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This study investigates the effect of knowledge distribution and group structure on performance in MBA game teams. We found that group performance was contingent on the distribution of knowledge within the group and networks of social relationships among group members. Studying 39 teams of MBA students in two management simulation games, we found that, in general, groups that had broadly distributed knowledge, i.e., groups made up of members who had general knowledge, outperformed groups that had knowledge concentrated in different members, i.e., groups made up of members who had specialized or both specialized and general knowledge. However, the advantage that the former enjoyed over the latter disappeared when groups of specialists or mixed groups had decentralized network structures.
(*Small Groups*; *Networks*; *Group Knowledge*)

Introduction

Group members differ in their expertise, knowledge, and information that they bring to the group (Jackson 1992). Research has found that the characteristics of prior knowledge possessed by group members and how information is distributed within the group affect group performance (Laughlin 1980, McGrath 1984, Wegner et al. 1991, Wegner et al. 1985, Stasser 1992). The literature of small groups also indicates that group performance depends on not only the information resources available to the group, but also the processes or structures which groups use to utilize these resources (Hackman 1987, Steiner 1972). This paper investigates one such structure—group social network structure—and its joint effect with the distribution of knowledge on group performance.

Distribution of Knowledge and Group Performance

The literature on small groups has shown a strong relationship between knowledge possessed by group members and group performance (Shaw 1981, Steiner 1972, Stasser and Stewart 1992). In particular, researchers have considered the knowledge possessed by group members as varying along the dimensions of the type of knowledge/ability (Jones 1974, Kennedy 1971), the level of knowledge/ability (Tziner and Eden 1985), and the distribution of knowledge (Liang 1994).

Liang (1994) found that groups made up of generalists performed better than groups consisting of specialists. She argued that generalist groups outperformed specialist groups because the former had a higher level of similar knowledge that was broadly distributed across group members, while the latter had nonoverlapping or unique information that was concentrated in different group members. Thus, in generalist groups, minimal effort was needed for members to retrieve the knowledge they needed. Consistent with this argument, Stasser and colleagues (Stasser et al. 1989, Stasser and Titus 1985, 1987) found that broadly distributed or shared information is more

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likely to be retrieved by the group than unshared information. Stasser and his colleagues further found that as a piece of information was distributed across more individuals within the group, the retrieval of this information became more likely and thus facilitated group decision making.

Another reason why shared knowledge may improve group performance is that when information is held by multiple members, not only more people within the group possess the information, but group members who possess the information may also provide retrieval cues to each other to aid the introduction of the knowledge and decision making (Liang et al. 1995, Moreland et al. 1997, Larson and Christensen 1993, Larson et al. 1994, Wegner 1986). Finally, in groups made up of generalists, group members may be more likely to share conceptualizations of one another's expertise, whereas in groups made up of specialists, group members may be more likely to form different conceptualizations of one another's expertise. Shared conceptualization of other members' expertise enables group members to pool information more effectively and make better group decisions (Gruenfled et al. 1996, Stasser et al. 1995).

Obversely, when group members have nonoverlapping information, group members have difficulty discussing or sharing that knowledge; and, as a result, the group does not reach the optimal decision (Stasser and Titus 1985, 1987, Stasser and Stewart 1992). In addition, in groups that have nonoverlapping information, confirmative pressures or the mere presence of other group members may suppress the retrieval of the knowledge and decrease group performance (Janis 1982, Markus 1978).

We thus argue that the distribution of knowledge among members of a group should affect group performance. We define the distribution of knowledge in terms of who has what types of information. In some groups, group members have highly specialized knowledge and information tends be concentrated in specific individuals or pockets within the group. In other groups, members have a mastery of knowledge across various domains and thus information is broadly distributed within the group. At the group level, we measure the distribution of knowledge by assessing the distribution of individuals who are specialists or generalists.

In groups where information is distributed broadly across group members, group members share common information and conceptualization, and this in turn should facilitate group performance. In groups where pockets of unique knowledge are concentrated in different group members, critical information possessed by certain members may never be shared or retrieved by the group, and this should hurt group performance. We hypothesize that:

Hypothesis 1 (H1). *Groups that have knowledge broadly distributed across group members* (*groups consisting of generalists*) *will outperform groups that have unique knowledge concentrated in different group members* (*groups consisting of specialists*).

The Contingent Effect of Group Structure

One factor that could modify the effect of the distribution of knowledge on group performance is the structure of the group. By group structure we refer to the quality and patterns of relationships existing among group members (Argote et al. 1989). Group researchers have long studied the effects of group structure on the effectiveness and efficiency of groups (Bavelas 1950, Leavitt 1951). More recent work suggests, however, that group structure has a modifying rather than a direct effect on group performance (Bass 1980, Schoonhoven 1981, Shaw 1981). For example, hierarchical structures tend to be more efficient for simple problems. For more complicated problems, the advantage of hierarchical systems diminishes (Back 1974). Argote et al. (1989) found that under conditions of high uncertainty, and low threat, groups tended to be more centralized and suggested that the degree of centralization may interact with uncertainty and threat to influence group performance.

