

Team Knowledge Representation and Measurement: A Network Analysis Approach

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ABSTRACT

Team knowledge has typically been conceptualized and measured at the aggregate level. While useful for studies that investigate team knowledge, this aggregate approach doesn't account for the effect that differing knowledge configurations among team members have on performance tasks. We propose a network analytic approach to represent and measure team knowledge in which network nodes (team members) across multiple content areas produce a team knowledge structure composed of isolates, cliques, and varying degrees of centrality. We illustrate our approach, including how to compute, analyze, and visually represent team knowledge, and provide preliminary validation results using data from 57 teams from MBA management decision teams. Finally, we discuss how our approach complements existing team knowledge measures and offer limitations and implications.

Keywords: team knowledge, shared knowledge, shared cognition, network analysis

Team Knowledge Representation and Measurement: A Network Analytic Approach

Researchers have described team knowledge in a variety of ways – using over 20 different terms, according to one count (Cannon-Bowers & Salas, 2001) – and have operationalized its measurement into an overall team knowledge score, whether shared (e.g., through schema similarity, Rentsch & Klimoski, 2001), aggregated as team level information (e.g., Faraj & Sproull, 2000; Levesque, Wilson, & Wholey, 2001; Lewis, 2003; e.g., Mathieu et al., 2000), or as a distribution across teams (cf. Cooke, Salas, Kiekel, & Bell, 2004). While this approach has been useful for connecting various aspects of team knowledge content to antecedents and outcomes, such as team performance (Cooke et al., 2003; Cramton, 2001; Faraj & Sproull, 2000; Nelson & Coopriider, 1996; Rentsch & Hall, 1994), it does not help us understand how this knowledge is organized across within the team. Researchers and managers are thus stymied from understanding the dynamics of team interaction, such as whether knowledge resides in cliques or certain clusters of individuals and the specific location of given content domains, especially in larger teams. In this paper, we offer a method to represent and measure team knowledge using network analysis, which yields a more detailed depiction that accounts for both the structure and content of team knowledge.

To appreciate the benefits of the network analytic approach, it is important to note that team knowledge is more than simply content; the manner in which knowledge is structured across members influences team interaction and performance. Accordingly, we refer to team knowledge content as the pool of knowledge available to the team, including how it is relevant to a particular domain and its related task outcome (cf. Schultz, 2001), while team knowledge structure is the manner in which knowledge is held, organized, or distributed among members, influencing its readiness to apply to “decisions and actions” (Davenport et al., 1998). Structural complexity may escalate with team size, as potential patterns of interaction increase, and content includes

knowledge about both task and team characteristics (Klimoski & Mohammed, 1994).

Our proposed approach is based on network analysis methods, thus helping account for the various configurations of team knowledge that may result from different combinations of knowledge content of the team's members and the way this knowledge interrelates among each other. Similarly to its use in social network research describing complex relations in systems of social actors (Carley & Krackhardt, 1996), network analysis can represent multiple knowledge domains of each team member as nodes in a team knowledge system (Scott, 1991; Wasserman & Faust, 1994). The link between any two members nodes (knowledge domains of given members) depicts the knowledge relationship between the members, such as whether knowledge is shared in some domains but not others. When all linkages relevant to a given research question are included, the result is a team knowledge network with multiple knowledge metrics (e.g., densities, centralities, isolates, structure, cliques) that more completely describe knowledge relationships among members. Not incidentally, this network can be depicted visually, simplifying the identification of knowledge configurations for teams of increasing size and complexity.

A strength of a network analytic approach is that knowledge distribution can be analyzed at the individual, dyadic, subgroup, or overall levels, which helps identify the location of knowledge centralities (e.g., which members share more knowledge with others) and deficits (e.g., knowledge isolates who share little task knowledge with others), who can substantially influence the team's ability to carry out certain tasks, even if the aggregate knowledge of the remaining members is relatively high (Tziner & Eden, 1985). For example, research has shown that the most central members on a group attain higher performance levels (Ahuja, Galletta, & Carley, 2003) and provide more useful knowledge to their peers (Wasko & Faraj, 2005). Centrally knowledgeable members can act as hubs through which most knowledge is exchanged, thus influencing how the

team coordinates and processes information, even if the overall aggregate knowledge other team members is low, which underscores the importance of understanding how knowledge is structured in a team. Finally, team-level depictions will specify these lower-level structure (isolates, dyads, and subgroups) as well as the overall availability of relevant knowledge that has been shown to relate to team performance outcomes (cf. Cooke et al., 2004; Faraj & Sproull, 2000). This multilevel depiction may be especially useful as teams become larger, with more complex knowledge distributions.

Our paper contributes to the understanding of team knowledge because it offers an approach that represents and measures team knowledge as a network, describing its content and structural aspects. As we discuss, this perspective also helps us reconcile the multiple representations of team knowledge and extend current measurement approaches. In the remaining sections of this paper, we first describe team knowledge as both content and structure. We then discuss our proposed network analysis approach in detail and empirically illustrate the approach, including computational and visual examples, offer a preliminary empirical validation, and discuss how current approaches to team knowledge measurement relate to network analysis. We conclude with implications and limitations, including examples of network metrics.

Team Knowledge Content and Structure

The literature on team knowledge includes various representations and measures (Cannon-Bowers et al., 2001), giving researchers a wide selection of constructs to fit the needs of their specific inquiry. At the same time, the variety of constructs blurs our understanding of team knowledge and makes it difficult to compare and validate empirical findings across studies. We believe that these various perspectives of team knowledge can be reconciled by taking a multi-dimensional perspective, formulating these various constructs from more basic dimensions of team

knowledge content and structure. As such, team knowledge structure is distinguished from its individual counterpart in the cognitive literature (e.g., Cooke et al., 2003; Mathieu et al., 2000; Rentsch et al., 2001), which refers to internal knowledge organization and how various task activities relate to one another. We extend this conceptualization to the team level by considering how knowledge is distributed and organized within the team; that is, how a team member's knowledge interrelates with other members' knowledge.

Team knowledge is thus represented as a set of knowledge dimensions describing its content and a set of relational dimensions describing its structure. Prior seminal research has applied the concept of individual and relational attributes to describe other aspects of teamwork and member interaction dynamics (Barley, 1986, 1990). Our team knowledge representation is an extension of this concept in which knowledge is viewed as a network of content nodes, one for each team member, with every pair of nodes connected with links describing their respective knowledge relationships. For instance, content dimensions can be used to describe the knowledge domain, which can include knowledge about various aspects of the task itself – i.e., “taskwork” – and about various aspects of team members – i.e., “teamwork” (Cooke et al., 2000; Klimoski et al., 1994; Rentsch et al., 1994). This classification is also consistent the research literature on familiarity suggesting two main types of familiarity for working teams: task familiarity and team familiarity (Gruenfeld et al., 1996; Harrison et al., 2003; Littlepage et al., 1997). Further, taskwork and teamwork knowledge can be decomposed into further subdomains, as applicable for the task itself.

For example, the taskwork knowledge required to develop software collaboratively may involve more persistent knowledge of the software processes and methods employed, the software tools used, and the application domain (e.g., accounting, telecommunications) (Curtis et al., 1988), or simply more fleeting knowledge or “awareness” of which software files have been tested on a

given day (Greenberg et al., 1996; Gutwin & Greenberg, 1999; Gutwin & Greenberg, 2004; Gutwin et al., 1995). Similarly, a management team may require task knowledge of financial, marketing, and production issues. Teamwork knowledge may also include various things like knowing who has which expertise – i.e., “transactive memory” (Faraj & Sproull, 2000; Lewis, 2003; Wegner, 1995) and awareness of who is around when needed (Boyer et al., 1998), among other things.

