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The Effects of Communication Networks and Turnover on Transactive Memory and Group Performance

Linda Argote,[a] Brandy L. Aven,[a] Jonathan Kush[b]

[a] Tepper School of Business, Carnegie Mellon University, Pittsburgh, Pennsylvania 15213; [b] Charlton College of Business, University of Massachusetts Dartmouth, North Dartmouth, Massachusetts 02747

Contact: argote@cmu.edu, http://orcid.org/0000-0002-4149-6968 (LA); aven@cmu.edu, http://orcid.org/0000-0001-7086-5876 (BLA); jkush@umassd.edu, http://orcid.org/0000-0003-4872-8650 (JK)

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Abstract. We theorize that the effect of membership turnover on group processes and performance depends on a group's communication network. We describe two mechanisms through which communication networks affect group performance: (1) the number of direct communication paths and (2) the clarity of the coordination logic. These mechanisms map onto two network dimensions: density, which affects a group's behavior through the number of available communication paths, and centralization, which affects a group's behavior through the clarity of the coordination logic. We empirically analyze the effects of turnover on the performance of fully connected all-channel networks and hub-and-spoke or wheel networks in an experiment of 109 four-person groups performing two collaborative problem-solving tasks. The greater number of direct communication paths enabled fully connected groups with stable membership to develop stronger transactive memory systems (TMSs) and perform better than fully connected groups that experienced turnover. By contrast, the clear coordination logic of perfectly centralized groups that experienced turnover facilitated more frequent dyadic communication, which enabled them to strengthen their TMSs, incorporate the contributions of new members, and improve their performance. Thus, our results indicate that communication networks condition the effect of membership turnover on group processes and performance.

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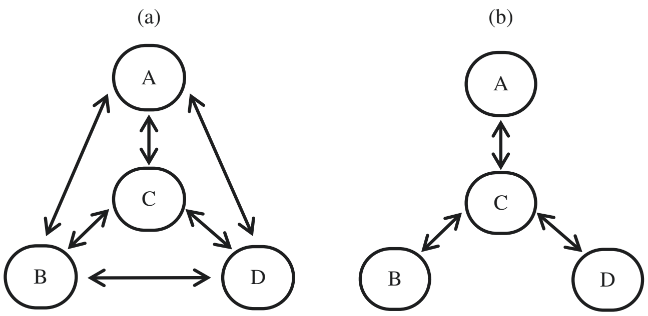
Introduction

Organizational activity comprises the coordination of individuals to solve complex problems. Group members must identify the expertise of others, access information held by different members, and coordinate that information to accomplish shared goals. Member turnover, the exit of an incumbent member and introduction of a new member, in groups can complicate the identification and coordination of expertise and information (Arrow and McGrath 1995). Groups with stable membership are able to learn each other's skills and expertise, allocate tasks to the most qualified members, and coordinate the interdependent activities of their members. When turnover occurs, however, incumbent members know little about the expertise and skills of the new member, and coordination can become challenging (Lewis et al. 2007). Yet new members can nonetheless be a source of new ideas and perspectives that improve group performance (Choi and Thompson 2005).

We theorize that the effect of turnover on group performance depends on the group's communication network. From a network perspective, groups can be categorized by their structural features—in particular, their centralization (Katz et al. 2004, Leavitt 1951, Rulke and Galaskiewicz 2000) and their density (Freeman 1979, Friedkin 1981, Balkundi and Harrison 2006). Centralization increases for a group as the inequality or variance in the number of connections group members have to others increases. A group's density increases as the ratio of actual to potential connections increases.

We identify two mechanisms through which a group's communication network affects performance: (1) the number of direct communication paths available to group members and (2) the clarity of the coordination logic. The first mechanism maps onto network density, which affects a group's behavior through the number of available communication paths. High levels of density in communication networks allow team members to communicate directly with one another. The second mechanism maps onto network centralization, which affects a group's behavior through the clarity of the coordination logic. Centralized communication networks direct how information is shared and inform how members coordinate (Blau 1974, Bunderson and Boumgarden 2010).

Figure 1. Fully Connected and Perfectly Centralized Communication Networks



Notes. Panel (a) represents the fully connected communication network. Panel (b) represents the perfectly centralized communication network. C is the central member, whereas A, B, and D are peripheral members.

We focus on the two network structures that maximize one structural dimension while minimizing the other: a perfectly centralized or "hub-and-spoke" network that has the highest degree of centralization and minimizes density (see Figure 1), and a fully connected, "all-channel" network that maximizes density and minimizes centralization. These two network structures not only allow the investigation of centralization and density in tandem but are also structures common in organizational settings. For example, programming groups' communication networks have often been found to be fully connected, where members can communicate directly with any other member in an open-source setting (Tsay et al. 2014). By contrast, particularly in proprietary software, programming groups generally have a perfectly centralized communication network where one central member acts as the "software architect," and other members can communicate directly only with this central member (Kruchten 2008, Bosch and Bosch-Sijtsema 2010). In addition, even though project groups in organizations commonly communicate in a fully connected manner, groups engaged in covert projects typically communicate in a centralized fashion (Aven 2015).

In the case of stable group membership, high centralization, such as in our perfectly centralized groups, limits direct communication among members through their restricted communication network, which hinders members from learning about others' expertise. Centralized communication networks also force members to coordinate in a particular manner, irrespective of members' preferences and abilities. Rather than provide members with the opportunity to customize their coordination logic, centralized group members must channel information to the central member(s), who then orchestrate the group's activities. Hence, the coordination logic in centralized groups is independent of the particular members and their attributes.

When turnover occurs, the communication network of perfectly centralized groups improves the group's ability to integrate a new member. The coordination logic of perfectly centralized networks is readily discernible by both incumbent and new members, which enhances their ability to contribute to the group (Bunderson and Boumgarden 2010, Morrison 2002). Because members' roles in perfectly centralized groups are not customized to individual members, it is more likely that the new member can adequately perform the activities of the departing member in centralized than in decentralized groups. Finally, the restricted communication pathways in centralized networks require reliance on the few existing pathways to coordinate, which reduces the likelihood that any communication pathway and its respective member are neglected. These factors enable a perfectly centralized group to incorporate the contributions of a new member and improve group outcomes for tasks involving problem solving and creativity (e.g., Wells and Pelz 1966, Choi and Thompson 2005).

When membership is stable, high density in communication networks, such as in the fully connected groups, enables members to establish a strong transactive memory system (TMS), a collective system for encoding, storing, and retrieving information (Wegner 1987, Lewis and Herndon 2011). Because of fully connected group members' greater ability to communicate directly with other members, group members are able to learn about each other's expertise and, in turn, develop a shared cognitive map of expertise. In addition, fully connected networks allow members to tailor the group's coordination logic to account for each member's preferences and abilities.

Although fully connected communication networks facilitate group performance by encouraging the development of a strong TMS, fully connected networks can also hinder the integration of new group members when turnover occurs. New members often do not have the same attributes and knowledge as departing members, which makes the substitution of a new member challenging for these groups because their coordination logic is tailored to the original members' unique abilities and characteristics. Furthermore, the group's coordination logic cannot be readily observed by new members, which impairs their ability to contribute to the group.