Drawing on the discussion above, we propose that group structure can modify the effect of knowledge distribution on group performance. All else being equal, the performance of groups that have broadly distributed knowledge (generalist groups) should not be contingent on the structure of the group. Information in these groups is already broadly shared, and group structure therefore should have little effect on their performance. However, the performance of groups that have pockets of unique knowledge distributed across different group members (specialist groups) should vary depending upon group structure. In groups of specialists the work relationships among group members can either constrain or facilitate the flow of knowledge and information within the group.

In decentralized groups, i.e., where the intensity of ties is high and hierarchy is minimal, the flow of knowledge and information should be maximal. That is, thick, flat networks provide opportunities for task-related communication and information exchange (Albretcht and Ropp 1984). Decentralized network structures should help groups of specialists to overcome their lack of common knowledge and understanding and pool unshared critical information for better decision making. These groups may thus perform as well as groups of generalists. In groups where ties are less intense and interaction only takes place through one or two group leaders, communications among specialists is stymied. This could exacerbate the problems of unevenly distributed knowledge in these groups. We therefore expect poorer performance in groups of specialists when ties are less intense and the network of ties is hierarchical, i.e., more centralized.

Thus, we hypothesize the modifying effect of group structure on the relationship of knowledge distribution and group performance:

HYPOTHESIS 2A (H2A). *Groups that have narrowly distributed knowledge will perform as well as groups that have broadly distributed knowledge if group structures are more decentralized.*

HYPOTHESIS 2B (H2B). *Groups that have narrowly distributed knowledge will perform significantly poorer than groups that have broadly distributed knowledge if group structures are centralized.*

In other words, we expect, on average, that groups with broadly distributed knowledge should outperform groups that have narrowly distributed knowledge. However, as the structure of relationships in groups with narrowly distributed knowledge becomes more decentralized, the difference in the performance of the two types of groups should decrease. Also, as the structures in groups with narrowly distributed knowledge become more centralized, the difference in the performance of the two types of groups should become even greater.

Methods

Participants

Second-year full-time MBA students at a major university participating in the "Management Game" were asked to fill out questionnaires regarding their game teams. In 1992, 35 four-, five-, or six-person top management teams were formed among the 210 participants. In 1993, 34 four-, five-, or six-person groups were formed among 187 participants. Ideally there would be only six-person teams, but due to the number of students available and the need to create equal number of teams in each game nation, a few groups had four or five members.

Procedure and Task

Since the 1960s the business school has required all second-year MBA students to participate in a management simulation game, The Management Game. Each group plays at being the top management team of a detergent company. The Game involves a variety of business skills, such as the ability to develop, execute, and adjust business strategies, the ability to negotiate with bankers and labor representatives, and the ability to apply mathematical models and statistical analysis techniques. The main responsibility of a game group is to develop long-range corporate strategy, and to implement this strategy into operating plans through monthly decisions in marketing, finance and accounting, production, and research and development. A computer simulation algorithm processes these decisions. Operating results depend on the actions of both the focal group and its competitors. Each game group competed in a simulated national market with three other firms. Firms in different nations did not compete directly. However, firms could trade raw materials, products, and managerial services across nations.

The presidents of game groups were first nominated and then elected by all members of the class in the spring semester. The Management Game office announced their names after the election. A week prior to the group selection meeting, the Game office gave presidents a vita for each student in the class. Each vita contained self-reports of how good a person was at different subjects (e.g., accounting/finance, marketing, and production), how much effort he or she was willing to put into the Game, with whom he or she would not work, what positions he or she preferred, and his or her relevant background and work experiences. On the date of selection, the elected presidents gathered to pick their teams. The Game office required that each game team had one president and one vice president in each of the finance/accounting, marketing, and production divisions. Two other members of the group could be assigned to any positions that the team president saw fit.

At the team selection meeting, presidents took turns picking people they wanted on their teams. Each president could only pick one person per round. Once a president selected a person, he or she was no longer available for further selection. The picking order was randomly determined, and picks went from one end of the table to the other and then back again. Thus, each president had equal opportunities to pick her/his team members. Typically, presidents had definite preferences before they began to choose. After team members were selected, the teams were announced.

