, simulations can be executed for all groups to create learning curve data that can be analyzed using ordinary least squares regression (for example, using models suggested in Equations 5.2 and 5.3). Distributions

Figure 5.2. Process for combining simulation and empirical methods.



of parameters used in agent-level learning curves should be estimated based on assumptions derived from prior empirical research (for example, see Uzumeri and Nembhard, 1998 and Shafer, Nembhard, and Uzumeri, 2001) and validated by archival data and interviews with group managers.

The resulting simulations are necessarily expected to create a large amount of data. For example, for each group and simulation time period, essentially *all* variables used in the empirical analysis of Chapter 4 are calculated based on each period's simulation results. For the learning curves to be useful in a cross-sectional analysis, at least 48 to 50 calendar months of data for each group are required. With completed sets of simulation-induced data, boundaries of theory can be explored using conventional hierarchical regression techniques. In addition, sensitivities to changes in assumptions as well as agent-level parameter distributions can be conducted to examine robustness of the computational outcomes.

APPENDIX

Appendix A. Capability Evaluation Factors

Capability Evaluation Factor		Mapping to Construct in Simulation Framework
Organization Designs (7)	Hierarchy	Organizational Context
	Network	Organizational Context
	Team –	
	Standard	Organizational Context
	Autonomous	Organizational Context
	Distributed	Organizational Context
	Matrix	Organizational Context
	Bureaucracy	Organizational Context
Entities (7)	People (Agents, Actors)	Resources
	Technological Agents	Technology
	Unit-level (I.e., group-level) Actors	Resources
	Knowledge	Resources
	Physical/Financial Capital	Resources
	Tasks	Technology
	Units of Units actors	Resources
Actions (2)	Physical	Action
	Cognitive	Action
Entity and Environment Characteristics (36)	Number of Agents Unlimited	Resources
	Number of Knowledge Units Unlimited	Resources
	Number of Physical/Financial Resources Unlimited	Resources
	Number of Tasks/Actions Unlimited	Technology
	Number of Units Unlimited	Resources
	Number of Levels Unlimited	Organizational Context
	Number of Locations Unlimited	Resources
	Ownership Type	Organizational Context
	Organization Strategy	Strategy
	Cooperation	Interactive Processes
	Conflict	Interactive Processes
	Competition	Interactive Processes
	Peace/War	External Environment
	Complexity	External Environment
	Product/Market/Action Diversity	External Environment
	Environmental Uncertainty	External Environment

	Type (Customizable Categories)	Organizational Context
	Growth Rate (No. of Agents)	Organizational Context
	Industry growth	External Environment
	Age (relative to organization life cycle)	Organizational Context
	Centralized/Decentralized	Organizational Context
	Legal Form	Organizational Context
	Military Form (if any)	Organizational Context
	Ethnic Context	External Environment
	Religious Context	External Environment
	Political Context	External Environment
	Internal Trust	Interactive Processes
	Historical Motivation	History
	Organizational Culture	Organizational Culture
	Empowerment	Organizational Context
	Leadership	Organizational Context
	Organizational Justice	Interactive Processes
	Goal-Setting	Interactive Processes
	Cohesiveness	Psychosocial Traits
	Formality	Organizational Context
	Multi-culturalism	Organizational Context
Performance Measures (12)	Efficiency	Performance
	Productivity	Performance
	Information Diffusion	Performance
	Accuracy	Performance
	Consensus	Performance
	Adaptive Capability	Performance
	Errors	Performance
	"Fitness" Function (multivariate objective) - often measured as wealth	Performance
	Exceptions/Omissions	Performance
	Turnover	Performance
	Custom-defined	Performance
	Other	Performance
Agent Characterisitics (24)	Race	Composition
	Gender	Composition
	Age	Composition
	Ethnicity	Composition
	Religious Affiliation	Composition
	Political Affiliation	Composition
	Organizational Role	Composition
	Education Level	Composition
	Experience Level	Composition
	Training Level	Composition
	Tenure in organization	Composition
	Tenure in role	Composition
	Physical Location/Movement	Composition
	Information Processing Capabilities	Composition
	Personality	Psychosocial Traits
	Intelligence	Psychosocial Traits
	Trust	Psychosocial Traits
	Cooperativeness	Psychosocial Traits
	Commitment to Organization	Attitudinal
	Satisfaction	Attitudinal
	Intention to Leave	Attitudinal
	Beliefs/Values	Psychosocial Traits
	Morale	Psychosocial Traits
	Emotion	Psychosocial Traits