Communication Networks and Transactive Memory Systems

A group's communication network serves to channel information among group members and coordinate their activities (Leavitt 1951, Faucheux and Mackenzie 1966). In a dense, fully connected network (see Figure 1(a)), all of the members share the same number of communication pathways as all of the other members. By contrast, in the perfectly centralized group (see Figure 1(b)), only member C has communication pathways to the other members (A, B, and D), and members A, B, and D have only one pathway each to member C. To both communicate and coordinate activity in the centralized group, the peripheral members (A, B, and D) must rely on the central member C. Thus, the perfectly centralized communication network both minimizes the number of available communication pathways and maximizes the clarity of the coordination logic for the group: all peripheral members communicate to the central member, and the central member dispatches information to peripheral members. By contrast, the fully connected network maximizes the number of communication paths but reduces the clarity of the coordination logic.

The greater number of communication pathways in fully connected networks promotes information sharing and fosters an understanding of member expertise. When group members learn information about other members and their expertise, the group's transactive memory system develops (Moreland and Myaskovsky 2000). The transactive memory systems of fully connected groups become tailored to the different skills, knowledge, and preferences of group members.

Within perfectly centralized groups, the communication network prevents group members from directly interacting with one another and developing a coordination logic that is well suited to the particular members of the group. Instead, the communication network of perfectly centralized groups requires that certain members relay information to others and thus imposes a particular coordination logic on the group (Gouldner 1954, Weber 1947). The limited number of communication pathways also hinders members from directly learning about each other's areas of expertise, which in turn inhibits the development of a strong transactive memory system.

Transactive memory systems have been found to improve group performance (see Ren and Argote 2011 for a review) on outcomes such as time to complete tasks (Faraj and Sproull 2000), errors (Liang et al. 1995), and creativity (Gino et al. 2010). Transactive memory systems can be distinguished from related constructs such as shared mental models, because the knowledge held by group members with a strong TMS is differentiated through specialization (Lewis and Herndon 2011). In groups with a strong TMS, members have different information about how to complete their subtasks, whereas in groups with shared mental models, members have the same information (DeChurch and Mesmer-Magnus 2010).

Transactive memory systems develop from experience working together. As individuals work with the same group members, they discern each other's skills and abilities, which allows them to specialize their expertise, fine-tune their division of labor, and coordinate effectively (Wegner 1987). The strength of a group's TMS is affected by its communications (Hollingshead 1998, Yuan et al. 2010). We predict that differences in communication networks influence the strength of a group's TMS. Furthermore, we predict that the effect of a group's communication network depends on whether turnover occurs.

Turnover

Turnover, or membership change, is a common occurrence within work groups (Kush et al. 2012). In some instances, turnover can benefit the group by invigorating it with information and perspectives from the new member, which improves its performance (Choi and Levine 2004, Choi and Thompson 2005, Hancock et al. 2013). The positive effect of turnover on group performance is most likely to occur on tasks involving creativity and innovation (Choi and Thompson 2005). For example, Wells and Pelz (1966) found that turnover in groups of scientists improved group performance. The introduction of a new member, even a novice, into an existing group can enhance the group's performance (Ferriani et al. 2009, Uzzi and Spiro 2005). For new members to benefit a group, however, they must be integrated into the group by existing members.

Membership change can hinder group outcomes because the new member might not have the same skills as the departing member, understand the coordination logic of the group, or be integrated into the group (Hausknecht and Holwerda 2013). Lewis et al. (2007) found that when only one group member was replaced in a group, those groups performed worse than either groups whose membership was stable or groups whose membership changed totally. The advantages conferred on fully connected groups by their strong TMSs when membership is stable are undermined when turnover occurs. Because TMS is a cognitive division of labor, the group's implicit coordination logic is not easily observed by the new member (Wegner 1987). Hence, for a fully connected group, a new member would have difficulty contributing because he or she would not understand how the group communicates or organizes its activities. When a group has developed a strong TMS, the incumbent members of the group tended to ignore the contributions of a new member and expect him or her to fill the role of the departing member (Lewis et al. 2007). Thus, we anticipate that turnover will harm the performance of fully connected groups.

The features that undermine TMS formation in perfectly centralized groups with stable membership—limited communication pathways and mandated coordination logic—aid in the integration of new members when turnover occurs. New members in perfectly centralized groups can easily discern the simple organizing principle: all members contribute their information and views to the central member(s), who then integrate the information for the group (Guetzkow and Simon 1955). In turn, understanding the group's coordination logic helps new members to work effectively with other members, which is critical to group performance (Chao et al. 1994, Morrison 2002). Moreover, the limited connectivity of perfectly centralized groups also requires greater reliance on the extant pathways for members to communicate. Frequent communication improves the new member's knowledge of how to perform his or her tasks and provides clarity in terms of the responsibilities associated with the position, which expedites the new member's ability to contribute to the group (Morrison 2002). When the group incorporates the new member's ideas and perspectives, the group is able to perform its task more effectively (Levine et al. 2003). In addition to increasing the creative problem solving of incumbent members (Choi and Thompson 2005), new members can also introduce new insights that improve group performance.

We theorize two mechanisms through which network structure affects performance: (1) the number of direct communication paths available to group members and (2) the clarity of the coordination logic. We have argued that the first mechanism is more important when membership is stable and that the second mechanism is more important when turnover occurs. Thus, we expect that fully connected groups have stronger TMSs and better performance under stable membership than when turnover occurs, because of their greater number of communication paths. The greater number of paths, however, undermines their ability to integrate a new member when turnover occurs. We anticipate that the clarity of the communication logic of perfectly centralized groups enables them to integrate the new member, benefit from his or her new ideas and perspectives, and thereby improve their performance when turnover occurs. Thus, we predict the following.

Hypothesis 1. *Communication networks and turnover interact to affect group performance: fully connected groups perform better when group membership is stable than when turnover occurs, whereas perfectly centralized groups perform better when turnover occurs than when group membership is stable.*

Hypothesis 2. *Communication networks and turnover interact to affect transactive memory systems: fully connected networks have stronger transactive memory systems when group membership is stable than when turnover occurs, whereas perfectly centralized networks have stronger transactive memory systems when turnover occurs than when membership is stable.*

Dyadic Communication Frequency

Dyadic communication frequency represents the total communication that occurs in a group relative to the number of available communication paths in the group. The greater number of communication pathways in fully connected relative to perfectly centralized groups increases the demands on members' time and attention and reduces the frequency of communication along any one pathway. As opposed to fully connected groups, perfectly centralized groups must rely on fewer pathways to communicate, increasing group members' dependence on each individual pathway, potentially strengthening one-on-one relationships. Thus, the communication constraints of perfectly centralized groups increase members' reliance on the available pathways and result in greater dyadic communication frequency than in less restricted, fully connected groups.

Dyadic communication along each pathway is especially important in integrating a new member. The fewer paths available to perfectly centralized groups make each connection more salient to group members. The greater amount of dyadic communication in perfectly centralized groups conveys the group's coordination logic, which is critical in integrating a new member, and allows members to update the group's knowledge of who knows what and to perform better when turnover occurs. By contrast, when turnover occurs in fully connected groups with strong TMSs, incumbent members neglect to communicate with the new member, which impairs their performance. Formally, we predict the following.