The Management Game lasted 24 simulation months and 16 weeks in real time. Teams reported their marketing, finance/accounting, and production decisions to the Management Game office every simulation month. After all teams turned in their inputs on the due date, the Game office entered these inputs into the computer program and ran the simulation. It then published the results of these "moves" in the Game Newsletter. During the Game, each team met with its Board of Directors three times to report their business plans and progress. The Board of Directors consisted of executives from corporations and faculty of the business school. The stock price of a firm reflected its financial performance. It was determined by a number of factors, including the firm's overall performance, the consistency of the firm's performance, and the financial and market strength of the firm. The grades of teams were determined by a set of factors, including an evaluation by the Board, the firm's financial performance throughout the simulation, and its success in negotiations with bankers and labor representatives. Though the Game office held most elements of the Game constant across years, it changed certain conditions if it thought it would be useful. In 1993, the Game office decided to simulate natural-life markets by giving different initial market position and financial strength to different firms. Specifically, it gave the sixth firm in each nation a slight advantage over others in the nation. Because of the change in this year, in our analysis we had to control for whether a firm was the sixth firm. (We will address this issue again in the Measures section.)

Since the Game is the single most important class in the two-year MBA education at the university, participating students took it very seriously. In most cases, participants were highly motivated and committed to "win" the game. In particular, students' performance in the Game had implications for future employment opportunities, as corporate executives sat on the Board.

Measures

The research team (which included the first author) used questionnaires to collect information about group structures. It sent out and collected questionnaires from all full-time second-year MBAs for both 1992 and 1993. The team assured students that their response was voluntary and that their responses would be kept confidential and used only for research purposes. The team used the students' self-reported game vitae to assess information about the distribution of knowledge in groups.

Group Structure. There are many ways to operationalize group structure. We focused on two dimensions of network decentralization: the intensity of ties among group members and the degree to which networks of relations were hierarchical or flat. Ties were intense if members of the group related to one another on several criteria, i.e., ties were multiplex and thick. For the purpose of the paper, network structures were hierarchical if members were related to each other through ties to only one or two others. We defined network structures as being decentralized if group members were directly connected to one another and the intensity of ties was strong.

At the end of the game, the research team asked each team member (including the president) to fill out a questionnaire in which she or he indicated her or his work relationships with each of the other team members. Team members were asked to report (1) how much they had depended on each of their team members, (2) how much each of their team members had depended on them, (3) how much they had worked with each of their team members, and (4) how much they communicated with each of their team members. Each question was on a 5-point scale from "not at all (1)" to "a lot (5)". We included all groups that had six members and at least three of the six provided us with data ($n_6 = 31$),[1] all groups that had five members and at least three provided us with data ($n_5 = 12$),[2] and one four member group ($n_4 = 1$). The number of groups dropped from 69 to 44, because in many groups not enough respondents answered the social network questions.

Note that we have four reports on ties between two group members from two perspectives—ego and alter. Thus a team member i may think that she was highly dependent on another team member j, the other team member was highly dependent upon her, she worked extensively with the team member, and communicated extensively with that team member. However, that team member may not have the same perception of the relationship as she. We coded team member i's perception of team member j, on question k ($k = 1$ to 4) as f_{ijk} and team member j's perception of team member i, f_{jik}. To simplify matters, we divided f_{ijk} and f_{jik} by 5, giving us a tie strength value between 0 and 1. We then aggregated the responses across the four network questions, computing the average tie strength between members i and j ($f_{ij} = \sum_{k=1,4} f_{ijk}/4$ and $f_{ji} = \sum_{k=1,4} f_{jik}/4$). Again, the values ranged between 0 and 1. Note there are two summary measures for each dyad, one from the perspective of ego and one from the perspective of alter.[3]

We first measured the intensity of ties among members in each group. Since we were only theorizing about the ties among members, and not about ties between leaders and members, we set the cells describing the ties between leaders and members to missing values. The number of members in the group (excluding the leader) equaled m. In a group of six students, for example, we focused on the 20 ties among the $m = 5$ members; in a group of five students, we focused on the 12 ties among the $m = 4$ members. To derive a summary measure of tie intensity for each group we computed the average intensity of ties among these members (ignoring, of course, values in the diagonals). Formally,

$$I_L = \left(\sum_{i=1,m} \sum_{j=1,m} f_{ij} \right) / m(m-1) \quad (\text{where } i \neq j), \quad (1)$$

where I_L was the summary intensity score for group L (excluding the leader), f_{ij} was the average intensity of the relationship between members i and j, and m was the number of members in the group excluding the leader.[4]

The second component of our decentralization index measured the degree to which network structures were hierarchical. We computed a network hierarchy score for each group based on the variability in members' degree centrality scores. To compute this measure we first had to compute degree centrality

[1] There were 10 six-member groups where all six members provided us with data; 6 six-member groups where five members provided us with data; 8 six-member groups where four members provided us with data; and 7 six-member groups where only three members provided us with data.

[2] There were 7 five-member groups where all five provided us with data; 4 five-member groups where four provided us with data; and 1 five-member group where three provided us with data.