Agent Behavioral Attributes (12)	Temporal/Chronological Representation	Action
	Efficacy	Psychosocial Traits
	Affect	Psychosocial Traits
	Turnover (Quitting)	Behavioral
	Absenteeism	Behavioral
	Citizenship Behaviors	Behavioral
	Social	Psychosocial Traits
	Self Aware	Psychosocial Traits
	Multi-goal	Psychosocial Traits
	Self Directed	Psychosocial Traits
	Influenced by others	Psychosocial Traits
	Task Oriented	Psychosocial Traits
Agent Cognitive Attributes (7)	Capability (Skill)	Composition
	Knowledge (Cognition)	Composition
	Working (short-term) Memory	Composition
	Long-Term Memory	Composition
	Transactive Memory	Psychosocial Traits
	Adaptive Capability (Learning)	Composition
	Forecasting/Planning	Composition
Task Characteristics (8)	Task assigned by: Manager Self-assignment Fixed	 Technology Technology Technology
	Interdependence	Technology
	Complexity	Technology
	Location	Technology
	Physical Layout/Environs	Technology
	Type	Technology
Informal and Formal Network Representation (57)	Social Network: People to People	
	Formal Authority	Technology
	Informal Friendship	Informal Network Environment
	Formal Communication	Interactive Processes
	Informal Communication	Informal Network Environment
	Capabilities Network: Actor to Resources	
	People to Resource	Technology
	Technology to Resource	Technology
	Unit to Resource	Technology
	Unit of Units to Resource	Technology
	Knowledge Network: Actor to Knowledge	
	People to Knowledge	Composition
	Technology to Knowledge	Technology
	Unit to Knowledge	Composition
	Unit of Units to Knowledge	Technology
	Task Assignment: Actor to Task	
	People to Tasks	Technology
	Technology to Tasks	Technology
	Unit to Tasks	Technology
	Unit of Units to Tasks	Technology
	Action Assignment: Actor to Action	
	People to Actions	Action
	Technology to Actions	Action
	Unit to Actions	Action
	Unit of Units to Actions	Action
	Workforce: People to Unit	Technology
	Skills Needed: Knowledge to Resources	Technology
	Skills for Tasks: Knowledge to Task	Technology
	Unit Competence: Knowledge to Unit	Technology
	Unit of Units Competence: Knowledge to Unit of	Technology

	Units	
	Resource Needs: Resources to Tasks	Technology
	Core Competence: Resource to Unit	Technology
	Core Processes: Task to Organization	Technology
	Information: Knowledge to Knowledge	Technology
	Substitutes: Resources to Resources	Technology
	Task-to-task relations:	
	Coincidence	Technology
	Precedence	Technology
	Coordination	Technology
	Inter-Unit (Unit-to-Unit)	
	Alliance	Strategy
	Competition	Strategy
	Knowledge Flow	Interactive Processes
	Supply Chain	Interactive Processes
	Coordination	Interactive Processes
	Accountability	Strategy
	Overlap	Strategy
	Leadership	Strategy
	Action Types	
	Communication	Action
	Resource	Action
	Political/Social	Action
	Economic	Action
	Other	Action
	Action Ability: Actor to Action	
	Execution	Action
	Capability	Action
	Action Outcomes: Action to Effects	
	Intention	Action
	Prediction	Action
	Result	Action
	Action Impacts: Effects of Units' Actions	
	Enablement	Performance
	Disablement	Performance
	Encouragement	Attitudinal
	Discouragement	Attitudinal
	Inter-Effect: Effect to Effect	
	Reinforcement	Action
	Inhibition	Action
Network Evolution (52)	Add Agents	Technology
	Drop Agents	Technology
	Add Links between agents	Informal Network Environment
	Drop Links between agents	Informal Network Environment
	Add Knowledge	Technology
	Drop Knowledge	Technology
	Add Links Agents to Knowledge	Composition
	Drop Links Agents to Knowledge	Composition
	Add Links Knowledge to Knowledge	Technology
	Drop Links Knowledge to Knowledge	Technology
	Add Resources	Technology
	Drop Resources	Technology
	Add Links Agents to Resources	Technology
	Drop Links Agents to Resources	Technology
	Add Links Knowledge to Resources	Technology
	Drop Links Knowledge to Resources	Technology
	Add Links Resources to Resources	Technology
	Drop Links Resources to Resources	Technology