Structure dimensions can be used to describe knowledge relationships among team members such as “sharedness” – i.e., how much knowledge similarity or overlap there is among members. How much knowledge two members share will influence how much they interact and how much further knowledge they exchange (Carley, 1986), how effectively they communicate (Cramton, 2001) and how well they coordinate (Cannon-Bowers et al., 1993; Klimoski et al., 1994). The knowledge that team members share helps create team knowledge structures that are different and more complex than the aggregation of the parts (Cooke et al., 2003), which enables members to synchronize their actions based on accurate expectations about what others in the team are likely to do (Wittenbaum & Stasser, 1996). This shared portion of team knowledge has been characterized in a number of ways, including: shared mental models (Cannon-Bowers et al., 1993; Klimoski et al., 1994; Kraiger & Wenzel, 1997), schema similarity (Mathieu et al., 2000; Rentsch et al., 2001), mutual knowledge (Clark & Carlson, 1982; Clark & Marshal, 1981; Cramton, 2001; Fussell & Krauss, 1992; Krauss & Fussell, 1990); and simply shared knowledge (Nelson et al., 1996). Other structure dimensions would include things like knowledge dependencies, who seeks knowledge from who (Cummings & Chosh, 2005), and possibly others.

Investigating all possible content and structure dimensions of team knowledge, and the extent to which these dimensions are orthogonal, is beyond the scope of this paper. Instead, we next focus on one content dimension – knowledge domain – and one structure dimension – sharedness –

to illustrate our approach.

A Network Analytic Approach to Team Knowledge Representation

We offer network analysis as a method for capturing team knowledge across multiple dimensions, with each node representing a team member's knowledge content in a particular domain, while links among these nodes represent various knowledge structures among members, dyads, and subgroups (Carley, 1997). Our approach involves five steps: (1) identifying the relevant content and structure dimensions of interest for the particular study; (2) measuring all relevant knowledge content dimensions for each team member – i.e., for each network node; (3) measuring all knowledge structure dimensions for every dyad in the team – i.e., for each network link; (4) incorporating all the node and link measures into sociomatrices – i.e., matrices with each cell representing the knowledge relationship between two members of a dyad – and sociograms – i.e., network diagrams representing all nodes and links; and (5) applying the relevant network analysis tools from the rich set of methods available to compute and visually represent useful network analysis metrics (e.g., centralities, isolation, cliques, clusters, structure, etc.). It is important to note that the particular set of content and structure dimensions must be tailored specifically for the goals of each research study; the network analytic method can be adapted for the number of dimensions used (such as in a “slice” for each dimension, described below).

Using this network analytic approach, all individual and relational measures of knowledge can be represented as a multidimensional “sociomatrix” (Scott, 1991; Wasserman et al., 1994). If only one dimension of team knowledge needs to be represented, the sociomatrix will only contain one row and one column for each member. So, cell i,j (off-diagonal) will contain a value corresponding to the knowledge relationship (e.g., shared knowledge) between members i and j . One useful property of a sociomatrix is that it can represent not only relational attributes, but also

individual attributes. For example, cell i,i (diagonal) will contain a value corresponding to the individual knowledge attribute (e.g., amount of knowledge in a particular domain) for member i . Therefore, a sociomatrix can be used to represent one content dimension of team knowledge along with one structure or relational dimension, provided that these dimensions are conceptually related. We illustrate this concept in Figure 1¹.

Because the knowledge shared by i and j is the same as the knowledge shared by j and i , the shared knowledge matrix is symmetrical with respect to the diagonal. However, this is not necessarily true for other structural aspects of team knowledge. For example, also as illustrated in Figure 1, if we want to represent knowledge of who knows what in the team using a sociomatrix the diagonal elements would be null (i.e., not relevant) or, alternatively, 1 (i.e., one knows 100% what one knows). The off-diagonal elements x_{ij} would contain how much member i knows about j in a particular aspect or task domain. Because this value is different than how much member j knows about i , the matrix is not symmetrical with respect to the diagonal (i.e., $x_{ij} \neq x_{ji}$). The sociomatrix relationship is generally interpreted as row \rightarrow column when the matrix is asymmetrical. For example, member 1's knowledge about member 6 is 0.1, whereas member 6's knowledge about member 1 is 0.6, thus member 6 knows more about member 1 than member 1 knows about member 6. Another advantage of sociomatrices is that they can represent more than one dimension at a time by superimposing multiple layers of matrices, one for each dimension or knowledge domain being considered. For example, a sociomatrix representing individual task knowledge, shared knowledge and knowledge of who knows what can be composed by superimposing the two sociomatrices illustrated in Figure 1.

*** Insert Figure 1 about here ***

¹ For simplicity of illustration all the matrix elements are normalized to a 0-1 scale.

A “sociogram” is the visual representation of a sociomatrix. As illustrated in Figure 1, each member is depicted as a node in this graph, and the relationship between any two members (e.g., their shared knowledge) is represented as a link between the two nodes. The link connecting members i and j represents the knowledge relationship between these two members and is equivalent to the value x_{ij} , in the respective sociomatrix. Individual attributes from the diagonal elements of the respective sociomatrix are represented as recursive relationships or as a circular link from a node to itself, as illustrated in the shared knowledge sociogram in Figure 1.

Sociograms can also be “valued” or “dichotomized”. In a valued graph all dyads are connected and the line densities are proportional to the value of the relationship value x_{ij} . However, valued graphs can be somewhat confusing, especially when representing large teams because each node needs to connect to every other node. Figure 1 shows one valued graph containing many links of various densities. A valued graph for a team of n members would have $n(n-2)/2$ lines of various densities, which is not very informative. Instead, such tightly-packed populations are often represented using “dichotomous” graphs, in which a link is drawn only if the relationship value exceeds a certain threshold amount deemed important. For example, in Figure 1 we used the midpoint of the scale as a cutoff point to illustrate the sociograms. The respective dichotomized sociogram includes a line for every relationship in which $x_{ij} \geq 0.5$ (bold-faced figures).

Sociograms can also be “directed” or “undirected”. A sociogram is “undirected” if the sociomatrix is symmetrical with respect to the diagonal, that is if $x_{ij} = x_{ji}$, so the relationship links between nodes don’t need arrows in their visual representation, as in the shared knowledge example in Figure 1. In contrast, a sociogram is “directed” if the sociomatrix is asymmetrical with respect to the diagonal ($x_{ij} \neq x_{ji}$), so the relationship links between nodes need arrows in their visual

representation, as in the example about who knows what in Figure 1. The arrow is generally drawn in the direction of the relationship. For example, member 3 knows the expertise of member 1 but not the other way around.

Network analytic tools like sociograms and sociomatrices are ideally suited to represent and analyze multiple dyadic relationships in a group. In particular, they allow the researcher to aggregate either individual or dyadic relationship attributes, if appropriate, to reproduce some of the existing aggregate or collective measures of team knowledge. At the same time, because the representation and measures we propose are based on individual and dyadic measures of various dimensions, network analysis methods allow us to retain the structural detail that makes up the knowledge in the team. This is particularly important for larger teams for which it is important to understand relationships such as who talks to whom, who shares knowledge with whom, and who knows what others know. Also, the measures that can be derived from such a representation are based on basic, computationally simple network analysis methods that include useful information, such as: “slices” (all relationships for dyad or clique of interest); members’ knowledge centralities; and the presence of knowledge clusters.

For example, there are two 3-member cliques (3-5-6 and 2-5-6) for the knowledge domains of interest in Figure 1. Taking a slice for these two cliques and jointly analyzing their individual knowledge, shared knowledge and transactive memory reveals interesting insights on this team. For instance, members 5 and 6 are in both cliques and are also the most knowledgeable members of the team. Member 5 has a higher “degree” centrality (i.e., more links than other members) and is the most knowledgeable member of the team. Interestingly, member 6 is highly knowledgeable, shares knowledge with 3 other members, and knows the expertise of every member, but only member 5 knows what this member knows. In contrast, everybody knows what member 5 knows, but this

member doesn't know what other members know, except for member 6. Such interesting insights into the team's knowledge structure are not possible with pure aggregate measures only.