[3] At this point, we addressed the missing data problem. If we had data from i about her relation to j, but not from j about his relation to i, we assigned the value from the i, j cell to the j, i cell. If we had only one missing case in the group, this was straightforward. Where we had two or three missing cases, we of course, did not have data on the relationship between these two or three cases. In this circumstance we took the row sum for member i (outdegree) and the column sum from member j (indegree), added them together and divided by the number of cells for which we had data. Thus our estimate of the relationship between two group members with missing data was based on these members' proclivity to give or receive ties from others—as reported by others.

[4] There are similarities between our measure of network intensity and standard measures of density. The only difference is that f_{ij} can take values between 0 and 1, while density measures typically use binary data.

Table 1 Correlation Coefficient Matrix of Variables Measured ($N = 39$)

	Last 2-mo. Stock Price	Generalist Group	Specialist Group	Mixed Group	Network Decentralization	GPA	Year	Mean	STD
Last 2 Month Average Stock Price								44.63	23.42
Generalist Group	0.35*							0.26	0.44
Specialist Group	−0.40**	−0.42**						0.33	0.48
Mixed Group	−0.07	−0.49**	−0.59**					0.41	0.50
Network Decentralization	0.13	−0.03	−0.19	−0.21				0.47	0.12
Group Ability Proxy	−0.19	−0.19	−0.07	0.11	0.03			0.44	0.50
Year	−0.29	−0.29	0.18	−0.32*	−0.05	0.15		0.56	0.50
Firm-Six	0.22	0.22	−0.11	0.15	−0.10	0.13	0.33*	0.13	0.34

* $p < 0.05$ ** $p < 0.01$.

scores for each member of the group (again excluding the leader). We did this by symmetrizing the matrix of intensity scores, taking the average of the tie strength reported by i and by j, $(f_{ij} + f_{ji})/2$. We then added up the row entries of the symmetrized matrix and divided by the number of members in the group less one, $m - 1$ (diagonals are ignored):

$$C_{D,i} = \sum_{j=1,m} f_{ij}/m - 1 \quad (\text{where } i \neq j). \tag{2}$$

Once we had a degree centrality score for each group member, $C_{D,i}$, we used Freeman's (1979) network centralization index to compute a centralization or hierarchy score for the entire network (see also Wasserman and Faust 1994 p. 180). The rationale was that groups where a large proportion of ties go through one or two members is more hierarchical, whereas groups where the number of ties are more equally distributed across members is more egalitarian:

$$H_L = \left(\sum_{i=1,m} [C^*_{D,i} - C_{D,i}] \right) / [(m-1)(m-2)], \tag{3}$$

where H_L is the network hierarchy score for group L, $C_{D,i}$ is the degree centrality of member i, $C^*_{D,i}$ is the largest value of $C_{D,i}$ for any point in the network, and m is the number of members in the group.[5] The index takes a value of 0 when the centrality scores of all group members are the same, i.e., no one has more ties than anyone else. The index takes a value of 1 when one member has ties to everyone else, but others only are tied to that one member (Wasserman and Faust 1994).

[5] The denominator may be difficult to interpret. According to Freeman (1979, p. 229), it is equivalent to the maximum sum of differences in point centrality for a graph of m points.

Our measure of network decentralization for group L multiplies these two components:

$$D_L = I^*_L(1 - H_L). \tag{4}$$

We subtract the network hierarchy score from 1, because we want our index to be larger if network ties are intense and the structure is less hierarchical, and smaller if ties are not intense and the structure is hierarchical. The statistics for D_L, our measure of decentralization, are in Table 1.

Distribution of Knowledge and Group Members. In determining the distribution of knowledge among group members we proceeded in two steps. Each nonpresident game participant was required to turn in a game vita in which they rated their abilities in three functional areas: accounting/finance, production, and marketing. Students used a Likert scale ranging from 1 (not good at all) to 5 (very good). We used these self-ratings of functional abilities reported in the vitae to measure the distribution of knowledge possessed by individuals. To avoid aggregating data across individual and group levels, we first determined whether an individual was a specialist, a generalist, or neither. Then we counted the number of specialists, generalists, and neithers at the group level to determine whether a group was dominated by specialists, generalists, neithers, or was a mix of specialists and generalists. The last two groups we simply called mixed groups.

To determine if a student was a specialist, generalist, or neither, we first computed the standard deviation across the three functional areas for each student. The larger the score, the more specialized the student's competencies. Second, the individuals whose scores were among the top one-third of all specialization scores (i.e., their standard deviations were the highest) were categorized as specialists, while the middle one-third was typed as neither, and the lower one-third as generalists.

