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When ties bind and when ties divide: The effects of communication networks on shared social identity and group performance

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Abstract:	We demonstrate that density and centralization, two conceptually distinct but difficult to empirically separate dimensions of social networks, interact to influence group performance through their effect on the extent to which group members share a social identity. In Study 1, we manipulate the density and centralization of group communication networks in a laboratory experiment. We hypothesize and find that density and centralization interact to affect the extent to which members share an identity and that shared social identity mediates the effect of the interaction on group performance. The effect of density on shared social identity is more negative when groups are high in centralization than when they are low in centralization. In Study 1, we found that increasing density reduces the number of group members who are "positionally equivalent"—have a similar pattern of connections—when the network is centralized but increases the number of individuals who are positionally equivalent when the network is decentralized. This, similarity increases the extent to which members feel that they share a social identity. In Study 2, we provide empirical evidence that positional equivalence affects perceptions of similarity. In exploratory analyses, we find that the effects of density and centralization on perceptions of identity are present when the accuracy of group members' perceptions of their network is at the mean or higher. We conclude with a discussion of the implications of our findings for theory and for practice.

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Abstract

We demonstrate that density and centralization, two conceptually distinct but difficult to empirically separate dimensions of social networks, interact to influence group performance through their effect on the extent to which group members share a social identity. In Study 1, we manipulate the density and centralization of group communication networks in a laboratory experiment. We hypothesize and find that density and centralization interact to affect the extent to which members share an identity and that shared social identity mediates the effect of the interaction on group performance. The effect of density on shared social identity is more negative when groups are high in centralization than when they are low in centralization. In Study 1, we found that increasing density reduces the number of group members who are "positionally equivalent"—have a similar pattern of connections—when the network is centralized but increases the number of individuals who are positionally equivalent when the network is decentralized. This, similarity increases the extent to which members feel that they share a social identity. In Study 2, we provide empirical evidence that positional equivalence affects perceptions of similarity. In exploratory analyses, we find that the effects of density and centralization on perceptions of identity are present when the accuracy of group members' perceptions of their network is at the mean or higher. We conclude with a discussion of the implications of our findings for theory and for practice.

Keywords: Social networks, density, centralization, positional equivalence, shared social identity, group performance

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The communication relationships within a group affect its performance not only by influencing how its members exchange information but also by affecting how members think and feel about the group. Prior research on small group networks has largely focused on ties as affecting information flow and suggests that having more ties—a denser network—would increase group performance (Balkundi and Harrison 2006, Park et al. 2020). The centralization, or the inequality in the distribution of ties in a network, can also affect group performance (Balkundi and Harrison 2006). While density and centralization can influence performance through their effects on information flow (Shaw 1964), we hypothesize that these structural characteristics also affect group performance by influencing the extent to which members categorize themselves as similar (Michaelson and Contractor 1992) and feel that they share a social identity (Postmes et al. 2005, Tajfel and Turner 1986). Hence, examining small group communication ties not only as conduits to distribute information but also as creating social categories among members provides a useful vantage for understanding group outcomes and emergent states such as shared social identity.

A shared social identity increases group performance (van Knippenberg 2000) in part by encouraging members to cooperate and share information (Kane et al 2005, Tyler and Blader 2000). As members of a group feel increasingly similar to other members, they are more likely to see themselves as sharing a social identity (Ip et al. 2006, Kane et al. 2005, O'Leary and Mortensen 2010). Taking into account the role of networks in the formation of shared social identity within small groups, we focus on density and centralization, the two most theoretically relevant and commonly researched network characteristics in small groups (Park et al. 2020, Wölfer et al 2015). Based on the information-flow perspective for network ties, we would expect that groups with greater opportunities to interact (high density) would be more likely to develop a shared social identity than groups with less ability to interact with one another (Postmes et al. 2005). High density, however, does not denote that all members are equally connected. Instead, high density can occur in networks with high centralization, where the communication ties are concentrated to only one or a few members (Freeman 1979). Considering networks as a source of social categories, such cases of high density coupled with high centralization might undermine the extent to which members share a social identity because fewer members would share similar patterns of ties. When centralization is low, however, and ties are more evenly distributed, increased density might increase shared social identity as more of the group's members would have matching tie patterns. Thus, we predict that the effect of increasing density on shared social identity depends on the degree of centralization. When centralization is low, increasing density increases the extent to which members share an identity; when centralization is high, increasing density decreases the extent to which members share a social identity. Further, we expect that the extent to which members share an identity positively predicts group performance and that shared social identity mediates the effect of the interaction of network density and centralization on group performance.