By way of example, in the next section we will formulate measures for one content dimension – task knowledge – and one structure dimension – sharedness, both popular dimensions in the team knowledge literature (space limitations preclude examination of further dimensions but their analysis follow a similar pattern). We also detail a preliminary validation of the derived measure. We then discuss how this measure can be used for another structure dimension of interest – shared knowledge of the team (similar to concepts such as directory structure (Anand et al., 1998), transactive memory (Wegner, 1986); and expertise coordination (Faraj & Sproull, 2000)). We then discuss how similar measures can be developed for other dimensions of team knowledge, including useful measures such as knowledge distribution, knowledge isolates, and knowledge cliques, and how network analysis methods can be used to provide visual representations of team knowledge using network diagrams. We then briefly compare network analysis to commonly used team knowledge measures and offer concluding remarks.

Network Analysis of Team Knowledge:

An Illustration Measuring Sharedness & Task Knowledge

Because a team's shared task knowledge is a function of the task knowledge shared by every dyad in the team (Klimoski et al., 1994), we begin by measuring shared task knowledge at the dyad level, then discuss how to incorporate all dyadic measures into a network model representing the knowledge of the entire team. We then describe our measurement approach.

The individual knowledge content pool in the team can be represented as a knowledge matrix $\mathbf{K}_{(N \times T)}$ with one row for each of the \mathbf{N} team members and one column for each of the \mathbf{T}

task-relevant knowledge domains, with elements k_{it} representing the amount of knowledge that member i has with respect to task domain t . For example, in a software task, \mathbf{T} would represent the number of areas that a software developer would need to know to do the job competently (e.g., coding in a particular language, application domain, software tools used, software libraries used), or knowledge about team process techniques that may be useful in completing the task (e.g., communication styles, decision modes). This is referred to as an “*incidence*” matrix in network analysis terminology, because it represents people’s relations to matters such as knowledge areas, professions, or other associations (Scott, 1991).

Similarly, the shared task knowledge for the team in one particular task domain t can be represented in a sociomatrix $\mathbf{STK}_t(N \times N)$ containing one row and one column for each team member. The element stk_{tj} of this “sociomatrix” represents the task knowledge shared by members i and j with respect to task domain t . The diagonal cells stk_{tj} in this matrix can either contain the amount of knowledge of member i in task domain t or can be left blank if individual knowledge is not of interest. The values in each cell stk_{tj} can be computed in a number of ways and the computation will differ depending on whether the cell is in the diagonal or off-diagonal. The diagonal elements (i,i) for each task domain t would simply contain these ratings in that domain. The off-diagonal element (i,j) for each task domain t can be computed using any knowledge or schema similarity metric such as within-team agreement rating {James, 1984 #74}, correlation, quadratic assignment procedure (QAP) correlation (Hubert, 1987), which have been used in team cognition studies {Cooke, 2003 #311; Levesque, 2001 #18; Mathieu, 2000 #17; Rentsch, 2001 #71}. Alternatively, other methods quantifying the amount of knowledge overlap or knowledge distance (i.e., reverse similarity) can be utilized.

The advantage of representing shared task knowledge using this network analysis approach is that the respective matrices and measures can then be decomposed to any level of detail desired. For example, instead of aggregating the \mathbf{STK}_t matrices into an overall matrix \mathbf{STK} , the team's shared task knowledge can be modeled as a three-dimensional matrix $\mathbf{STK}_{(T \times N \times N)}$, with elements \mathbf{stk}_{tij} representing the task knowledge shared by members i and j with respect to task domain t . Measures can then be obtained for the shared task knowledge for the whole team (i.e., aggregate), for any dyad (i.e., a matrix "slice" across all task domains), and for any task domain (i.e., one layer of the matrix). This multi-dimensional sociomatrix can also be used to compute metrics that describe shared task knowledge structure in the team (e.g., centralized, dispersed), and allows us to use powerful network analytic methods to do things like: computing key network attributes (e.g., densities, centralities), identify relationship patterns (e.g., cliques, clusters, sub-groups, isolates, gaps), performing network-based statistical analysis, and providing visual representations using sociograms.

*** Place Figure 2 about here ***

The example in Figure 2 illustrates this computation and visual representation for a team of $N=6$ members based on $T=3$ task knowledge areas: financial management, production and marketing. The links in the sociogram were drawn using a cutoff value of 4, which is the mid-point of the rating scale. We can see that the $\mathbf{STK}_{\text{FINANCE}}$ matrix is very sparse, with only members 5 and 6 sharing substantial task knowledge in this area, reducing the likelihood of full group discussions about finance. The $\mathbf{STK}_{\text{PRODUCTION}}$ matrix shows a fair amount of task knowledge shared by some members but not by others. In contrast, the $\mathbf{STK}_{\text{MARKETING}}$ matrix represents a fully connected network, evident of substantial shared marketing knowledge, providing a common ground for

marketing discussions. We can also see that on the aggregate **STK** matrix that member 1 is a knowledge isolate, while 5 and 6 have the highest amounts of shared task knowledge with other members in all task areas and on the aggregate. This could be valuable information, for example, when analyzing decision flow or team leadership factors.

A similar method can be used to represent other aspects of team knowledge, such as shared knowledge of the team. While knowing who knows what in the team is important (Faraj & Sproull, 2000; Liang et al., 1995; Wegner, 1995), recent transactive memory research suggests that this knowledge is more effective when members have a shared understanding of what team members know (Brandon & Hollingshead, 2004; Lewis, 2003) because it allows team members to make more effective task assignments that integrate this expertise. Therefore, a representation and measure for shared knowledge of the team can be constructed in a similar fashion to the shared task knowledge variable, but using knowledge similarity members have about each other rather than about the task. Members' beliefs can be elicited by asking questions about one another. As suggested in the team cognition literature (Cooke et al., 2003; Cooke et al., 2004) the questions asked about members should relate to important characteristics about these members, relevant to the task as uncovered during the task analysis. For example, in a given software task, team members will need to know each other's knowledge about software languages, software development processes, software tools, application domain, and how different members interact, or other process issues. Responses to such task-specific questions can then be compared between pairs of member to evaluate their similarity.

In sum, network analysis tools such as sociograms and matrices can be applied to the measurement of team knowledge so as to account for multiple content and structure dimensions. Further, dyadic knowledge can be aggregated into team-level knowledge depictions without

sacrificing valuable information about the distribution of the knowledge in individual members and subgroups. In the section below, we conduct a preliminary validation of these network analysis tools through a set of teams that combine their members' knowledge to complete a management simulation task.

Preliminary Empirical Validation of Network Analytic Measures

In this section we provide support for the use of network analytic measures for team knowledge by conducting preliminary validity tests (cf. Ghiselli et al., 1981). The validity sample was a set of 57 teams, ranging from 4 to 6 members (75% had 5 members), engaged in a graduate level management simulation course for approximately 10 weeks at a Midwestern U.S. university. The average response rate for this sample was 89%, 84% and 72% for teams of 4, 5 and 6 members respectively. Each team managed a simulated firm and reported to an external board of directors composed primarily of professionals from the local business community. Teams (as firms) competed against each other by formulating strategies based on multidisciplinary decisions involving production, distribution, finance, marketing and strategy. These decisions were entered into the simulation software for fourteen quarters, which produced quarterly financial statements for each firm based on all decisions made by all teams.

Data was collected during the simulation period from: (1) voluntary student surveys conducted at 3 time periods, with an approximate response rate of 70% including only data for teams in which at least 3 members responded; and (2) team performance ratings from external board evaluations. A number of variables (explained below; items unique to the study are listed in Appendix A) were computed using this data. Table 1 shows descriptive statistics and the correlation matrix for these variables. The two shared task knowledge measures were constructed using the method described in the previous two sections using responses to peer ratings of each other's

knowledge in specific task domains (i.e., financial, production and marketing management of the team's simulated companies).

Because we asked members to rate the knowledge of each of the other members with respect to their knowledge of their simulated company's management in each task domain, we computed knowledge similarity between two members in a dyad as a measure of knowledge overlap. To do this we first computed the average knowledge rating for each member in each task domain (including self-rating and the rating provided by others in the team). Then for each dyad (i,j) , we derived a rating of knowledge overlap in a given task domain based on the lowest knowledge rating average between the two members. For example, if one member's average rating on his/her knowledge of the financial management aspects of the company was high and the other one was only average, we represented the knowledge overlap of the dyad as average – i.e., the knowledge overlap between any two members cannot be greater than the knowledge possessed by the least knowledgeable member. We also normalized all measures to a 0-1 scale by dividing the respective rating averages by the scale range used to measure task knowledge.