We determined the composition of a group by comparing the number of specialists, generalists, and neithers in the group. We labeled the group a specialist group if the largest number of members were specialists. We labeled the group a generalist group if the largest number of members were generalists. The group was labeled a mixed group if the largest number of members were neithers or there was an equal number of specialists and generalists. We coded groups accordingly using three dummy variables.[6] In 1992, six groups were made up primarily of specialists, ten groups of generalists, and nineteen groups were mixed. In 1993, there were eleven groups made up primarily of specialists, eleven made up of generalists, and twelve groups that were mixed.

Group Performance. Since the Game teams served as top management teams for simulated detergent companies, we used firm performance as measured by stock price as the indicator of group performance. We obtained monthly stock prices calculated for each firm by the simulation algorithm. Each firm in the Game was a publicly held corporation whose stock was traded on the international Game Stock Exchange. The stock prices of the firms rose and fell according to the financial performance and public perception of the company. The stock price for each firm was a deterministic function designed as a long-term index to reflect past performance and include future expectations. We used the average of the last two months' stock prices to assess each firm's and its management team's performance at the end of the Game.

[6] Mixed groups were the reference group and coded 0 = no, 1 = yes; generalist groups were coded 0 = no, 1 = yes; and specialist groups were coded 0 = no, 1 = yes.

Control Variables. *Group Ability Proxy*. Because of the privacy act, we were only able to obtain the rankings based on group average GPA for the 35 groups in 1992 and the actual group average GPA for the 34 groups in 1993. In order to compose a comparable measure of group average ability across the two years, we separated the groups into the high GPA category if the group was either among the highest ranked 18 groups in 1992 or above the medium score in 1993, or the low GPA category if the group was either among the lowest ranked 17 groups in 1992 or below the medium score in 1993. A dummy variable was then created as a proxy for the average group ability, with 1 = high GPA group and 0 = low GPA group. We used this variable to control for the possible effect of group ability on performance.

Firm Six. The Management Game office gave all game teams in 1992 the exact same starting position when the game began. However, in 1993 the game office decided to give some firms an advantage (such as stronger financial condition or market position) at the beginning of the game. Their rationale was that a real-life market is never a level playing field and the game should reflect such a reality. Therefore, at the beginning of the game in 1993 they assigned a stronger market position to the sixth firm in every nation, giving it a competitive advantage over other firms in its nation. We thus included a dummy variable representing whether a firm was the sixth firm in the nation (1 = firm six; 0 = not firm six) to control for the effect of a stronger initial position.

Year. A dummy variable (0 = year 1992; 1 = year 1993) was created to control for the cohort effect.

Results

Descriptive Statistics

As described earlier, missing data that was incurred because of unreturned social network questionnaires reduced our original N from 69 to 44. Five of the 44 remaining teams were suspended from trading for the last 3–5 months of the game for reasons that we do not know. We thus dropped these five cases from our analysis, which yield a final sample size of 39. There were 23 six-person teams, 13 five-person teams, and 3 four-person teams in these 39 cases. The average size of the team in 1992 was 5.35 and in 1993 was 5.76.

Table 1 presents the means, standard deviations, and the correlation matrix (using listwise deletion) for all our variables. As we can see, groups of generalists tended to perform at higher levels and groups of specialists tended to perform at lower levels.

In Table 2 we listed the means and standard deviations for both the group performance score and the measure of network decentralization for groups made up primarily of generalists, mixed types, and specialists. The results showed that the average performance for generalist groups was higher than that for mixed and specialist groups ($F = 4.53$, $p < 0.05$). However, there were no differences in the network decentralization scores across these three types of groups ($F = 0.97$, $p = ns$). This corroborates the nonsignificant correlations between the decentralization scores and the group composition variables in Table 1.

Distribution of Knowledge, Network Structure, and Performance

Our first task was to see if the distribution of knowledge had any effect on performance in a multivariate analysis (Hypothesis 1). In Model 1 listed in Table 3, we regressed group performance on the dummy variables for generalist and specialist groups (mixed groups were the comparison group), the network decentralization score, group ability proxy (0 = low GPA group; 1 = high GPA group), year (0 = 1992; 1 = 1993) and firm six (1 = firm six; 0 = firm 1–5). We normalized group performance, measured by the average firm stock prices in the last two months, by taking the square root of the raw stock prices plus 0.5. The statistics in the table are unstandardized regression coefficients with standard errors in parentheses. Results showed that groups made up of generalists outperformed both specialist and mixed groups, and supported our first hypothesis. The group structure variable had no effect on performance. The group ability proxy had no effect on performance. Teams from 1992 and teams given an initial advantage tended to perform better.