We test these hypotheses in Study 1. Our experimental design investigates both the main and interactive effects of density and centralization on shared social identity and group performance. We hypothesize and find that density and centralization interact to affect shared social identity and that shared social identity mediates the effect of that interaction on group performance. Exploratory analyses at the individual level revealed that for centralized networks, increasing density reduced the number of group members who were "positionally equivalent" or had a similar number of connections, whereas for decentralized networks, increasing density increased the number of positionally equivalent members. We found that the greater the number of members who were positionally equivalent in a group, the greater the group's shared social identity. In Study 2, we provide empirical evidence from a second experiment that positional equivalence affects perceptions of similarity.

We advance research on group dynamics by showing that network characteristics affect the psychological state of sharing a social identity, which affects group performance. Thus, our work advances understanding of the psychological effects of networks—as called for recently in a special issue of *Organization Science* (Casciaro et al. 2015) —as well as contributes knowledge about the effects of networks in small groups, as advocated by group's researchers (Park et al. 2020). In particular, this research responds to specific entreaties to investigate the role of networks on the formation of social identity in groups (Wölfer et al 2015). Our study also has implications for managers attempting to increase group performance by encouraging more connections among members (Methot et al. 2018).

Social Networks in Small Groups

Organizational theorists largely conceptualize social networks in two ways: networks as conduits for information to *flow* and networks as *bonds* (see Borgatti and Halgin 2011).[1] Instead of bonds, we prefer to refer to networks as sources of social categories because social categorization can occur in the absence of direct ties. Social network ties have been studied as conduits through which information is communicated among group members (Cummings 2004, Granovetter 1977, Reagans et al. 2004, Tröster et al. 2014). From this information-flow perspective, characteristics of the network affect a group's ability to communicate and coordinate, which in turn, influence its collective performance (Balkundi and Harrison 2006, Shaw 1964, Sparrowe et al 2001, Tröster et al. 2014). For example, increased density increases the ability to exchange information within a group (Lee et al. 2014). Similarly, centralized network structures provide an implicit coordination logic assisting in increasing the group's performance (Argote et al. 2018, Balkundi et al. 2009).

Network scholars also conceptualize networks as a source of social categories informing individual identity either through associations to others (McPherson et al. 2001, Podolny and Baron 1997) or through particular configurations of relations (Aven and Hillmann 2018, Michaelson and Contractor 1992, Mizruchi 1993, White et al. 1976, Winship 1988). Conceptualizing network ties as sources of social categories, however, has garnered less attention in small groups research where most work is on the effects of the network on information exchange and coordination (Shaw 1964, Park et al. 2020). The social categories perspective generally focuses on how similarity in patterns of connections inform perceptions of individuals' social categories and qualities (Borgatti and Halgin 2011). For example, if individuals have similar patterns of ties, they are viewed as similar even if they themselves are not

[1] There have been a variety of other terms used in the literature, including *pipes* and *prisms* (see Borgatti and Halgin 2011, Podolny 2001).

connected (Aven and Hillmann 2018, Michaelson and Contractor 1992). In essence, a similar configuration of connections between individuals suggests that they belong to the same social category. That is, ties do not merely influence a group's ability to process information, but they can also affect how group members perceive themselves and others. In cases where an additional tie in a group reduces differences between individuals' network patterns, the information flow and social categorization perspectives would be in alignment in suggesting that groups would be more connected and have more in common. Yet, the information flow and the social categorization perspectives diverge when the addition of a tie introduces differences in members' network patterns. In this paper, we compare conditions when the addition of a tie diminishes a group's feelings of shared social identity and conditions when it does not.