We first analyzed the validity of the aggregate measure of shared task knowledge for all dyads and all task domains. Then, in order to assess the importance of measuring and representing team knowledge from a network analytic perspective, we analyzed a structural equation model to evaluate whether network analytic measures added explanatory power to aggregate measures of shared knowledge.

*** Place Table 1 about here ***

Validity Analysis of the Aggregate Share Task Knowledge Measure

Measures achieve convergent validity when they converge towards expected values and

when they actually measure the characteristics we intend to measure (Ghiselli et al., 1981). Because shared knowledge of the task is expected to develop through working together over time (Cannon-Bowers et al., 1993), we tested for knowledge increase as the task progressed chronologically. Results worth noting are illustrated as box plots in Figure 3 (shaded regions represent quartiles above and below the median, while the lines represent the 25th and 75th percentiles). Shared task knowledge increased steadily and significantly over the task period ($F=50.902$, $p<0.001$), providing some evidence of team learning being coincident with the strengthening of members' shared knowledge of the task.

*** Place Figure 3 about Here ***

Next, we checked for convergence of shared task knowledge with team interaction, on the basis that teams whose members communicated more frequently would gain more knowledge of task domains. Team interaction was operationalized as the within-team average of self-reported communication frequency (a 1-6 Likert-type scale). Communication frequency had a significant and positive correlation with shared knowledge of the task ($r=0.53$, $p<0.001$). However, this significant correlation was only observed at time 1 ($r=0.45$, $p=0.001$) and was not significant at time 2 or time 3. This suggests some convergence of team interaction with shared task knowledge, although it may be that they are most affected by team interaction during the early stages of the task.

We then tested for convergence of shared task knowledge with perceived member substitutability, based on the expectation that teams with stronger shared task knowledge would believe that they had more overlapping knowledge with other members and could, therefore, substitute for each other more easily. Member substitutability was measured as the average response to three questionnaire items (Appendix A, $\alpha = 0.75$) that asked the member's perceptions

of task knowledge overlap and member substitutability. This measure was significantly correlated with shared task knowledge ($r=0.55$, $p<0.001$), supporting convergence.

Next, following Ghiselli et al. (1981), we tested preliminary concurrent validity by exploring the correlation of shared knowledge of the task with process variables of “appropriate team strategy” and “task coordination”, previously linked to the constructs by Klimoski and Mohammed (1994). The team’s strategy, an important factor within the simulation in order to achieve financial performance and good evaluations, was assessed as the average response to six questionnaire items ($\alpha = 0.84$) that asked about members’ perceptions of the cohesiveness of their functional strategies. Task coordination was measured with five questionnaire items ($\alpha = 0.71$) that asked about the team’s state of task coordination.

Overall, we found strong positive correlation of shared task knowledge with both strategy coordination ($r=0.59$, $p<0.001$) and task coordination ($r=0.40$, $p<0.001$). Finally, strategy coordination had a strong positive correlation with the firm’s performance reported in the simulated financial statements ($r=0.29$, $p<0.001$), suggesting an indirect association between shared knowledge and team performance, which provides some empirical validation for our measures.

Analysis of Network Measures

In order to evaluate whether network analysis measures like isolates, cliques and centralities provide additional explanatory power to measures of shared knowledge, we constructed a structural model in which team knowledge measures were modeled as antecedents to two coordination variables – task and strategy – and coordination variables were in turn modeled as antecedents to two team outcome variables. We used team cohesion, an attitudinal variable, as the first outcome variable and financial performance as the second outcome variable. The measurement model for variables constructed with survey items were analyzed using factor analysis with Varimax rotation.

The respective survey items and factor loadings are presented in Appendix A. As can be seen from the appendix, variables aggregated from survey items had acceptable reliability factors above 0.70 and the respective factor loadings grouped as expected, providing assurance of their discriminant validity.

The regression models were constructed with team knowledge variables modeled as antecedents to coordination variables, while coordination variables were modeled as antecedents to outcome variables. To test all possible mediation paths of the model, team knowledge variables were also included as antecedents of the outcome variables. Because general task activity coordination can lead to effective strategy coordination, and not the other way around, we also modeled task coordination as an antecedent of strategy coordination. We first evaluated the model using hierarchical regression analysis by first entering shared task knowledge as the only measure of team knowledge, and then adding three other network measures of team knowledge to evaluate if these measures increased the predictive power of the models.

The three network measures (Wasserman et al., 1994) we entered were: (1) degree of isolation – measured as the number of team members not sharing financial, production, or marketing task knowledge (i.e., below the average for all teams) with other team members, divided by the total members; (2) proportion of task cliques – measured as the number of 3-member cliques (i.e., members sharing knowledge above the average for all teams) in each of the three task areas divided by the maximum number of 3-member cliques that can be formed in a team of equal size; and (3) team knowledge centrality – measured as the standard deviation of the degree centrality of all members in all areas (i.e., the degree centrality of a member is equal to the number of other members the member shares knowledge with, divided by the total number of other members); a low standard deviation in the degree centrality is an indication that knowledge is shared evenly,

whereas a high standard deviation is an indication that there are one or two members that are more centrally knowledgeable than others.

In the models without network variables, shared task knowledge was a significant predictor of task coordination, strategy coordination and team cohesion, but had no direct effect on firm performance (only indirectly through strategy coordination). When the network variables were entered, the predictive power of the task coordination, strategy coordination and team cohesion models had significant increases ($p=0.007$, $p=0.004$ and $p=0.018$ respectively), suggesting that network variables can provide a richer explanation of the effects of team knowledge. Furthermore, the effect of shared task knowledge became non-significant in both coordination models—degree of isolation became significant in the task coordination model, whereas team knowledge centrality became significant in the strategy coordination model. While the shared task knowledge did not lose its significance in the team cohesion model, the proportion of task cliques also became significant. In other words, it may be that some of the effects of shared team knowledge may be properly accounted for by isolates, cliques, and centrality, rather than simply aggregate shared knowledge.

All models were subsequently estimated, first using seemingly unrelated regression (which estimates all equations simultaneously as a single large model and is more robust when external variables not included in the model cause the error terms of the various regressions to be correlated), then using random effects to control for group effects. All three regression methods yielded nearly identical results, providing assurance of the efficiency and lack of endogeneity problems with the models. We use the random effects model shown in Table 1 to discuss our results, because random effects are more appropriate for panel data. We also control for the fixed effects of survey wave. In order to test for mediation effects of the network variables, we included

three more regression models with shared task knowledge as predictor for each of the three network variables. Figure 4 shows the graphical representation of these results.

As Table 2 and Figure 4 show, degree of isolation fully mediates the effect of shared task knowledge and has a negative effect on task coordination ($\beta=-0.56$, $p=0.016$). Team knowledge centrality fully mediates the effect of shared task knowledge and has a positive effect on strategy coordination ($\beta=0.56$, $p=0.016$). Also, the proportion of cliques partially mediates the effect of shared task knowledge and has a negative effect on team cohesion ($\beta=-0.66$, $p=0.029$). Because task coordination influences strategy coordination ($\beta=0.44$, $p<0.001$), and strategy coordination in turn affects both team cohesion ($\beta=0.39$, $p<0.001$) and firm performance ($\beta=0.65$, $p=0.001$), all network variables affect team outcomes, directly or indirectly, whereas shared task knowledge only affects team cohesion.

Measuring Further Dimensions of Team Knowledge

We have described, illustrated, and validated network analysis measures that assess shared knowledge of the task as examples of the many possible team knowledge content and structural dimensions. Because formulating measures for all such dimensions is beyond the scope of this paper, we can only briefly speculate how our approach can be used to represent and measure other dimensions. For example, the measures discussed to this point are suitable for relatively durable knowledge. However, more fleeting knowledge like team situation awareness (only relevant for particular situations) requires additional matrices for each relevant slice of awareness (e.g., task awareness, presence awareness) at both individual (i.e., content) and shared (i.e., structure) levels. While relatively durable knowledge can use recall-based elicitation methods (e.g., surveys), more fleeting awareness knowledge requires more dynamic methods, such as asking a participant questions during task execution (Cooke et al., 2000).