Since specialist groups did not outperform mixed groups in Model 1, we decided to collapse these two groups into one. We created a new variable named *distribution of knowledge*, where we assigned 1 to generalist groups and 0 to specialist and mixed groups. There were two reasons for doing this. First, it allowed us to address directly the issue of knowledge distribution, network structure, and their interaction. The interpretation of the results would be easy to understand. Second, given our sample size, we could not afford to include two variables measuring group knowledge and their interactions with group network structure measures without losing power in our test. The new variable allowed us to maintain the degree of power that we needed to test our hypotheses.

However, before we collapsed specialist and mixed groups into one category, we conducted two regressions using the initial 3-way knowledge measures to further test whether combining specialist and mixed groups was justified. We first regressed group performance on the dummy variables for generalist and specialist groups, network decentralization, the

Table 2 Mean and Standard Deviation for Group Performance ($N = 39$)

	Generalist Groups ($N = 10$)		Mixed Groups ($N = 16$)		Specialist Groups ($N = 13$)	
	Mean	Standard Deviation	Mean	Standard Deviation	Mean	Standard Deviation
Group Performance—Last 2 Months Stock Price	58.32	28.16	46.73	18.48	31.49	19.10
Network Decentralization	0.47	0.13	0.50	0.11	0.44	0.12

Table 3 Regression Analysis of the Effects of Distribution of Knowledge and Decentralization Measure on Group Performance (Average of the Last Two Months Stock Price)

Independent Variables	Model 1	Model 2	Model 3	Model 4	Model 5
Generalist Group	1.54*	1.51*	1.58*		
(1 = yes; 0 = no)	(0.65)	(0.65)	(0.66)		
Specialist Group	−0.52	−0.47	−0.53		
(1 = yes; 0 = no)	(0.63)	(0.61)	(0.62)		
Distribution of knowledge				1.82**	1.76**
(1 = generalist group; 0 = specialist/ mix groups)				(0.55)	(0.57)
Network Decentralization	2.40	5.00^t	2.98	2.85	5.43*
	(1.08)	(2.78)	(2.63)	(2.07)	(2.71)
Network Decentralization × Generalist Group		−4.33^t			
		(2.33)			
Network Decentralization × Specialist Group			1.42		
			(2.51)		
Network Decentralization × Distribution of Knowledge					−4.82*
					(2.29)
Year	−1.68**	−1.75**	−1.67**	−1.86**	−1.92**
(0 = 1992; 1 = 1993)	(0.56)	(0.56)	(0.57)	(0.52)	(0.51)
Firm-Six (1 = firm six; 0 = firms 1–5)	2.32**	2.26**	2.22**	2.51**	2.42**
	(0.80)	(0.78)	(0.79)	(0.76)	(0.75)
Group Ability Proxy	−0.61	−0.71	−0.66	−0.56	−0.67
	(0.49)	(0.49)	(0.50)	(0.49)	(0.49)
Intercept	5.98	7.25	7.21	5.58	7.09
N	39	39	39	39	39
F	4.63**	4.37**	4.16**	5.47**	5.06**
R^2	0.4647	0.5268	0.5141	0.4530	0.5168

$^t p < 0.10$, $^* p < 0.05$, $^{**} p < 0.01$.

interaction between network decentralization score and generalist groups, and the control variables including firm six, year, and the group ability proxy.[7] The results listed in Model 2, Table 3 indicated that generalist groups performed better than mixed groups, while the network decentralization score was marginally significant ($p < 0.10$). Although only marginally significant ($p < 0.10$), the negative interaction term suggested that the difference in performance between groups of generalists and mixed groups was significantly less when the group structure was more decentralized. Firm six and year were also significant in the equation. By including the interaction term, this model explained 6.21% more variance than Model 1 ($F_{(1,31)} = 4.07$, $p < 0.10$) (Jaccard et al. 1990). We then performed the same regression, substituting the interaction term with the interaction between network decentralization and specialist groups. The results listed in model 3, Table 3 showed once again that groups made up of generalists tended to outperform mixed groups and groups of specialists did not outperform mixed groups. All other variables, aside from firm six and year, had no effects on group performance, nor was the interaction term significant. That is, the difference in the performance of specialist and mixed groups did not change depending on the structure of the group. By including the interaction term, this model explained only 4.94%

[7] Here and in subsequent analyses where we computed a product term with the network decentralization score, we centered this variable beforehand so as to avoid problems of multicollinearity and to make the interpretation of our results simpler.