Network Density and Centralization

Density and centralization are two particularly important network characteristics for understanding group outcomes (see Balkundi and Harrison 2006, Katz et al. 2004, or Park et al. 2020 for reviews). Both characteristics influence group processes through their effects on how information flows within the group. Yet, density and centralization also inform group members' perceptions of themselves and each other. We investigated density and centralization because they have implications for group performance and because they are malleable features that leaders can affect within their teams through various interventions (Methot et al. 2018).

Network density is defined as the number of actual communication ties divided by the total possible ties that could exist among all members of the group (Wasserman and Faust 1994). For instance, in groups with a network density of one, all the members have connections to every other group member. When network density is .5, half of the possible connections exist between members. As such, groups with higher network density have the ability to quickly distribute information among group members because there are more communication pathways from one person to another (Argote et al. 2018, Balkundi and Harrison 2006, Friedkin 1981).

Network centralization is a group level measure based on the variance of the individual member's network centrality scores (Freeman 1979). If there are large differences in individual-level centrality scores within a group, the network has high centralization. When a group has a high level of degree centralization, one or a few members have the majority of ties while the other members have very few ties, such as in a hub-and-spoke configuration (see Figure 1 Network 3). High centralization of a network influences a group's ability to communicate effectively by making simple information easier to aggregate or providing a coordination logic (Argote et al. 2018, Balkundi et al. 2009, Guetzkow and Simon 1955, Leavitt 1951, Shaw 1964) but can also lead to central members being overwhelmed if the shared information is complex (Cummings and Cross 2003, Faucheauz and Mackenzie 1966).

-Insert Figure 1 about here-

Instead of thinking of network ties only as conduits through which information flows, it is important to consider ties as providing information about members. Individuals often use network characteristics to make inferences about others, including whether individuals are similar to oneself (Burt 1987, Shah 1998). Group members are more likely to share an identity when members perceive themselves as belonging to similar categories or sharing similar characteristics (Ashforth and Mael 1989, Ip et al. 2006). When a network is dense, there are many ties for members to use to communicate, but, if those ties are to only a few members, group members might feel more isolated, knowing that there are others who are better connected than themselves. Consider, as an example, a globally distributed team with four interdependent members who are each at a different office: Alice, Bob, Candace, and Daivik. These teammates may communicate in a similar manner as presented in Network 1 in Figure 1, the low density, low centralization network. Alice, though she is more peripheral than Bob or Candace, recognizes that Daivik is in the same position within the network and thus is someone with whom she can feel similar. Bob and Candace also have the same types of connections in the network. If we add a tie to Network 1, increasing density but keeping centralization low, we create Network 2 in Figure 1. In this network, no member would feel left out, and all members could recognize that they all have similar connections to one another.

By contrast, increases in density can also lead to members feeling less similar, as is the case for groups with high centralization. In a low density, high centralization network as shown in the lower left quadrant of Figure 1 (Network 3), all team members communicate primarily with Candace and not directly with each other. Alice, Bob, and Daivik recognize that they all have one communication tie to Candace, thus they each have equivalent network patterns, which leads them to all feel similarly connected to the group. In contrast, if density is increased by adding a tie between Alice and Bob, Daivik—who can still only communicate with Candace—might feel left out as he no longer has someone else with the same pattern of ties as himself (see Figure 1, Network 4). Not only does Daivik feel left out in having fewer connections, but the other members are also aware that Daivik is being left out, which could reduce members' feelings of social similarity as a group. The addition of a tie in low centralization groups (row 1 in Figure 1), thus increases similarity of members' pattern of ties, whereas in high centralization groups (row 2 in Figure 1), the additional tie serves to differentiate group members' configuration of connections.

As demonstrated above, though increasing density can be a means to improve information flow, increasing density in groups high in centralization could decrease member's perceptions of similarity within the network. We propose that high density within a network can reduce the extent to which members share an identity if the additional ties leads members to differ in their pattern of relationships to other group members. If members of a group have similar connections to others in their group or members of an organization, they are more likely to develop positive trust relationships with those similar others, work toward each other's benefit, and to be seen by others as a cohesive subset with those alters (Borgatti and Everett 1992, Ferrin et al. 2006, McPherson et al. 2001).