Hypothesis 3. *Dyadic communication frequency mediates the interaction of communication network and turnover on transactive memory systems, and the mediation is stronger when turnover occurs than when group membership is stable.*

Scope Conditions

Given that our primary interest is in the interactive effect of communication networks and turnover on the processes and performance of small groups, we focus on perfectly centralized groups and fully connected groups of four members. Small groups are a predominant means by which tasks are accomplished within organizations as well as an important unit of analysis for organizational research (Katz et al. 2004, Leavitt 1996, Uzzi and Spiro 2005). In addition, because we are interested in communication networks, we selected interdependent tasks that require coordination, so that we could observe how information was shared in the group. We focus on nonroutine, complex tasks; therefore, our theory applies to complex problem-solving tasks that require coordination and creativity. Examples of such tasks include product design, prototype development, engineering design processes, and software engineering. Last, because our tasks involve creative problem solving, we expect that the contributions of the new member have the potential to improve group performance (e.g., see Choi and Thompson 2005). We have hypothesized that whether the group benefits from the new member depends on the group's communication network.

Methods

Participants

One hundred and nine four-person groups composed of 503 individuals (49% female) were recruited from a mid-Atlantic American university participant pool.[1] Participants received $20 or course credit for their participation, and an additional reward of $20 per person was given to the members of the best performing group in each condition. The ages of participants ranged from 18 to 37, with an average age of 22.0 years. Forty-nine percent of the participants were Asian or Indian, 37% were Caucasian, and 14% were other ethnicities.

Tasks

Because our focus is interdependent problem-solving tasks, we used two tasks that fell in the conceptual cooperative quadrant of McGrath's (1984) circumplex model. Both tasks required creative problem solving. The first task was a programming task with the possibility of errors; the second was an idea-generating task. Both tasks were based on an online graphical programming interface. This interface allowed participants to design programs—called pipes—that collect, manipulate, organize, and filter information from the Internet to create a desired output. Although similarities exist between this interface and other programming languages, knowledge of other programming languages would not provide direct benefits because of the unique graphical programming interface of our tasks. The preponderance of participants were unfamiliar with this interface: 94.2% rated themselves as unfamiliar or very unfamiliar with the interface in a postexperiment survey.

The programming task required each group to work together to create a pipe that (1) sorted selected news items by publication date, (2) removed any repeated articles, and (3) allowed a user to specify a search keyword. The task required the use of five specific modules. Although working on separate computers, participants had access to a virtual work environment, allowing them to contribute and to see the contributions of their group mates simultaneously. All members could access and make changes to the pipe. In the idea-generating task, participants were asked to generate collectively as many new features or functional improvements as possible to enhance the pipe that they had created in the programming task. The new features had to be both novel and feasible to implement, and therefore required the module expertise of all of the members. For both tasks, group members never interacted face-to-face and communicated only through an instant messaging client.

Manipulations

We manipulated two variables in the experiment: communication network and turnover. We manipulated the communication network by controlling who could communicate with whom through an instant messaging client. In the perfectly centralized condition, three peripheral members could contact only one central member who could communicate with all the peripheral members. In the fully connected condition, all members could communicate with all other members (see Figure 1). In both conditions, group members could send only one message to one member at a time. Throughout both tasks, the communication network remained unchanged.

We manipulated turnover by replacing a randomly selected member from each group after the practice task with another participant who acquired the network position of the departing member. Participants were not warned that their group might experience turnover. The new member received the same training and training materials as the departing member but had not previously worked with the graphical programming tool or with a group. In fully connected groups that experienced turnover, a randomly chosen member was selected to be replaced. In the perfectly centralized groups that experienced turnover, either a peripheral member or a central member was replaced. For example, in the centralized (see Figure 1(b)) peripheral turnover condition, a peripheral member (A, B, or D) was randomly selected and replaced. In the centralized central turnover condition, the central member (C) was replaced. We did not predict that turnover of the central member would have a significantly different effect than turnover of peripheral members, but we allow for the possibility in our design by including both types of centralized turnover.

Procedures

After arriving at the laboratory, participants were randomly assigned to one of four isolated rooms, each associated with a member ID and a position within the network. We allowed members to communicate using only an instant text messenger and limited their opportunities to see one another. The participants attended a training phase where they received information about the programming task as well as instructions for the experiment. The materials explained how to communicate with other members through the instant messenger, directed participants to a short video demonstrating the creation of a sample pipe, and provided detailed information about the programming modules available. Additionally, we provided each group member with different, randomly assigned, specialized information about one of the modules necessary for completing the task to ensure that group members were interdependent. We did not tell members that each had specialized information. For groups experiencing turnover, the new member received the same specialized information as the member whom he or she replaced.

Once all the participants had read the training materials, they were given 30 minutes to practice the task together. After they finished the practice task, group members completed the first survey. At this point, for groups in the turnover condition, an announcement was made: "One new member will be joining your group, and another will be randomly chosen to leave." A randomly chosen group member was then removed from the communication network and dismissed from the experiment, and a new member was introduced to the group. The new member occupied the same position in the communication network as the departing member and received the same specialized information during training. Groups were then given instructions for the programming task, which they had 30 minutes to complete. The programming task was followed by the 5-minute feature-generating task.[2] Group members then completed the second survey. Finally, we debriefed and thanked participants.

Measures

Several variables in this study were behavioral measures, including our two dependent measures: the number of errors in the programming task and the number of functional improvements in the feature-generating task. The dyadic communication between group members was also a behavioral measure based on the messages sent on the instant messaging client. The remaining measures were collected from a survey that measured the group's TMS, perceptions of the communication network, and group member demographics and experience, such as their familiarity with the programming interface.

Errors. We calculated the number of errors in the pipe that each group submitted. Errors included both cases when the group used incorrect modules and cases when the group omitted modules required for the program to function properly. To calculate the errors, we categorized errors into four comprehensive categories: missing modules, incorrect settings, incorrect modules, or unconnected modules. The number of errors for a module was based on the number of settings in that module. For example, if a group did not include a particular module in their program and that module had three required settings, three errors would be recorded for the group. If a module was included but one of the settings was wrong, the group was coded as having one error. These errors were summed into a single measure for each group. A portion of the groups had their errors assessed by two coders ($n = 70$). A Cohen's kappa of 0.72 ($p < 0.001$) indicated good agreement between coders (Cohen 1960). A single coder then coded errors for the remaining groups.

New Features. During the feature-generating task, participants responded to the question, "Think of any ways that you think the pipe you just built could be improved by creating new features. What other ways could this pipe be more helpful to an end user, be more simply designed, etc.?" Two coders coded a subset of the groups ($n = 40$), assessing each new feature on whether it introduced novel functionality and was feasible to implement. Two coders attained very good reliability, as indicated by a Cohen's kappa of 0.88 ($p < 0.001$). Any disagreements between coders were addressed and resolved. A single coder then coded the number of new features for the rest of the groups.

Transactive Memory Systems. Lewis's (2003) 15-item survey measure was used to measure the groups' transactive memory systems. The survey instrument was administered at the end of the study, after groups had completed both tasks. The overall reliability was acceptable (Cronbach's alpha = 0.82). The average intergroup reliability (r_{wg}) was 0.95, indicating that it is appropriate to aggregate the individual-level measures to the group level. The intraclass correlation coefficient (ICC(2)) value was 0.61, indicating acceptable reliability of the measure. These reliability statistics provide evidence for general agreement among group members and the appropriateness of aggregating to the group level (LeBreton and Senter 2008). The ICC(1) value, which indicates the extent to which the variability in individual responses can be predicted by group membership, was 0.28. Values of 0.25 or higher are considered to be large effects (Murphy and Myors 1998).