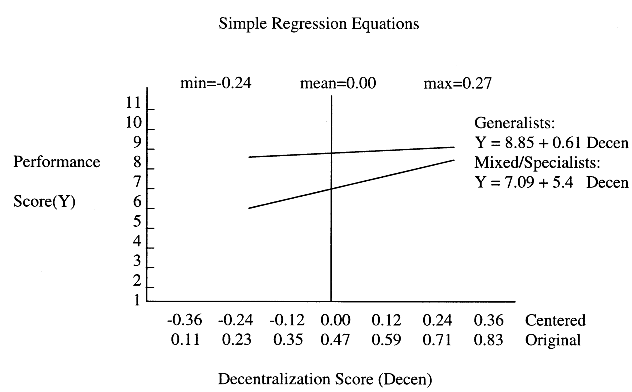
more variance than Model 1 ($F_{(1,31)} = 3.15$, $p = NS$). The results of both Models 2 and 3 gave us further confidence to combine specialist and mixed groups to create the measure of knowledge distribution.

To test Hypotheses 2A and 2B, we regressed group performance on the group structure measure, the new dummy variable measuring knowledge distribution (generalist vs. specialist/mixed groups), and a multiplicative interaction term,[8] with group ability proxy, year, and firm six as control variables.

As we did before, we proceeded hierarchically. Model 4 presents the results of a regression without the interaction term. Model 5 included the interaction term. The t-test associated with the interaction term and the F statistic associated with the change in the adjusted R^2 were both significant at the 0.05-level (change in $R^2 = 6.38\%$, $F_{(1,32)} = 4.23$, $p < 0.01$). The substantive results of the regression, listed in Model 5, Table 3, showed that all the hypothesized effects were statistically significant at the 0.05-level. Again, unstandardized regression coefficients and their standard errors are reported. First, as suggested by H1, at the sample mean of decentralization scores, groups made up of generalists outperformed mixed and specialist groups. Second, as suggested by H2A, among groups of specialists (and mixed groups), performance was much higher if group structures were more decentralized. Third, as suggested by H2B, in groups that were centralized, the gap between the performance of generalist and specialist/mixed groups was greater, with the former outperforming the latter. Fourth, groups with more decentralized structures performed at a higher level if members were mixed or specialists. And, finally, group structure had little effect on performance if members were predominantly generalists. In other words, for groups with more generalists, the structure of network ties was unrelated to group performance. However, for groups with more specialists (or mixed groups), performance was significantly higher if ties were intense and group structures were less hierarchical, and much lower if ties were weak and group structures were hierarchical.

The interaction effect can be illustrated more vividly by graphing the slopes describing the relationship between group structure and performance. In Figure 1 the X-axis represents the centered and original decentralization scores. The standard deviation for these scores is 0.12; the minimum centered score is -0.24, and the maximum centered score is 0.27. The Y-axis is the rescaled performance scores. The range is from 1.02 to 10.86. Using the results from the final regression analysis (Model 5), we graph the slopes for groups of specialists (and mixed groups) and for groups of generalists. This graph is based on the computation of the simple regression equations that are also presented in Figure 1 (Aiken and West 1991 p. 124). For specialists groups, the intercept, 7.09, is taken from Table 3 and is the predicted score for mixed and specialist groups at the mean decentralization score of the entire sample (since the decentralization scores were centered). The intercept for groups made up of generalists is equal to 7.09 plus the regression coefficient associated with the distribution of knowledge scores, 1.76. The slope for mixed and specialist groups is the coefficient associated with the decentralization scores in Table 3, 5.43; and the slope for groups made up of generalists equals 5.43 plus the coefficient associated with interaction term in Table 5, -4.82. As we can see, at the mean

Figure 1 **Graphs of Simple Regression Equations with Group Performance as the Dependent Variable**



[8] Again we centered our measure of network decentralization before we computed the interaction term. The zero order correlations between the interaction term and its components: the distribution of knowledge and network decentralization measure were -0.14 and 0.60, respectively.

decentralization score for the entire sample, generalists outcompete specialists. However, as we move 1 or 2 standard deviations to the right of the mean, the difference in the performance scores of the two groups decreases. In contrast, as we move 1 or 2 standard deviations to the left of the mean, the gap in the performance scores increases. Thus, as we hypothesized, in general, groups that have knowledge broadly distributed across group members will outperform groups that have unique knowledge concentrated in different group members. However, groups that have narrowly distributed knowledge will perform at levels comparable to groups with broadly distributed knowledge if group structures are more decentralized; while groups that have narrowly distributed knowledge will perform significantly more poorly than groups that have broadly distributed knowledge if group structures are centralized. Another way of saying the same thing is that the performance of groups of generalists is relatively indifferent to differences in group structure; while mixed groups and groups of specialists perform at higher levels if group structures are dense and nonhierarchical, and more poorly when group structures are centralized.