	Add Tasks	Technology
	Drop Tasks	Technology
	Add Links Agents to Tasks	Technology
	Drop Links Agents to Tasks	Technology
	Add Links Knowledge to Tasks	Technology
	Drop Links Knowledge to Tasks	Technology
	Add Links Resources to Tasks	Technology
	Drop Links Resources to Tasks	Technology
	Add Links Tasks to Tasks	Technology
	Drop Links Tasks to Tasks	Technology
	Add Units	Composition
	Drop Units	Composition
	Add Links Agents to Units	Composition
	Drop Links Agents to Units	Composition
	Add Links Knowledge to Units	Technology
	Drop Links Knowledge to Units	Technology
	Add Links Resources to Units	Technology
	Drop Links Resources to Units	Technology
	Add Links Tasks to Units	Technology
	Drop Links Tasks to Units	Technology
	Add Links Units to Units	Informal Network Environment
	Drop Links Units to Units	Informal Network Environment
	Add Actions	Action
	Drop Actions	Action
	Add Links People to actions	Action
	Drop Links People to actions	Action
	Add Links Knowledge to actions	Action
	Drop Links Knowledge to Actions	Action
	Add Links Resources to Actions	Action
	Drop Links Resources to Actions	Action
	Add Links Tasks to Actions	Action
	Drop Links Tasks to Actions	Action
	Add Links Units to actions	Action
	Drop Links Units to actions	Action
Internal Processes (11)	Innovation/Discovery	Interactive Processes
	Culture/Socialization	Interactive Processes
	Turnover	Interactive Processes
	Recruitment	Interactive Processes
	Promotion	Interactive Processes
	Goal Interdependence	Interactive Processes
	Outcome Interdependence	Interactive Processes
	Norms	Psychosocial Traits
	Training	Technology
	Misinformation	Interactive Processes
	Negotiation	Interactive Processes
Communication Characteristics (12)	Communication Frequency	Interactive Processes
	One-to-one Personal	Interactive Processes
	Email	Technology
	Avatars	Technology
	Databases	Technology
	Referential DataBases	Technology
	Group Meetings	Interactive Processes
	Broadcast	Technology
	Phone/Fax	Technology
	Voice Mail	Technology
	Books/Manuals	Technology
	Memos	Technology

Appendix B. Actor Vector

1	LDR	Project Manager
2	M1	Art Director
3	M2	Technical Lead
4	S1	Design Lead
5	S2	Interactive Lead
6	S3	Data Architect
7	S4	Application Architect
8	EE1	Designer
9	EE2	Web Developer
10	EE3	Usability Engineer
11	EE4	Business Analyst 1
12	EE5	Business Analyst 2
13	EE6	Software Engineer 1
14	EE7	Software Engineer 2
15	EE8	Software Engineer 3
16	EE9	Software Engineer 4

Appendix C. Knowledge Vector

S1	Project Management Training/Experience
S2	Administrative Training
S3	Software Engineering Experience
S4	Team Supervision Experience
S5	General Programming Supervision Experience
S6	Application Architecture Design
S7	Creative Design
S8	Screen Design
S9	Network Management
S10	Data Modeling
S11	Database Programming
S12	Content Design and Development
S13	Usability/Navigation Design
S14	Web Development (HTML)
S15	ATG Dynamo Platform
S16	Unix/Java/C++ Programming
S17	Interwoven Platform
S18	Interface Design/Development
S19	Apache Platform

Appendix D. Task Vector

T1	Project Management
T2	Administration
T3	Detailed Supervision
T4	Reporting
T5	Usability/Wireframe
T6	Comps Design
T7	Content Development
T8	Screen Design
T9	Application & Network Management
T10	Data Model
T11	Application Architecture – Flows
T12	Application Architecture – Content
T13	Application Architecture – Screen Objects
T14	Application Architecture – Interface Design
T15	Application Architecture – Technology
T16	Development – Data Repository
T17	Development – Screens
T18	Development – Content
T19	Development – Interfaces
T20	Testing – Integration
T21	Testing – System
T22	Testing – User Acceptance
T23	Migration
T24	Deployment