Network Analysis and Current Approaches to Team Knowledge Representation and Measurement

The value of the network analysis approach can be further understood in the context of extant team knowledge measures. In this section we briefly overview several measures that have been used to represent team cognition, shared knowledge, and transactive memory, discussing their relative contributions and relationships. In general, while these methods are very useful for measuring specific aspects of team knowledge, they focus primarily on dyadic and aggregate measures. Our approach builds upon these measures by providing a multidimensional perspective that can include multiple dimensions of team knowledge content and structure for all members and dyads as a decomposable knowledge network. Because network analysis allows measures to be aggregated or kept in smaller unit, it can reproduce existing measures or be represented through network tools such as sociomatrices, isolates, and centralities.

Shared knowledge has been represented through a variety of measures, including textual analysis, task important ratings, quadratic assignment, and within-team agreement. Textual analysis (Carley, 1997) builds cognitive maps through identification of word sequences commonly used by team members, drawn from work documents, memos, electronic mail, discussion boards, interview transcripts, and other written materials available. This method is particularly useful for archival research. In another study with student teams working on software projects, Levesque and her colleagues (Levesque et al., 2000) used similarity metrics to measure shared knowledge using within team agreement ratings (James *et al.*, 1984) on responses to a number of task-related questions. Related to shared knowledge is the concept of schema similarity, which focuses on similarity of knowledge structures among team members, rather than similarity of the content of that knowledge (Cooke et al., 2003; Cooke et al., 2004). This has been measured by through

compiling networks of members who similarly rate the importance of list of team tasks, such that individual networks for each task activity is represented as a node, and task relationships represented by links among these nodes.

Numerically, these networks can be represented as squared matrices with the nodes or task activities listed in both, the row and column headings, and the respective cells containing the value of the relationship between the task activities in the respective row and column. The shared schema metrics for any given dyad are then computed using a metric measuring the similarity between the individual schema networks of the two dyad members. The shared schema value for the entire team is then computed as an aggregation or average of all dyad shared schema measures. The dyad similarity metrics are computed in a number of ways. For example, one study used QAP (quadratic assignment procedure) correlation (Mathieu et al., 2000) to measure schema similarity through correlating two square matrices (Hubert, 1987). The resulting QAP correlation value is the same as a Pearson correlation value between all the corresponding elements of the two matrices, but QAP reports a non-parametric method to estimate the statistical significance value (i.e., p-value) because the relationship values in the matrix cells are not always independent. This method is very useful for network data and can also be used in multivariate regression analysis (Krackhardt, 1987, 1988).

Similarly, Cooke and her colleagues (2003) used task relatedness matrices to compute taskwork schema agreement in a simulated task involving helicopter missions, using the proportion of identical links between the task relatedness networks of the two dyad members rather than QAP correlation. They also computed teamwork schema agreement by asking members which types of information had to be exchanged among three different types of crew member roles, then also computing the proportion of identical responses among team members. Once again, these task relatedness networks and matrices are very useful to represent the individual knowledge structure

of each team member and the QAP correlation method is an excellent way of calculating a similarity metric between the respective knowledge structures of every dyad in the team. Our proposed approach extends methods like the ones we just described by representing every member knowledge and every dyad knowledge relationship in a network or sociomatrix for the entire team.

Several measures have also proposed measures of transactive memory. Lewis' review (2003) concludes that transactive memory can be measured by evaluating team members' agreement about who knows what in the team, a form of shared knowledge about teamwork, and proposed an aggregate measure that incorporates knowledge specialization, credibility and coordination. Similarly, Brandon and Hollingshead (2004) suggested using dimensions of accuracy, sharedness and validation to measure transactive memory effectiveness. Faraj and Sproull (2000) measured the similar concept of expertise coordination – i.e., the ability to find expertise in a team and use it when needed. While these are useful measures to evaluate the transactive memory of a team as a whole, our approach can be used to capture how this transactive memory is organized within the team. For example, some members may have very high knowledge of other members' areas of expertise, while others may have specialized knowledge only; yet others may have both or neither, which can make a difference in how the team performs.

Network analysis can successfully represent shared knowledge and transactive memory, whether as single dimensions or in greater detail as part of aggregated knowledge matrices and sociograms. For instance, specialization is a dimension of knowledge content of each member, while credibility and knowledge similarity are structural dimensions at the dyadic or aggregated levels. Without network analysis, measures of sharedness and transactive memory provide an incomplete picture of a team's knowledge distribution, especially as teams get larger. This knowledge organization may be a critical factor in team performance, particularly when certain

team members have roles that may be more critical to team success than others. Further, network analysis sociomatrices can be multidimensional, representing multiple aspects of team knowledge with a single multidimensional matrix and the corresponding layers of sociograms. This network representation also enables the extraction of a “slice” to analyze a particular dyad or clique of interest across all dimensions (Wasserman et al., 1994).

LIMITATIONS AND IMPLICATIONS

This paper proposes a network analytic method for measuring multidimensional team knowledge and provides a preliminary test through a survey-based study. There are several limitations that should be noted, both with the method chosen and the illustrative test. For the latter, one limitation may be seen in our use of self-report questionnaire data, which may be highly susceptible to response biases. In future studies, the addition of an alternative data source (external evaluations) and an objective measure of team performance may reduce the likelihood of such an effect. Because our purpose was to test a method rather than support theory-driven hypotheses, we believe that this does not seriously contest our results. Another limitation may be seen in the use of correlation to validate our preliminary investigation. Naturally more testing is needed to evaluate the internal and external validity of these measures, with respect to team processes and outcomes, including regression tests with appropriate control variables, mediation tests (i.e., whether the effect of shared mental models on performance is mediated by cohesive strategy and/or task coordination) and moderator variables. For example, it may be that accuracy of shared task knowledge mediates its effect on process variables, which we have not explored here.

What may be the most obvious limitation of the network analytical approach we are proposing is that appropriate measures of team knowledge content may be difficult both to design and collect. The design may be problematic in that knowledge associated with a particular task may

be complex and not easily amenable to explicit measures. Further, the knowledge may be proprietary, such that measures created may not be transferable or generalizable across organizations or tasks. Collection of such knowledge may also be hampered for similar reasons; more tacit team knowledge is difficult to tease out, especially in a quantifiable manner (Anand et al., 2003). Additionally, the process may involve significant expense to an organization that doesn't already collect such data. Finally, some employees may resist revealing information regarding the limits of their knowledge about the task or team.

A second limitation of our approach is that it describes knowledge held by a team and its members, but does not in itself indicate the success with which teams may use such knowledge. For instance, a team and its members may hold substantial knowledge of task domains and teamwork processes, but be woefully ineffective in addressing their collective task. Of course, this may be partially remedied through testing various configurations of such knowledge (about tasks and about team processes) against outcomes of interest. Additionally, it may be that knowledge of team processes could be assessed behaviorally (such as by a rating by an observer), rather than by self-report, which may provide a content domain of process effectiveness.

Despite these limitations, this paper contains important contributions. Current team knowledge measurements, while advancing considerably in recent years, do not depict how knowledge is distributed in a team, which becomes more important as teams become larger and subgroups hold specialized expertise. Our main contribution is an approach to represent and measure team knowledge, which among other things: (1) build upon strengths of current measures; (2) is computationally simple in the sense that no specialized statistical or network analysis software is necessary; (3) can be used at the highest aggregate level, or detail sublevels (members, dyads, or cliques), allowing analysis of "slices" across multiple dimensions of interest; (4) contains

individual knowledge attributes that describe content dimensions and relational attributes that describe structure dimensions, thus providing a more complete picture of the team's knowledge; (5) allows the computation and visual representation of various dimensions of team knowledge and how this knowledge is distributed in the team; (6) shows preliminary validity with other measures; and (7) provides a richer explanation of how the distribution of knowledge within a team influences performance and its antecedents. Our preliminary evidence suggests that viewing team knowledge from a network perspective adds explanatory power – having isolates may not be good for task coordination; having centrally knowledgeable members may help coordinated firm strategies; and shared task knowledge may be good for team cohesion, provided that there are not many cliques in the team. We have also developed and validated a measure for shared task knowledge and transactive memory, suggesting a method for their visual representation. Future work may build upon these proposed measures in order to conduct sound research on this important topic.