Thus, the extent to which members hold a similar pattern of network connections to others in their group cues identification or de-identification with those members and consequently the group itself. We propose that density and centralization have an interactive relationship on the extent to which individuals within small group networks share an identity. Density increases the extent to which individuals have similar relations, thus increasing their shared social identity within decentralized groups and has the reverse effect within centralized groups.

Shared Social Identity

Social identity is the psychological process whereby individuals place themselves and others into categories based on common characteristics. Social identity theory proposes that individuals classify themselves and others into categories that enable them to make sense of social relationships (Tajfel and Turner 1986). A shared social identity exists when members of a group perceive themselves as belonging to the same category (Ashforth and Mael 1989, Hogg and Turner 1985, Ip et al. 2006, Kane et al. 2005, O'Leary and Mortensen 2010). Although considerable work has investigated how the inter-group context affects social identity (Doosje et al. 2002, Postmes et al. 2005), we examine how intra-group factors affect shared social identity. If members do not perceive others as similar to themselves, they are less likely to see the group as sharing an identity (Ellemers et al. 2004). This shared social identity, in turn, can influence the feelings and behaviors of group members (Ashforth and Mael 1989, Doosje et al. 1995). For example, when group members share a social identity, they perceive each other more positively (Hewstone et al. 2002), are more willing to cooperate (Tyler and Blader 2000), engage in less conflict (Hinds and Mortensen 2005), and are more likely to trust one another (Foddy et al. 2009, Voci 2006).

The information-flow perspective suggests that a greater opportunity for communication within the group (i.e., the higher the density of the communication network) encourages a stronger shared social identity. Thus, the presence of more ties increases the group's shared understanding of norms, interests, goals, and consequently, strengthens its shared social identity (Postmes et al. 2005). Greater density also permits group members to develop and converge on norms and attitudes as a collective (Whitham 2018). Though the information flow perspective of ties emphasizes information exchange as a means of developing shared social identity, the perspective of network ties as a source of social categories considers the influence of the pattern of individual's ties on perceptions of similarity between members (Aven and Hillmann 2018, McPherson et al. 2001, Michaelson and Contractor 1992, Podolny and Baron 1997, White et al. 1976, Winship 1988). Generally, individuals who share similar patterns of communication ties are perceived by both themselves (Sparrowe and Liden 1997) and others (McPherson et al. 2001, Michaelson and Contractor 1992, White et al. 1976, Winship 1988) as similar and belonging to the same social category. Given that a shared social identity within a group is driven by perceptions of similarity between members (Tajfel and Turner 1986), when group members observe that others have a similar pattern of ties as themselves, they infer that those members are also similar to themselves, increasing shared social identity in the group.

We hypothesize that, within networks high in density, groups have higher shared social identity, contingent on the level of centralization. Within networks low in centralization, high density groups have higher shared social identity than low density groups because the high density group members are more similar in their patterns of connections. This effect reverses for groups high in centralization: high density groups have lower shared social identity than low density groups because the high density groups have members with less similar pattern of connections than the low density groups. In other words, we expect centralization to moderate the effect of density on shared social identity. Thus, we hypothesize:

Hypothesis 1: Density and centralization interact to affect the extent to which members share a social identity: density's effect on shared social identity is more negative when groups are high in centralization than when they are low in centralization.

A wealth of research has examined the influence of density and centralization on group performance (Argote et al. 2018, Balkundi and Harrion 2006, Lee et al. 2014, Sparrowe et al. 2001, Wölfer et al 2015). In a recent review of small group network research, Park et al. (2020) concluded that density generally had a positive impact on performance, whereas the effects for centralization, while generally negative, were mixed. We suggest that some of the inconsistent findings for the effect of centralization on performance can be understood better by incorporating the extent to which centralization affects a shared social identity.

As the development of a shared social identity increases individual's willingness to coordinate and collaborate (Liao et al. 2015, Tyler and Blader 2000), prior work has identified a positive relationship between shared social identity and group performance (Hinds and Mortensen 2005, Kane et al. 2005, van Knippenberg 2000). Thus, we expect that shared social identity increases group performance in our experimental setting. Further, we predict that the interaction of density and centralization affects group performance through its effect on shared social identity as proposed in hypothesis 1. That is, we hypothesize a mediation such that:

Hypothesis 2: Shared social identity mediates the effects of the interaction of network density and centralization on group performance.