Dyadic Communication Frequency. We calculated the dyadic communication frequency based on group members' instant text messages. As our theory is about the integration of new members, we chose to use a measure that would capture the strength of the communication relationships between individuals in the group. Dyadic communication frequency was calculated as the sum of all group messages exchanged between members during the task performance period, divided by the total available dyadic communication paths in the group (three for perfectly centralized and six for fully connected). This value was then divided by the time to task completion to account for variation in the groups' completion times. We calculated this variable separately for the programming task and the feature-generating task. Analyses predicting errors used the dyadic communication frequency during the programming task, and analyses predicting new features used the dyadic communication frequency during the feature-generation task. For Table 2, we used cumulative dyadic communication frequency, the combination of dyadic communication frequency across both task periods, to predict the effect of the network on communication and on TMS (Models 6 and 7), because TMS development should be affected by all prior communication in the group, not just communication relevant to a particular task. We present analyses for communication to and from the new member for groups in the turnover conditions in the online supplement. Because these measures of communication to and from the new member do not apply for groups that did not experience turnover, we use dyadic communication frequency in analyses involving both turnover and no-turnover groups. Dyadic communication frequency includes communication to and from the new member for groups that experienced turnover.

Results

We begin this section by discussing the effectiveness of the communication network manipulation. We then present results for errors and new features. Next, we provide mediation analyses indicating that dyadic communication frequency explains the effects of the communication network and turnover on TMSs. Last, we provide a test of the overall model implied by Hypotheses 1–3. The section concludes with a presentation of robustness checks.

Communication Network Manipulation Checks

First, we determined whether members correctly assessed their group's communication network. Each group member was asked which communication pathways existed among members of the group. Group members correctly identified the group's communication pathways 86% of the time. Fully connected groups were slightly more accurate (88%) than perfectly centralized groups (84%) in identifying communication pathways ($p < 0.1$). These results suggest that group members were aware of their available communication pathways in both the centralized and fully connected conditions.

Second, although it was not possible for the perfectly centralized groups to send messages in a decentralized pattern, it was possible for the fully connected groups to send messages in a centralized pattern. To explore this possibility, we calculated Freeman's (1979) degree centralization measure based on the communication messages shared within each group. Degree centralization is a group-level measure of the dispersion of group members' degree centrality scores. Given that degree centralization can be calculated only for dichotomous networks, we included a communication pathway only if two members communicated over a certain threshold. The threshold for inclusion was one standard deviation below the group's mean level of messages.[3] Using a threshold for tie inclusion is common in network research, and the threshold we applied provides a reasonable distribution of degree centralization values within the sample (Borgatti et al. 2013). The degree centralization measure was highly correlated with the manipulation of the communication network ($r = 0.81$, $p < 0.001$), which suggests that our communication manipulation influenced the pattern of messages exchanged among group members, as expected.[4]

Performance

We predicted that the communication network and turnover would interact to affect group performance (Hypothesis 1) such that fully connected groups would perform better when there was no turnover than when there was, and perfectly centralized groups would perform better when turnover occurred than when membership was stable. Next, we hypothesized that the communication network and turnover would interact to predict transactive memory systems such that fully connected groups would have stronger TMSs when membership was stable than when turnover occurred, and perfectly centralized networks would have stronger TMSs when turnover occurred than when membership was stable (Hypothesis 2). Finally, we proposed that dyadic communication would mediate the interaction between the communication network and turnover in predicting the TMS and that the mediation would be stronger when turnover occurred than when it did not (Hypothesis 3). A stronger mediation would mean that more of the effect of the network on the TMS was due to the network's effect on dyadic communication frequency when the group experienced turnover than when it did not.

We present descriptive statistics and correlations in Table 1. Table 2 presents the ordinary least squares estimates predicting errors based on the communication network, turnover, and their interaction.[5] In Model 1 of Table 2, the interaction of communication network and turnover was negative and significant ($B = -2.31$, $p < 0.05$), as predicted by Hypothesis 1. Additionally, we found a significant positive interaction between communication network and turnover on the number of new features ($B = 2.64$, $p < 0.05$) in Model 3 of Table 2. These interactions suggest that, for both errors and new features, fully connected groups performed better when group membership was stable than when turnover occurred, whereas perfectly centralized groups performed better when turnover occurred than when membership was stable. This pattern can be seen in Figure 2, which depicts the mean numbers of errors (left side) and new features (right side) as functions of communication networks and turnover. This pattern of results supports Hypothesis 1.

We turn now to a test of Hypothesis 2. As can be seen from Model 5 of Table 2, the interaction of the network and turnover was positive and significant in predicting TMS ($B = 4.71$, $p < 0.05$), consistent with Hypothesis 2. Fully connected groups developed stronger TMSs when membership was stable than when turnover occurred (55.1 versus 52.4), and

Table 1. Means and Correlations

	Mean	SD	1	2	3	4	5	6
1. *Errors*	2.04	2.87						
2. *New Features*	4.39	2.63	−0.33***					
3. *TMS*	52.84	5.17	−0.34***	0.19†				
4. *Dyadic Communication Frequency During Programming Task*	1.53	0.68	−0.24*	0.15	0.26**			
5. *Dyadic Communication Frequency During Feature Generation Task*	0.87	0.85	−0.05	−0.01	0.26**	0.63***		
6. *Dyadic Communication to New Member During Prog. Task*	0.83	0.51	−0.30*	0.21†	0.36**	0.85***	0.51***	
7. *Dyadic Communication from New Member During Prog. Task*	0.69	0.43	−0.27*	−0.01	0.35**	0.76***	0.53***	0.67***

†$p < 0.1$; *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$.

perfectly centralized groups developed stronger TMSs when turnover occurred than when membership was stable (50.9 versus 52.9).

Although not explicitly hypothesized, we examined whether transactive memory systems mediated the effect of communication networks on performance. As can be seen from Table 2, when TMS was included as a predictor of errors in Model 2, its coefficient was negative and significant. Furthermore, the comparison of results between Model 1 and Model 2 reveals that the interaction of communication network and turnover was no longer significant when TMS was included, suggesting that TMS accounted for the effect of the interaction on errors. Similarly, when TMS was included as a predictor of new features (see Model 4), it was positive and marginally significant and the interaction of network structure and turnover became less informative ($p < 0.05$ to $p < 0.1$).

Next, we investigated the role of dyadic communication frequency in explaining TMS. As can be seen from Model 6 of Table 2, the interaction of the communication network with turnover in predicting dyadic communication was marginally significant and positive ($B = 0.48$, $p < 0.1$). The mean levels of dyadic communication as a function of communication network and turnover can be seen in Figure 3. Fully connected groups had somewhat more dyadic communication when they did not experience turnover than when they did, whereas perfectly centralized groups had somewhat more dyadic communication when they experienced turnover than when they did not. These results are in line with Hypothesis 3.