Appendix E. Social Network Matrix ($\mathrm{N} \equiv N_{\hat{n}\times\hat{n}}$)

	LDR	M1	M2	S1	S2	S3	S4	EE1	EE2	EE3	EE4	EE5	EE6	EE7	EE8	EE9
LDR	0	1	1	1	0	0	1	0	1	0	0	0	0	1	0	0
M1	1	0	1	1	1	0	0	0	1	0	0	0	0	0	0	0
M2	1	1	0	1	0	1	1	0	1	0	0	1	0	1	0	0
S1	1	1	1	0	1	0	0	1	1	0	0	0	0	0	0	0
S2	0	1	0	1	0	0	0	0	0	1	0	0	0	0	0	0
S3	0	0	1	0	0	0	1	0	0	0	1	1	0	0	0	0
S4	1	0	1	0	0	1	0	0	0	0	0	0	1	1	1	1
EE1	0	0	0	1	0	0	0	0	1	0	1	0	0	1	0	0
EE2	1	1	1	1	0	0	0	1	0	0	0	0	0	1	0	0
EE3	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0
EE4	0	0	0	0	0	1	0	1	0	0	0	1	0	1	0	0
EE5	0	0	1	0	0	1	0	0	0	0	1	0	0	0	0	1
EE6	0	0	0	0	0	0	1	0	0	0	0	0	0	1	0	1
EE7	1	0	1	0	0	0	1	1	1	0	1	0	1	0	0	1
EE8	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
EE9	0	0	0	0	0	0	1	0	0	0	0	1	1	1	0	0

Appendix F. Assignment Matrix ($T_N \equiv T_{\hat{n}\times\hat{t}}$)

	T1	T2	T3	T4	T5	T6	T7	T8	T9	T10	T11	T12	T13	T14	T15	T16	T17	T18	T19	T20	T21	T22	T23	T24
LDR	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
M1	0	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
M2	0	1	1	1	0	0	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
S1	0	0	0	1	0	1	0	1	1	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0
S2	0	0	0	1	0	0	0	0	0	0	1	1	0	1	0	0	0	0	0	0	0	0	0	0
S3	0	0	0	1	0	0	0	0	0	0	1	1	0	1	0	0	0	0	0	0	0	0	0	0
S4	0	0	0	1	1	0	0	0	0	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0
EE1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	0	1	0	0	0	1	0	1
EE2	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1	1	0	1	0	0	0	0
EE3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	0	0	0	0	0
EE4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	0	1	0	0	0
EE5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	1	0	0	0	0
EE6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1	1	1	0	0
EE7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	1	1	1	0	1
EE8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	1
EE9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0

Appendix G. Raw Skill/Knowledge Matrix ($S_N \equiv S_{\hat{n}\times\hat{s}}$)

	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	S11	S12	S13	S14	S15	S16	S17	S18	S19
LDR	1	1	1	0	0	1	0	1	0	0	1	1	0	1	0	0	0	0	0
M1	0	1	0	1	0	1	1	1	1	0	0	1	0	0	1	0	1	0	0
M2	0	1	1	1	1	0	0	1	1	1	1	0	0	1	0	0	1	0	0
S1	0	0	1	0	0	0	1	1	0	1	1	0	0	0	1	0	0	0	0
S2	0	0	1	0	0	1	0	0	1	0	0	0	0	1	1	1	0	0	0
S3	0	0	1	0	0	1	0	1	0	0	1	1	0	1	1	0	0	0	0
S4	0	0	1	0	1	1	0	0	0	0	0	1	0	0	0	0	0	1	1
EE1	0	0	0	0	0	0	0	0	0	0	0	1	0	1	1	1	0	1	0
EE2	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	1	0	0
EE3	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	1	0	0	0
EE4	0	0	0	0	0	0	0	0	0	0	1	1	0	0	1	1	0	0	0
EE5	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	1	0	0
EE6	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	0	0	1
EE7	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0
EE8	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	0	1	0
EE9	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1	0	1	0

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