The primary implication associated with the network analytic approach is that the added knowledge metrics can be used to more accurately depict the distribution of knowledge within a team, including multiple domains as a coherent set. In practice, this more detailed depiction is accomplished by decomposing team knowledge into more granular levels of structure. For example, Figures 5 and 6 depict the decomposition and aggregation of the shared task knowledge networks in two high-performance teams and two low-performance teams in our validation sample. The aggregate networks of both teams look quite dense, suggesting that members share substantial amounts of task knowledge. However, the separate task domain networks tell different stories about these two teams, which cannot be discerned from aggregate measures. Team 1 has 4 members, including member 1, fully connected on their knowledge of finance issues. It also has 4 members fully connected on their knowledge of production issues, but with member 4 connected instead of

member 1. Only 3 members are fully connected on marketing issues, including member 5, who does not share knowledge with other members in either finance or production. Finally, member 3 is the only member that shares knowledge with others in all 3 task areas, making the team vulnerable to member turnover. On the other hand, Team 2 has more widespread shared knowledge about finance and marketing. Further, since members 5 and 3 share knowledge in all task areas, it gives the team some level of knowledge redundancy, making it less vulnerable to member turnover.

*** Place Figures 5 and 6 about here ***

In contrast, the low performing teams are quite disconnected in terms of their aggregate shared knowledge. Notice that while Team 3 has a three-way clique in finance and marketing, there is not a single member who has knowledge in all three task areas. This may account for the low performance of this team; that is, team members were unable to have an effective coordination and integration of their individual functional strategies. In contrast, Team 4 has a three-way clique in finance and only 2 members connected in production issues, but it has a fully connected knowledge network on marketing. This team's low performance may have been due to an excessive focus on marketing issues at the expense of not fully considering the impact on finance and production. None of these speculations would be possible with holistic or aggregate measures only, underscoring the importance of understanding the finer structural details of team knowledge.

Network analysis tools can be useful in gaining even further insights into team knowledge distribution. For example, as referred to previously, we computed an "isolation index" from the shared task knowledge networks to measure the presence of knowledge isolates in the team. For each team, we counted the number of members who did not share task knowledge with any member in each task domain. We used the overall shared task knowledge average for all teams as the cutoff value. In other words, a team member was considered a Finance isolate if his or her shared

knowledge in the Finance task domain with each of the other members was below average, and the same thing for the Production and Marketing task areas. The number of isolates in each team was then averaged across all task domains.

So, for example, a team with an isolate average of 1 indicates that, on average, there is one isolate in the team. This could mean that there is one isolate in each of the three task areas, three isolates in a single task area, or anywhere in between. This measure was then divided by the number of team members to obtain a normalized index value ranging from 0 to 1, such that a value of 0 indicates no isolates whatsoever (i.e., all shared task knowledge networks in all three task areas are fully connected) and a value of 1 indicates that all members are isolates in all task areas (i.e., there is no shared task knowledge in the team). We then computed a correlation value of this index with the other measures used in the validation analysis above and found that the isolation index is negatively correlated to team performance ($r=-0.373$, $p<0.001$), task coordination ($r=-0.265$, $p=0.003$) and strategy coordination ($r=-0.530$, $p<0.001$). As suggested in the preliminary validation, while further multivariate analysis is needed to test knowledge isolates in given contexts, these results suggest that network analysis metrics can be useful in understanding which aspects of team knowledge drive performance.

Separately or together, these tools extend the ability of network analysis to depict knowledge distribution in teams, potentially increasing our understanding of how such knowledge is related to team antecedents and consequences. Researchers may choose the tools most appropriate for their research questions, just as they choose relevant dimensions to include as “slices” of the multidimensional sociomatrix. Overall, the network analysis approach offers practical flexibility while maintaining an ability to credibly represent multidimensional team knowledge content and structure.

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Variable	Mean	Std Dev	1	2	3	4	5	6	7	8	9	10
1. Firm Performance	0.00	0.92		0.12	0.29 **	0.02	0.20 *	0.05	-0.08	0.09	0.15	-0.19
2. Team Cohesion	5.76	0.85	0.12		0.63 **	0.65 **	0.62 **	0.35 **	-0.29 **	0.26 **	0.35 **	0.04
3. Strategy Coordination	5.41	0.72	0.29 **	0.63 **		0.57 **	0.89 **	0.52 **	-0.37 **	0.32 **	0.42 **	0.24 **
4. Task Coordination	5.67	0.66	0.02	0.65 **	0.57 **		0.53 **	0.32 **	-0.39 **	0.26 **	0.24 **	0.02
5. Perceived Substitutability	4.99	0.62	0.20 *	0.62 **	0.89 **	0.53 **		0.55 **	-0.33 **	0.39 **	0.47 **	0.28 **
6. Shared Task Knowledge	0.54	0.10	0.05	0.35 **	0.52 **	0.32 **	0.55 **		-0.38 **	0.62 **	0.37 **	0.53 **
7. Degree of Isolation	0.17	0.26	-0.08	-0.29 **	-0.37 **	-0.39 **	-0.33 **	-0.38 **		-0.39 **	-0.40 **	-0.11
8. Proportion of Task Cliques	0.13	0.19	0.09	0.26 **	0.32 **	0.26 **	0.39 **	0.62 **	-0.39 **		0.35 **	0.19 *
9. Team Knowledge Centrality	0.12	0.11	0.15	0.35 **	0.42 **	0.24 **	0.47 **	0.37 **	-0.40 **	0.35 **		0.08
10. Communication Frequency	4.19	0.72	-0.19	0.04	0.24 **	0.02	0.28 **	0.53 **	-0.11	0.19 *	0.08	

* p<0.05 ** p<0.01

Table 1
Descriptive Statistics and Correlation Matrix

Variable	Isolation		Cliques		Centrality		Task Coordination				Strategy Coordination				Team Cohesion				Firm Performance				
	Coef	Sig	Coef	Sig	Coef	Sig	Coef	Sig	Coef	Sig	Coef	Sig	Coef	Sig	Coef	Sig	Coef	Sig	Coef	Sig	Coef	Sig	
T1 to T2	0.19	0.000	-0.23	0.000	-0.06	0.001	-0.31	0.003	-0.15	0.271	0.10	0.312	0.22	0.084	-0.35	0.000	-0.52	0.000					
T2 to T3	0.05	0.086	-0.01	0.790	-0.01	0.620	0.18	0.035	0.21	0.015	0.09	0.305	0.11	0.175	-0.11	0.175	-0.12	0.128	-0.12	0.480	-0.11	0.519	
Strategy Coordination															0.39	0.000	0.39	0.000	0.68	0.000	0.65	0.001	
Task Coordination											0.47	0.000	0.44	0.000	0.44	0.000	0.46	0.000	-0.35	0.045	-0.35	0.055	
Shared Task Knowledge	-1.48	0.000	1.91	0.000	0.54	0.000	2.35	0.000	1.10	0.262	2.22	0.000	1.19	0.185	1.61	0.006	3.05	0.001	-0.55	0.634	-2.30	0.238	
Degree of Isolation													-0.16	0.432			0.15	0.469			0.09	0.827	
Proportion of Task Cliques									0.17	0.608			0.04	0.896			-0.66	0.029			0.79	0.297	
Team Knowledge Centrality									0.18	0.696			1.55	0.001			0.31	0.489			0.97	0.350	