Subsequently, we examined how communication networks, turnover, and dyadic communication frequency affected TMS. Model 7 in Table 2 adds dyadic communication frequency as a predictor of TMS and shows that dyadic communication frequency had a significant and positive effect on TMS. Also, relative to Model 5, the interaction between network structure and turnover became marginally significant when

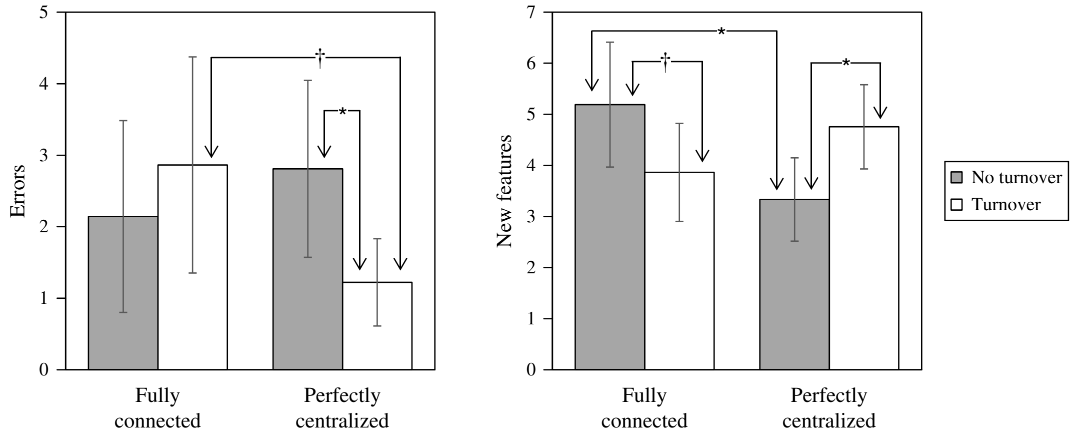
Table 2. Models of Errors, New Features, Dyadic Communication Frequency, and Transactive Memory Systems

	Errors	*Errors*	*New Features*	*New Features*	*TMS*	*Dyadic Communication Frequency*	*TMS*
Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Centralized Network	0.67	−0.14	−1.76*	−1.28	−4.24**	0.33†	−5.26***
	(0.87)	(0.85)	(0.80)	(0.83)	(1.56)	(0.18)	(1.49)
Turnover	0.72	0.21	−1.28	−0.98	−2.68†	−0.17	−2.15
	(0.86)	(0.82)	(0.79)	(0.79)	(1.55)	(0.18)	(1.46)
Centralized × Turnover	−2.31*	−1.42	2.64*	2.09†	4.71*	0.48†	3.28†
	(1.13)	(1.10)	(1.04)	(1.07)	(2.05)	(0.23)	(1.96)
TMS		−0.19***		0.10†			
		(0.05)		(0.05)			
Dyadic Communication Frequency							3.11***
							(0.80)
R^2	0.06	0.17	0.08	0.11	0.07	0.24	0.18
N	109	109	109	109	109	109	109

Notes. Values in parentheses are standard errors. Models 3 and 4 include a control for groups that inadvertently received additional time on the task; 1 = received 10 minutes, and 0 = received 5 minutes. The results are consistent if the groups who received 10 minutes are removed from the analysis. Cumulative dyadic communication frequency, which is used in Models 6 and 7, is the dyadic communication frequency for the combination of the programming task and the feature-generating task.

†$p < 0.1$; *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$.

Figure 2. Mean Errors and New Features as Functions of Communication Network and Turnover

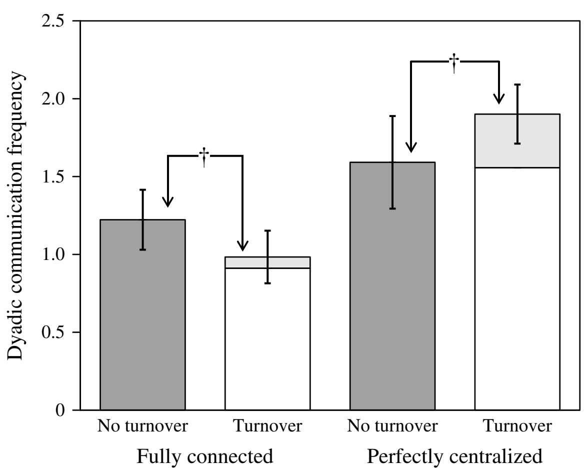


Note. Error bars are 95% confidence intervals.
$^{\dagger}p < 0.1$; $^{*}p < 0.05$.

dyadic communication frequency was included in Model 7. These results indicate that dyadic communication partially explained the effects of the interaction of network structure and turnover on the development of TMS, in support of Hypothesis 3.

Figure 3 also shows the amount of communication that was directed to the new member (see the darker bands in the turnover condition bars) compared with the other three members. As can be seen from the figure, the proportion of communication directed to the new member was much higher in perfectly centralized than in fully connected groups. The difference in the amount of communication to the new member was significant using planned contrasts ($p < 0.001$), indicating that perfectly centralized groups communicated more to their new members than fully connected groups. We also replaced the communication directed *to* the new member with the communication *from* the new member and found a similar pattern: the new member communicated more in perfectly centralized than fully connected groups.

Figure 3. Dyadic Communication Frequency by Network and Turnover During the Programming Task



Notes. Within each group that experienced turnover, the darker subsection is the portion of the communication within the group that went to the new member. The rest of the bar represents the communication to the other three members. Error bars are 95% confidence intervals on the group's dyadic communication frequency. Planned contrasts are on dyadic communication frequency. Planned contrasts were also performed comparing the proportion of dyadic communication that went to the new member in perfectly centralized versus fully connected groups. Perfectly centralized groups had significantly more communication to their new members than fully connected groups ($p < 0.001$).
$^{\dagger}p < 0.1$.

In addition, we analyzed communication to or from the new member as a predictor of TMS (see the online supplement for more details). Dyadic communication ($B = 3.59$, $p < 0.001$), communication to the new member ($B = 4.52$, $p < 0.001$), and communication from the new member ($B = 4.55$, $p < 0.01$) were all associated with increases in the strength of a group's TMS. When both communication to and from the new member were included, only communication to the new member was significant ($B = 3.20$, $p < 0.05$). Thus, the effect of incumbent members communicating to the new member is a more robust predictor of TMS than communication from the new member for groups that experienced turnover.

As a supplement to our quantitative results, we provide examples from groups' transcripts to illustrate the differences in how fully connected and perfectly centralized groups integrated the new member. The first quote is from a fully connected group that experienced turnover. Incumbent 1 wrote, "Are you working on it? Just checking." Incumbent 2 responded, "I think [New Member] is doing random shit" (Group 55). This quote illustrates that the incumbent group members in the fully connected groups did not directly communicate with the new member, whom they seemed to ignore and assumed would not contribute.

In a perfectly centralized group with peripheral member turnover, we see encouragement between incumbents and the new member. Incumbent 1 wrote, "We figured out up to part c, [but] we can't figure that out." After the new member works on the shared screen, the new member responded, "[That] should be [the solution to part c]." Incumbent 1 answered with "mmm . . . let me ask the others . . . you are amazin [*sic*]" (Group 70).