In sum, our proposed model is a moderated mediation. Figure 2 depicts the theoretical framework of our hypotheses. The interaction of density and centralization has a negative effect on shared social identity, represented by the solid black lines in Figure 2. As density and centralization increase, the extent to which members share an identity decreases, which in turn harms their performance. The dotted lines in Figure 2 represent this hypothesized moderated mediation.

-Insert Figure 2 about here-

We conducted two experiments that investigated the effect of the group's network on its processes and performance. Study 1 manipulated density and centralization and analyzed their effects on shared social identity and group performance. We also provided additional analyses at the individual-level that investigate the effect of positional equivalence, or the pattern of similar connections between members, on social identity. Study 2 investigated the relationship between positional equivalence and perceptions of similarity.

Study 1

Methods (Study 1)

Participants and Tasks. Participants were recruited through a public participant pool at a mid-Atlantic university, randomly placed into four-person groups, and randomly assigned to one of the four experimental conditions. Data were collected from 66 groups for a total of 264 participants. Participants received either $15 or course credit for their participation in the one-and-a-half-hour study.[2] There was an additional incentive of $60 for the best performing group in each condition. Four such rewards, one per

[2] There were no significant differences between participants who received cash or credit. Groups who received credit did not vary in shared social identity (3.2 vs. 3.4, t(64) = 1.4, *p* = .18), errors (6.9 vs. 6.5, t(64) = -.23, *p* = .82), or innovative ideas (7.3 vs. 6.8, t(64) = -.50, *p* = .62) compared to groups who received payment. No control was included in the analyses reported here.

experimental condition, were given. Fifty-one percent of the participants were female. As members did not directly interact face-to-face and all communication occurred through computers, no effort was made to ensure single gender groups. Fifty-seven percent of the participants were Asian or Asian American, 32 percent were Caucasian, eight percent African American, and three percent reported other ethnicities. The average age of participants was 25.1 years with a standard deviation of 7.9.

Participants completed two 15-minute task periods working on a programming task, first a training followed by performance.[3] This task is in the conceptual cooperative quadrant of McGrath's circumplex model of tasks (1984). Participants used a graphical programming tool to create a program that would allow a user to search Flickr—a popular photo-sharing website—for pictures. To ensure that the task was interdependent, each participant received unique information about one of four modules in the graphical programming language. The task could not be completed without all group members sharing their unique information. We also asked participant to complete an innovative idea generation task. Results for this outcome were generally not significant and are reported in Appendix A. We suggest reasons for differences in the results for the two tasks in the discussion section.

Manipulations. The design of the experiment was a 2 (Density) X 2 (Centralization) between-subjects factorial design. In order to reinforce these networks, no interaction between participants was allowed before the experiment began. Participants completed all tasks and surveys in separate rooms. Communication was restricted to members who were connected over an instant messenger platform; no other forms of communication were permitted. The four networks used in the experiment are presented in Figure 1. While density and centralization are independent measures, they are functionally related at their extremes. When density equals 1 (completely connected network), the network centralization necessarily equal to 0. Therefore, we selected density values at the mid-range for the manipulation. To manipulate network density, the communication networks contained either three or four ties, resulting in network

[3] Twelve groups received ten instead of fifteen minutes for each task. These groups were distributed across all conditions. Groups that received less time did not vary in shared social identity (3.3 vs. 3.3, t(64) = -.21, p = .83), errors (4.4 vs. 7.0, t(64) = -1.41, p = .16), or innovative ideas (6.0 vs. 7.1, t(64) = 1.21, p = .23) compared to groups who received more time. A control is included in all models.

densities of either .5 or .67, respectively. Maintaining a constant number of members and number of ties limited our choices for the centralization manipulation. Centralization was manipulated by varying the placement of ties between the members to create networks that were relatively high (.67 or 1) or low (0 or .33) in degree centralization. Although these network configurations may seem stark for small groups in face-to-face settings, they are becoming increasingly ubiquitous in online collaboration environments, such as Wikipedia, or in virtual R&D groups coordinating over email (Cummings 2004, Faraj and Sproull 2000, Hinds and Mortensen 2005, Keegan et al. 2013).