Table 2
Regression Analysis Results

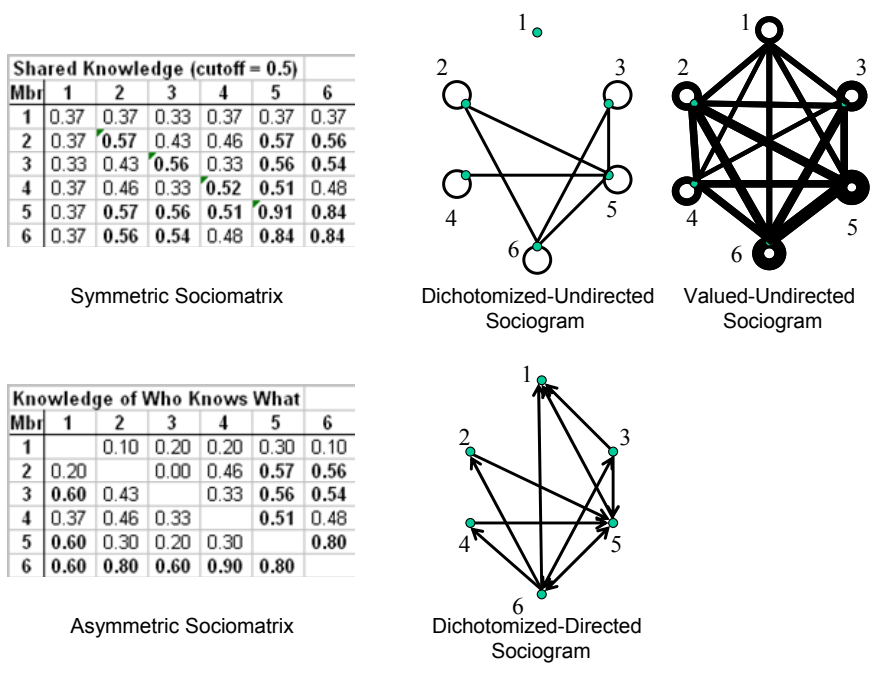
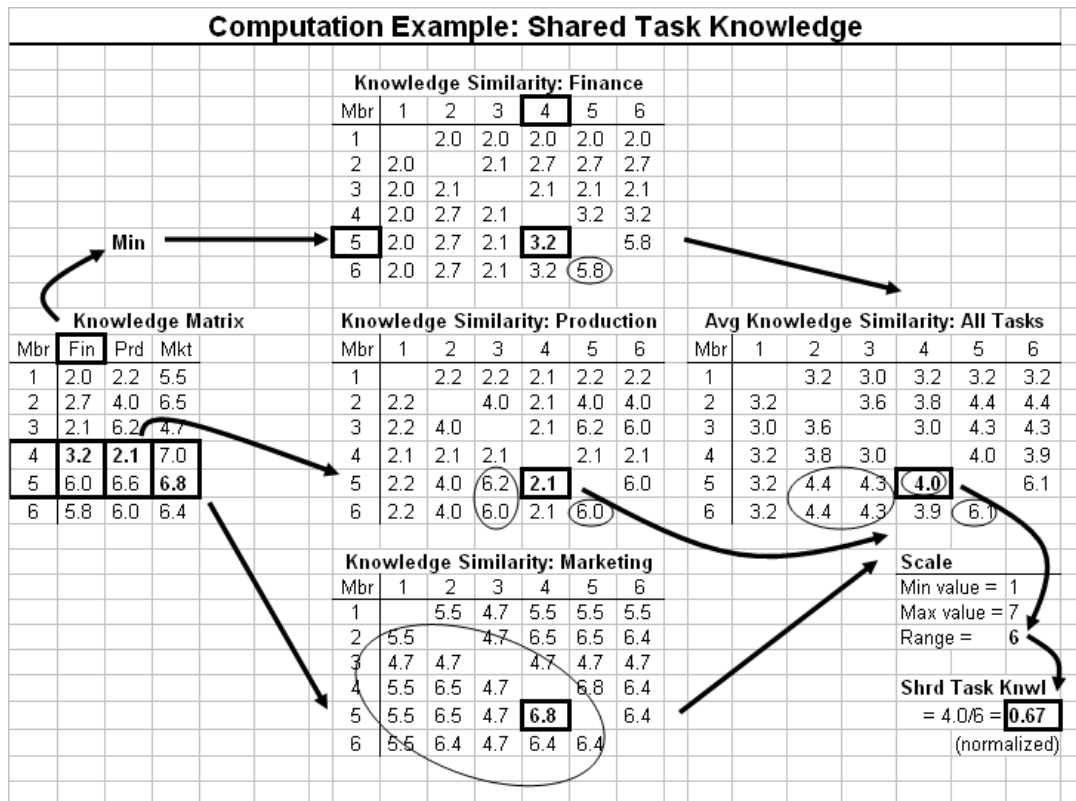


Figure 1: An Illustration of Sociomatrices and Sociograms²

² For simplicity of illustration all the matrix elements are normalized to a 0-1 scale.



Visual Representation: Shared Task Knowledge

Cutoff value: >=4.0 line (circled) - <4.0 no line

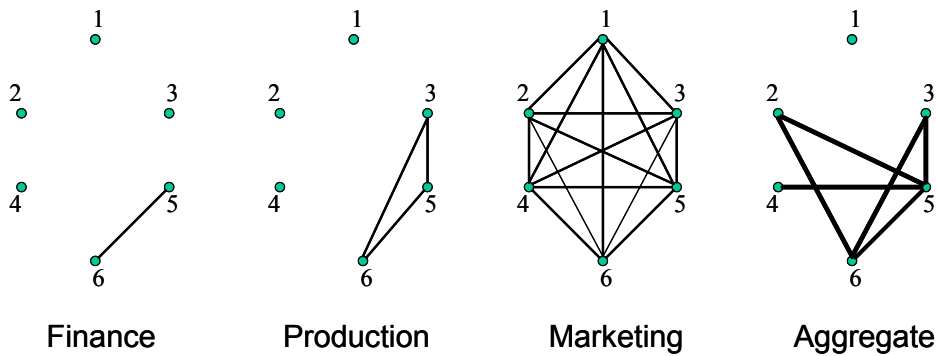


Figure 2: Illustration of Computation and Visual Representation of Shared Task Knowledge