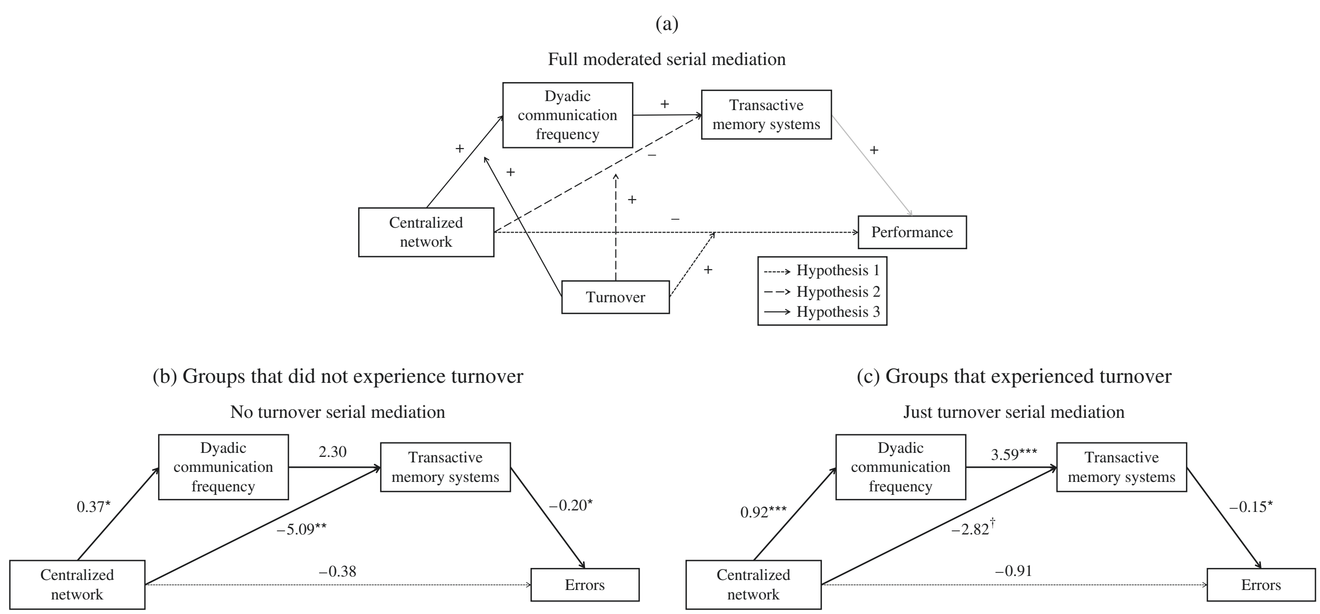
In a perfectly centralized group with central member turnover, incumbent members informed the new member about the organizing logic in the group. Incumbent 1 wrote, "[C]ould you speak with A and B???" The new member responded, "[Y]eah [I] think so. I can talk to B and B said he/she can only talk to me." Incumbent 1 answered with "you [perform] as a communicator for the group" (Group 70). These quotes reinforce the quantitative results indicating that perfectly centralized groups communicated more with their new members and incorporated their contributions better than fully connected groups did.

Moderated Mediation Analyses

We tested the moderated mediation proposed in Hypothesis 3 using PROCESS (Hayes 2013). Figure 4 provides a theoretical model of the moderated mediation we predict. The use of bootstrap sampling in PROCESS allows for tests of mediation and moderation that have more statistical power and violate fewer assumptions than other tests of mediation (Hayes 2013). For all of the analyses, we used 50,000 bias-corrected bootstrap samples. In the overall model, we used dyadic communication frequency because it occurs for both turnover and no-turnover groups. The results of the PROCESS analysis indicated that dyadic communication frequency mediated the relationship between the communication network and transactive memory systems, and that the relationship was stronger when turnover occurred ($B = 2.45$; 95% confidence intervals (CIs): 1.14, 4.28) than when it did not ($B = 1.02$; 95% CIs: 0.01, 2.69). The index of moderated mediation test (Hayes 2015) was significant (95% CIs: 0.20, 3.28), indicating that the strength of the mediation was significantly stronger for the turnover than no-turnover groups, providing additional support for Hypothesis 3.

We used the partially standardized indirect effect to determine the effect size of the network variable on TMS through dyadic communication frequency (Preacher and Kelley 2011). The partially standardized indirect effect can be interpreted the same as a Cohen's *d*—the number of standard deviations of change in TMS that occur as a result of the effect of the network on dyadic communication frequency. For groups that did not experience turnover, perfectly centralized groups had TMSs that were 0.22 standard deviations stronger than fully connected groups (95% CIs: 0.01, 0.56), due solely to centralized groups communicating more than fully connected groups. Because perfectly centralized groups communicated even more when they experienced turnover, centralized groups had TMSs that were 0.57 standard deviations stronger than fully

Figure 4. Theoretical Framework and Statistical Models Predicting Errors by Turnover Condition



Notes. Panel (a) shows the full statistical framework. Panel (b) shows coefficients for groups that did not experience turnover ($n = 42$), and panel (c) shows coefficients for groups that experienced turnover ($n = 67$) for errors.
†$p < 0.1$; *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$.

connected groups when turnover occurred (95% CIs: 0.27, 0.91), because of their communication. Cohen (1960) described 0.22 as a small effect and 0.57 as a medium effect. These calculations demonstrate that the importance of dyadic communication in explaining the network's effect on TMS increases substantially when groups experienced turnover.

We now turn to a test of a full "moderated serial mediation" model as seen in Figure 4. The analysis for errors indicated that for groups that did not experience turnover, the effect of communication network on errors was partially mediated by dyadic communication frequency and TMS ($B = -0.21$; 95% CIs: −0.66, −0.03); however, the majority of the effect was accounted for by TMS alone ($B = 0.98$; 95% CIs: 0.41, 1.92). By contrast, for groups that experienced turnover, the strength of the effect of communication network through dyadic communication frequency and TMS was larger in magnitude ($B = -0.52$; 95% CIs: −1.08, −0.21) than that of the effect through TMS alone ($B = 0.44$; 95% CIs: 0.0002, 1.1386). The index for moderated mediation (Hayes 2015) indicated that the effect of having a perfectly centralized network on errors through dyadic communication frequency and TMS was stronger in turnover versus no-turnover groups (95% CIs: −0.68, −0.05). The effect of having a perfectly centralized network on errors just through TMS did not differ in magnitude based on turnover (95% CIs: −1.35, 0.16).[6]

For groups that did not experience turnover, TMS explained the majority of the effect of the communication network on errors: perfectly centralized groups had weaker TMSs than fully connected groups, which led to more errors (see Figure 4(b)). There was a countervailing effect of the communication network through dyadic communication frequency—perfectly centralized groups communicated more than fully connected groups, which improved their TMSs and thereby reduced errors. But this second effect was smaller than the first when group membership was stable. Hence, when there was no turnover, the net effect of having a perfectly centralized network increased errors ($-0.21 + 0.98 = 0.77$). When groups experienced turnover, however, the magnitudes of the effects changed (see Figure 4(c)). For groups that experienced turnover, the effect of having a perfectly centralized network on dyadic communication frequency was much stronger than for groups that did not experience turnover, and the effect of dyadic communication frequency on TMS was also stronger. When groups experienced turnover, the effect of perfectly centralized networks reducing errors through their effect on dyadic communication frequency and TMS exceeded the perfectly centralized network's direct effect on increasing errors through TMS alone ($-0.52 + 0.44 = -0.08$).

To provide a sense of the size of these effects, we present the effect sizes for the moderated serial mediation. For groups that did not experience turnover, the partially standardized indirect effect of the network on errors through dyadic communication frequency and TMS was −0.07 (95% CIs: −0.23, −0.01), and there was also a significant mediation just through TMS (0.35; 95% CIs: 0.14, 0.68). The interpretation of these significant effect sizes is that for groups that did not experience turnover, there was a 0.28 ($-0.07 + 0.35$) SD increase in the number of errors for perfectly centralized versus fully connected groups. This effect reversed for those that experienced turnover, with a 0.18 SD (95% CIs: −0.37, −0.07) decrease in errors due to dyadic communication and TMS.