Discussion

The purpose of this study was to examine the joint effects of group structure and how knowledge was distributed among group members on performance. Our previous work (Liang 1994, Rulke 1996) found that groups of generalists outperformed groups of specialists. We argued that generalists possessed more shared information and knowledge, and that shared information enabled the group to retrieve and share necessary information with little effort when solving problems across functions. We replicated these findings and found support for Hypothesis 1. Generalist groups performed at higher levels than groups of specialists or groups made up of both specialists and generalists (mixed groups). We then tested if group structure modified the effect of knowledge distribution on performance. In support of Hypotheses 2A and 2B, we found that groups of generalists outperformed groups of specialists and mixed groups when group structures were centralized, but specialists and mixed groups performed at levels comparable to generalists when group structures were decentralized. In other words, the performance of generalist groups did not vary across group structures. However, if the group network structures were decentralized, the performance of specialist and mixed groups was considerably higher than if group structures were centralized. Finally, we found that decentralized groups outperformed centralized groups when groups were composed mostly of specialists or were mixed. However, group structure was unrelated to performance when groups were made up of generalists.

The current research extends the literature on the relationship between group knowledge and performance by taking into account the structural configuration within the group. We hypothesized and found that group structure measured by social network ties among members conditioned the effects of knowledge distribution on group performance. Using a social network approach, we were able to study group structure without having to aggregate individual measures to the group level, and yet capture the overall relational structure within the group. Our findings suggested that future research on knowledge sharing within groups would greatly benefit from taking a structural or network perspective. For example, research on transactive memory might examine the role of networks in assigning knowledge or expertise to different group members, and more importantly, helping to recall or retrieve that knowledge when the need arises.

Another contribution is that the research suggests that group structure may be an important factor influencing group performance—but only under certain conditions. The pattern of network ties may affect group performance, but only if group members are not generalists (i.e. they are either specialists or groups having both specialists and generalists). The small groups literature has long argued that patterns of social relationships are critical in explaining group performance and that structural effects are contingent upon local conditions (Argote et al. 1989, Shaw 1981), but seldom has this literature also taken into account compositional effects (Moreland and Levine 1992).

Our research alerts them to the importance of this, and that the latter can override the former in some circumstances.

In sum, the current study is one of the few cases that examined distribution of knowledge and group structure to provide a more comprehensive understanding of group performance. Extending previous research on group performance, this research suggests that group prior shared information in terms of the distribution of knowledge and the structural configuration work interdependently and simultaneously to affect group performance, and that future research needs to examine all these aspects of groups in such a manner to provide in-depth understanding of group performance.

Clearly the paper is exploratory, and there are four issues that our future research must address. First, the effects of how knowledge is distributed and group structure on group performance are often dependent on the task characteristics of group problem solving (Steiner 1972, Argote et al. 1989). This study only looked at one set of tasks. Our findings are then limited to situations where problems are complex and require pooling information from various domains. In additive tasks, for example, shared information or knowledge among group members may not be as critical to group performance. Furthermore, while we emphasized the importance of group structure in enabling mixed and specialist groups to compete against groups of generalists, it is noteworthy that structure had no effect on the performance of groups of generalists. While one might expect that in performing complex tasks, highly centralized structures would be dysfunctional for all groups, this is not what we found. This obviously merits further investigation.

Second, game teams were formed through presidents' selecting team members rather than through random assignment, and friendships that existed before the game may have affected the findings of the study. Although we sent out questionnaires assessing group members' prior work relationships with one another before the games started, the response rate was too low to provide reliable information on the matter. Thus we did not have information on an important factor which may have contributed to group dynamics. Information collected from post-study interviews with team presidents, however, may help to address some of these concerns. The interviews indicated that most team leaders knew little about or had little prior experience with the majority of prospective team members beyond that they knew who these individuals were and that they might have talked to them a few times during the first year. Most presidents relied a great deal on students' self-reported vitae or personal statements when selecting team members. Further, interviews also indicated that most presidents chose not to select their friends for the Management Game for a number of reasons. Some presidents believed that "business" should not mix with personal friendship. Some believed that not working with friends in the game would allow them to avoid unnecessary conflict and thus protect the friendship. However, future research needs to address prior friendship patterns and networks by collecting data on prior friendship or work relationship among team members.

Third, we used group average GPA as the control variable to represent the level of ability of team members. This measure is broad and aggregated and may not have represented the actual ability of the groups. Individual grades in actual courses such as finance, marketing, production, etc. could have been better measures of member/group ability. Also, these grades could help us check on the self-reported competencies of students. Unfortunately we were not able to obtain these grades due to university policies on grade privacy. More accurate measures of member ability should be collected in future research to control for the possible effect of ability on knowledge and performance.

Finally, we measured network ties at the end of the game instead of at the beginning or during the middle. Thus the causal order of knowledge distribution, network structure, and performance are left unclear. It is much safer to claim simply that knowledge was distributed among members in certain ways and there were certain patterns of work relationships among high performing teams at the end of the game, and avoid speculating on a causal order. However, future research needs to sort out the causal order among these effects and to see if structural patterns do indeed moderate the effect of knowledge distribution on outcomes.

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