Shared Knowledge of the Task

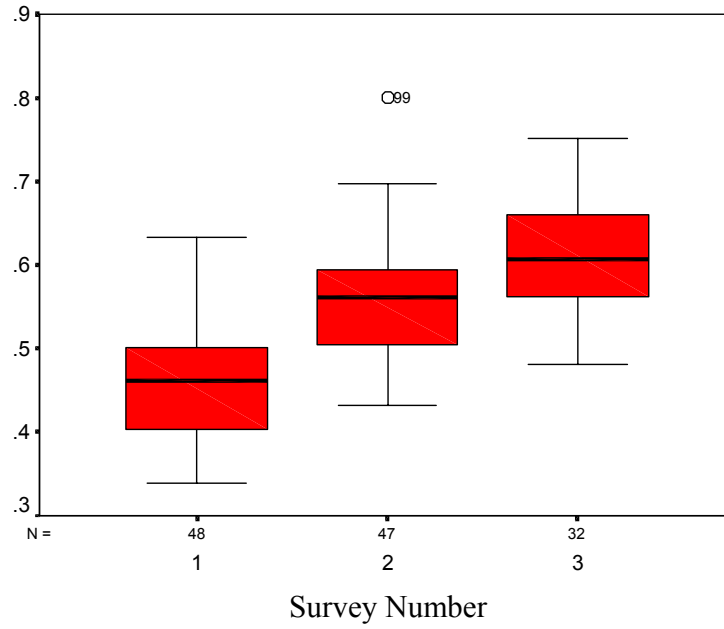
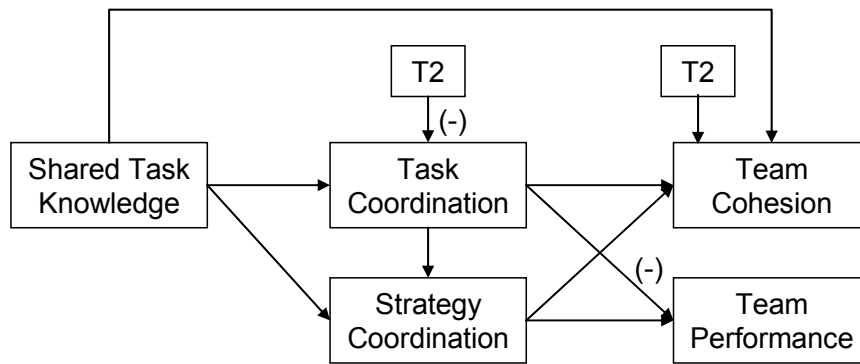
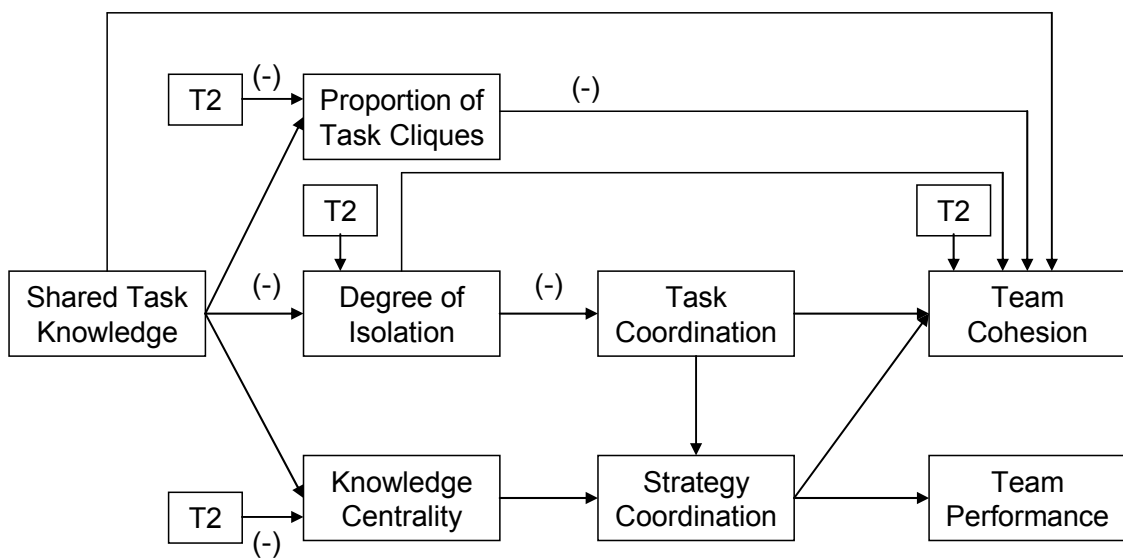


Figure 3: Shared Knowledge Over Time



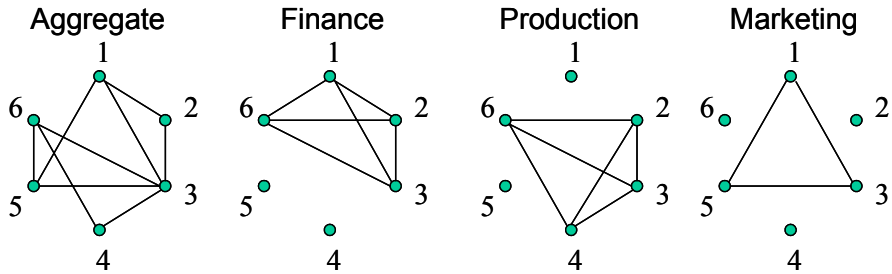
a) Without Network Variables



b) With Network Variables

Figure 4: Random Effect Regression Results

Team 1 – Rank: (2nd) BOD Eval; (4th) Financial Perf



Team 2 – Rank: (3rd) BOD Eval; (2nd) Financial Perf

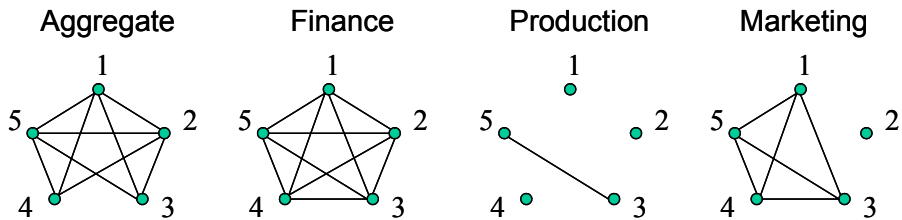
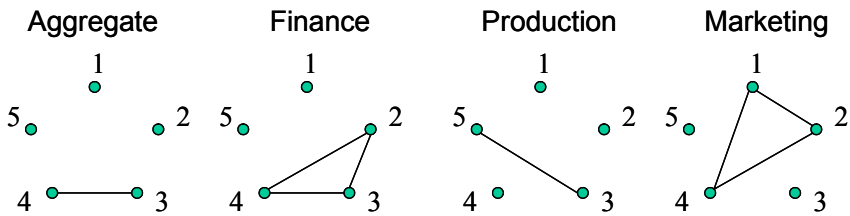


Figure 5: Illustration of Shared Task Knowledge Networks for High Performance Teams

Team 3 – Rank: (3rd lowest) BOD Eval; (19th lowest) Financial Perf



Team 4 – Rank: (3rd lowest) BOD Eval; (2nd lowest) Financial Perf

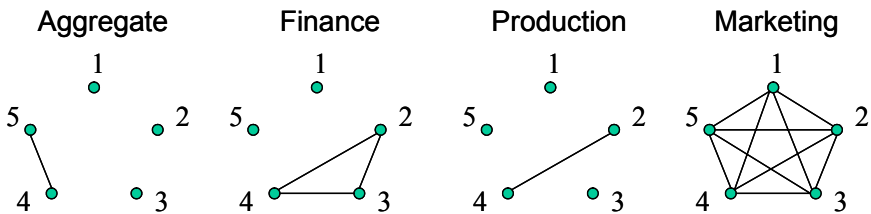


Figure 6: Illustration of Shared Task Knowledge Networks for Low Performance Teams

Appendix A Questionnaire Items for Study Variables

Factor Analysis Component Matrix

Survey Item	Component			
	1	2	3	4
Perceived Substitutability (Cronbach $\alpha = 0.75$)				
Members of my team know a lot about each others' areas of expertise (e.g., marketing, finance, production).	0.759	0.287	-0.084	0.175
Members of my team don't know much about the tasks others are working on.	0.748	0.172	0.161	0.161
If a member of my team couldn't finish his/her tasks, the rest of us know enough to take over.	0.710	0.177	0.071	0.246
Strategy Coordination (Cronbach $\alpha = 0.84$)				
My team has a clear idea of what our financial strategy should be.	0.362	0.669	0.043	0.075
My team has a clear idea of what our marketing strategy should be.	0.082	0.729	0.161	0.281
My team has a clear idea of what our production strategy should be.	0.260	0.688	0.081	-0.004
Members of my team have a clear idea of our team's goals.	0.195	0.559	0.262	0.467
My team knew exactly what it had to get done in order to succeed in Game.	0.030	0.775	0.079	0.263
Members of my team fully understand how competitors' actions will impact our performance.	0.168	0.619	0.202	0.255
Task Coordination (Cronbach $\alpha = 0.71$)				
Members of my team often disagreed about who should be doing what task.	0.258	0.011	0.698	0.077
Members of my team did their jobs without getting in each others' way.	0.011	0.112	0.551	0.333
Members of my team often duplicated each others' work.	-0.113	0.098	0.776	-0.012
Tasks were clearly assigned to specific team members.	0.155	0.402	0.511	0.234
My team wasted a lot of time.	0.006	0.247	0.554	0.372
Team Cohesion (Cronbach $\alpha = 0.86$)				
I felt I was really part of my team.	0.257	0.172	0.172	0.666
I am very satisfied with my team.	0.238	0.273	0.208	0.796
I looked forward to being with my team.	0.076	0.181	0.085	0.766
I'm extremely glad I got this team of people to work with.	0.211	0.160	0.163	0.843