We tested the same moderated serial mediation with new features as the dependent variable. The serial pathway of the centralized network effect on new features through dyadic communication frequency and TMS was not significant for groups with stable group membership ($B = 0.02$; 95% CIs: −0.04, 0.16) but was positive and significant for groups that experienced turnover ($B = 0.09$; 95% CIs: 0.01, 0.28). TMS by itself acted as a significant mediator of the effect of having a centralized network on new features for groups with stable membership ($B = -0.55$; 95% CIs: −1.34, −0.09) but not for groups that experienced turnover ($B = -0.03$; 95% CIs: −0.33, 0.26).[7] These results are similar to the results for errors; however, neither of the mediations was moderated by turnover. In these analyses, we found general support for our hypotheses and for the overall model in Figure 4(a). Results were stronger for errors than for new features.

Robustness Checks

Because the central and peripheral turnover conditions did not differ in their errors (1.22 and 1.23, respectively; $p = 0.99$), new features (4.52 versus 5.00, respectively; $p = 0.54$), or the strength of their transactive memory systems (52.2 versus 53.6, respectively; $p = 0.37$), these two centralized turnover conditions were combined into a single centralized network turnover condition for the analyses shown in Table 2. We repeated these analyses but included only one form of centralized turnover at a time. When either of the centralized turnover conditions (central member or peripheral member turnover) was removed from Model 1 in Table 2, the interaction of network structure and turnover on errors was in the same direction and marginally significant ($p < 0.1$). This reduction in significance is likely due to a reduction in power. No differences were detected when Model 3 in Table 2, predicting new features, was run with only one of the perfectly centralized turnover conditions included in the analysis at a time. Second, we reran all moderated mediation analyses with data from only one of the two perfectly centralized turnover conditions included at a time and did not find any significant differences for turnover based on whether the peripheral or central member left the group.

We created two variables that measured the imbalance of messages sent and received among the group members, using the Herfindahl–Hirschman index of communication corrected for the number of pathways as an alternative explanation of our findings. These indices measure imbalances, and they increase to 1 as more communication is either sent or received by a single individual and decrease to 0 if there is perfect equality in the number of messages sent or received. Although the imbalance of sent messages ($B = -14.89$, $p < 0.001$) and the imbalance of received messages ($B = -18.73$, $p < 0.1$) were both negatively related to TMS, neither measure was statistically significant when dyadic communication frequency was added to the model, and dyadic communication frequency was significant and positive ($p < 0.01$) in both cases. These results suggest that dyadic communication frequency is a more robust predictor of TMS than imbalanced communication.

Discussion and Conclusion

Our results indicate that perfectly centralized communication networks can reverse the negative effect of turnover in groups. When turnover occurred in fully connected groups, incumbents tended to ignore new members who could not readily understand the group's implicit coordination logic or their roles within the group. By contrast, the explicit coordination logic of perfectly centralized groups enabled them to make use of the contributions of new members. In centralized groups, the means of coordination, which were largely determined by the communication structure, were simple and explicit. The high dyadic communication frequency in the perfectly centralized groups reduced the likelihood that the incumbent members ignored the new member. The active integration of the new member not only fostered the formation of a strong TMS but also improved the creativity and problem-solving capabilities of centralized groups.

The experimental manipulation of communication networks we use here provides two distinct methodological advantages. First, identifying the direct causal effects of networks has proven challenging in field settings, particularly because of endogeneity issues (Ferriani et al. 2009, Lee et al. 2014, Uzzi and Spiro 2005). Our study design provides insight into communication networks and group processes and is unhampered by endogeneity concerns (see Croson et al. 2007 for a discussion of the advantages of experimental research). The experimental design and random assignment of participants to communication networks and to positions in the networks also enabled us to attribute effects to the communication network rather than to conditions that led to the formation of the networks or to qualities of individuals who might gravitate to certain positions in the networks (Sasovova et al. 2010). Thus, directly manipulating the communication network allows us to make causal claims about the effects of communication networks on group performance (Manski 1993). Second, where possible, we used behavioral measures, such as the amount of communication, which are more objective than self-reported variables (Spector 1994). In particular, self-reports of communication and social networks have been found to be heavily biased by social factors, such as individual status (Bernard et al. 1984).

In addition to providing insights difficult to obtain by other methods, the design of our study maps well to organizational phenomena. The two tasks we used—the programming task and the idea-generating task—parallel many tasks found in organizational settings. Within organizations, groups often work on complex tasks, which involve both problem solving and creativity (Devine et al. 1999). Thus, our realistic tasks provide external validity. In addition, we trained individuals on different information to increase task interdependence among the group members, which captures the challenge of integration and coordination among group members with specialized members. Group members also communicated through computers located in separate rooms and thus operated as a distributed group. This arrangement is analogous to contemporary project-based work conducted in organizations via email (Kleinbaum et al. 2013, Aven 2015). This feature of our experiment not only represents a condition under which many groups operate in organizations today but also allows us to control the communication network and to capture all communication that occurs among group members. Although the features of our experimental design were chosen to reflect characteristics of real organizations, these design features also present boundary conditions to which our findings are most likely to generalize. Therefore, we anticipate that our findings will generalize to small groups in which members perform complex interdependent tasks and communicate in a distributed manner.

Another boundary condition of our findings is the experience of the new member. The new member in our study received the same individual training as the departing member but did not work with a group previously. We chose this study design because we felt that new members to groups typically would have received some training but would have limited group experience. Understanding the effect of the prior experience of the new member on group processes and performance is an interesting issue for future research.

Although we did not hypothesize differences in the effects of turnover in central and peripheral members in perfectly centralized groups, we included both types of turnover in our design to be able to ascertain whether any differences observed were due to the structure, as we hypothesized, or to the position. To accomplish this, we randomly assigned individuals to networks and to positions rather than allowing individuals to gravitate to the networks or positions that they preferred or for which they believed they were especially qualified. Furthermore, the new member received the same training as other members and the same specialized information as the departing member. These features of the design enabled us to investigate the causal effects of the communication network, a major goal of the study. We did not find differences between turnover in the central or peripheral positions in dyadic communication, TMS, or performance. It is important to note that turnover of central and peripheral members might have different effects in groups where members' positions are correlated with other characteristics, such as experience or skills, which is often the case in organizations. By using random assignment, our study enabled us to determine the effect of network structure, independent of these individual factors, on group outcomes.

One limitation of our study was that the feature-generating task always followed the programming task. We thought that this was the most realistic sequence: it would be more natural for groups to identify "ways that the pipe you just built could be improved by creating new features" after rather than before they had built the pipe. The correlation between errors in the programming task and new features in the feature-generating task was −0.33, which indicates a moderate relationship between the two tasks: as errors on the programming task decreased, the number of new features typically increased. Thus, performing well on the first task did not constrain members from being able to identify ways the pipe could be improved on the second task. Nonetheless, it would be useful in future work to develop an idea-generating task that could occur before or after the programming task and thus allow the order of tasks to be counterbalanced.

This paper contributes to several literatures as well as highlights their intersections. In a review of the transactive memory literature, Ren and Argote (2011) recommended greater research on how social networks affect the development of transactive memory systems. Our research shows that the communication network is an important predictor of transactive memory systems. In addition, our findings demonstrate that communication networks condition the effect of turnover on TMS development. Previous work has shown that membership change disables a group's TMS, which impairs its performance (Lewis et al. 2007, Moreland et al. 1996). Our study demonstrates that perfectly centralized communication networks can reverse the negative effect of turnover of one member. Relative to fully connected groups, incumbent members of centralized groups communicate more with the new member, which enables them to update their TMS and improve their performance. Our results suggest that perfectly centralized groups are more receptive to newcomers and more likely to incorporate the ideas of new members than fully connected groups.

Our findings also offer insights into the effects of the communication network structure on group-level outcomes, such as group performance (Casciaro et al. 2015). Although there is a robust literature on the effects of communication networks on individual outcomes (Ahuja et al. 2003, Borgatti and Cross 2003), our work provides new insights into the effects of network configurations on group-level outcomes. In this study, we empirically established that, under stable membership, a fully connected communication network enables the development of a TMS, which in turn leads to positive performance. When turnover occurs, a perfectly centralized network enables the development of a TMS, which in turn improves performance. In addition, our findings begin to unpack how communication networks interact with membership change to affect group processes.

We described two mechanisms through which centralization affects performance: (1) the number of direct communication paths available to team members and (2) the clarity of the coordination logic. The first mechanism maps onto network density, which affects a team's behavior through the number of available communication paths. The second mechanism maps onto network centralization, which affects a team's behavior through the clarity of the coordination logic. We focused on the two network structures that maximize one structural dimension and minimize the other: (1) a fully connected, all-channel network that maximizes density and minimizes centralization and (2) a hub-and-spoke or perfectly centralized network that maximizes centralization and minimizes density. Network types, however, vary across both density and centralization. We suggest that an important issue for future research is to disentangle the effects of network density and centralization. Although it is not possible to make the two dimensions of density and centralization orthogonal,[8] one could design studies where the two dimensions were not highly correlated and thereby investigate their separate effects. On the basis of our theory and evidence, we would predict that density is a more important predictor of group performance when membership is stable and that the clarity of the coordination logic is more important when turnover occurs on complex interdependent tasks such as the ones used here. This theory leads to a variety of predictions about the effects of particular network typologies on group processes and performance under conditions of member stability or turnover. For example, one prediction would be that a ring or circle network would not perform as well as a hub-and-spoke network when turnover occurred, because of the lower centralization and correspondingly less clear coordination logic of the circle network. Another research approach would be to identify networks, such as certain lattices, that do not maximize one network dimension and minimize another but that are, rather, intermediate on both dimensions. Although not optimal for either stable or turnover conditions, such a network might perform better when there is uncertainty about whether turnover will occur. Testing these predictions is an interesting avenue for future research.

Our results suggest that environments where member turnover commonly occurs might benefit from encouraging centralized communication networks. The results of our mediation analyses provide further insights into how groups might address membership turnover, such as promoting communication, specifically to new members. Just as assigning a facilitator in brainstorming sessions improves creativity and efficiency (Sutton and Hargadon 1996), assigning an incumbent group member to communicate with new members and encourage them to contribute might facilitate the integration of new members even in decentralized communication settings. Alternatively, structured processes or formal procedures that facilitate contributions from all members could also be effective in offsetting the negative effects of membership turnover. Future research should examine additional mechanisms for onboarding new members effectively and enabling them to contribute to group performance.

Our results have implications for organizational design and contradict the classic advice in the literature (e.g., see Burns and Stalker 1961) that organizations in dynamic environments should be organized in an organic rather than hierarchical manner. Instead, our study indicates that centralized or hierarchical groups perform better in dynamic rather than in stable environments but fully connected groups do not when the dynamism is caused by membership change. Thus, our results suggest that taking a fine-grained approach to understanding the source of the dynamism will advance organization design research as well as contribute to a growing body of literature on the benefits of certain forms of bureaucracy (Bunderson and Boumgarden 2010).

In their seminal work, Burns and Stalker (1961) argued that groups can cultivate either efficiency through constrained, formal, or mandated structures or creativity by permitting more autonomy and emergent coordination. Centralized networks are rarely viewed to be useful for innovation, as their limited pathways reduce the interconnectedness and, thus, interactions of unique idea holders, undermining innovation. However, limited structures may help provide the necessary communication arrangement to share ideas when the group's membership is not stable. Our findings suggest that turnover provides a means to introduce innovation and creativity into mandated structures or centralized networks. Thus, organizations may be able to gain the benefits of efficiency while also increasing the innovation capabilities of their teams by adopting centralized structures coupled with the frequent rotation of team members.

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Endnotes

[1] Data from seven groups were dropped from the analysis. Two groups failed to follow the experiment's instructions, and five groups contained members who had previously participated in the experiment.

[2] Eleven groups were inadvertently given 10 minutes instead of 5. There was no main effect of this on new features, but a control variable was included in all predictions of new features (see the notes to Table 2).

[3] We used the R (version 3.1.3) package tnet (Opsahl 2012, version 3.011) to convert the networks, and we used the R package igraph (Csárdi and Nepusz 2006, version 0.7.1) to calculate Freeman's (1979) centralization.

[4] Betweenness centralization, variance in how often a member resides on the shortest communication path between all possible pairs, was also used as a robustness check. Similar to degree centralization, betweenness centralization had a positive correlation with centralization (0.79, $p < 0.001$).

[5] To aid in interpretation, we report coefficients for ordinary least squares models; however, all analyses involving errors and new features were repeated with Poisson regressions, a version of the generalized linear model appropriate for a dependent variable that is a count. These Poisson regressions produced results very similar to those presented here.

[6] As a robustness check, we repeated these analyses using just dyadic communication frequency that occurred within the first six minutes of the programming task. Six minutes was the minimum time to completion among all the groups on the programming task. Focusing on the first six minutes allowed us to explore variations in dyadic communication frequency without having to account for time to complete the task. Results from these analyses were identical to those using dyadic communication frequency across the entire time groups worked. The serial pathway in the moderated serial mediation predicting errors was smaller (no turnover, $B = -0.13$; 95% CIs:

−0.48, 0.05; turnover, $B = -0.41$; 95% CIs: −0.89, −0.16) though still significantly moderated by turnover (95% CIs: −0.71, −0.01).

[7] These analyses were repeated using communications from only the first five minutes of the task. Five minutes was the minimum time to completion for the feature-generating task. Results from these analyses are similar in pattern and direction to those reported here, indicating that the results are robust.

[8] The lowest possible network density in any fully connected network is always greater than the density for a perfectly centralized network. The formula for the density of a fully connected network with the lowest possible density would be $N/(N \cdot (N-1)/2)$, where N is the number of members of the group. The formula for the density of a perfectly centralized network is similar, but the numerator is $N-1$ instead of N. Thus, all fully connected groups have higher density than their perfectly centralized counterparts.

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Linda Argote is the David M. and Barbara A. Kirr Professor of Organizational Behavior and Theory at the Tepper School of Business at Carnegie Mellon University, where she directs the Center for Organizational Learning, Innovation and Knowledge. Her research focuses on organizational learning, organizational memory, knowledge transfer, social networks, and group processes and performance. She served as editor-in-chief of *Organization Science* from 2004 to 2010.

Brandy L. Aven is an associate professor of organizational behavior and theory at the Tepper School of Business, Carnegie Mellon University. She received her Ph.D. in sociology from Stanford University. Her research interests include market and organizational fraud, entrepreneurship, and social networks.

Jonathan Kush is an assistant professor of management at the Charlton College of Business, University of Massachusetts Dartmouth. He received his Ph.D. from the Tepper School of Business, Carnegie Mellon University. His research interests include group collaboration, collective cognition, social networks, and their effects on group performance.