Procedures. Participants were assigned to positions in their randomly assigned networks by randomly designating each participant to a cubicle as they arrived to the laboratory. Each cubicle contained a computer with an instant messaging client which allowed members to communicate with the groupmates to whom they were connected. Participants were not informed of their network configuration, their positions in the network, or the number of groupmates. After all group members had arrived, the participants individually watched a short training video to introduce them to the graphical programming tool. The group members then began a 15-minute practice period where they worked on a program collaboratively, communicating using an instant messenger. After the practice task, the group members completed the programming task and the innovation task, with the order of the two tasks randomly determined and counterbalanced to counteract any order effects.[4] Thus, the group worked together for three 15 minute task periods for a total of 45 minutes of interaction. Groups were not given any feedback on the quality of their work on any tasks until the debriefing at the very end of the experimental session, which occurred after all measures had been collected. Each group completed a short survey between the two tasks which contained an assessment of network accuracy. All survey responses reported here are from the end of the experiment, just prior to the debriefing. At the end of the experiment, group members were debriefed, thanked, and compensated for their participation.

Measures.

[4] There was no evidence that task order affected errors or innovative ideas; no control was included.

Shared social identity. Shared social identity was measured using survey items developed by Luhtanen and Crocker (1992) delivered to participants at the conclusion of the experiment. The Luhtanen and Crocker (1992) scale—which was modified to contain the five items that are most relevant to work groups—measures the extent to which members identify with the group and feel positively about their membership in the group. Representative questions include: "I feel good about the group I belonged to" and "Overall, I feel that my group was not worthwhile" (reversed).[5] This measure aligns with our theory as we hypothesized that communication networks affect the extent to which members feel connected with and positively about their group as a whole as opposed to specific group members. In order for a measure to be aggregated to the group level, it must demonstrate both internal consistency and within-group agreement (LeBreton and Senter 2008), meaning all members of a given group respond to the survey similarly. The Luhtanen and Crocker (1992) measure had acceptable reliability and agreement among group members [Cronbach's alpha = .76, rwg(j) = .74, ICC(1) = .12, ICC(2) = .35, p = .012).[6] We also assessed shared social identity with two other measures (Doosje et al. 1995, Hinds and Mortensen 2005). These measures did not have acceptable psychometric properties but are discussed in Appendix B.

As a complement to and validation of our survey-based measure of shared social identity, we measured group members' language similarity throughout their performance. Within a large organizational context, Srivastava et al. (2018) found that increased linguistic similarity led to stronger identification and commitment to the organization by its members. Following Srivastava and colleagues (2018) method, we used Linguistic Inquiry and Word Count (LIWC) to code all individual communications into different semantic categories (Pennebaker et al. 2015). A high linguistic similarity score for a group indicates that members are using verbs, affect words, tenses, articles of speech, etc. similarly to each other. This linguistic similarity score of similarity was positively correlated with the survey-based measure of shared social identity (r = .27, p = .020) and remains correlated when accounting

[5] All items are available in Appendix B.
[6] Due to a technical issue, one individual did not complete this scale. The average of the other group's reports is used for this group and this member is dropped from the individual-level analyses.

for the network variables in a partial correlation (r = .26, p = 039). Thus, this measure of group similarity based on behavior before the survey was administered was moderately correlated with the survey assessment of shared social identity. More information on the communication analysis is available in Appendix C.

Performance. We measured performance by calculating the measure of errors in the graphical programs, the work products that the groups created. The number of errors captured the difference between the program the group built and a correct program. Errors typically occurred due to missing modules, missing or incorrect settings within modules, or the use of incorrect modules. All errors were based on the number of settings that the missing module contained or the number of incorrect settings in a completed module. This approach provided a measure of errors, corresponding to the number of steps needed to make the program functional. Two coders assessed all errors with acceptable levels of agreement (Cohen's Kappa = .74, p < .001). The coders met to discuss and resolve any disagreements for the final assessment of errors.

Network Manipulations Checks. We provided two manipulation checks of the network. In the first manipulation check, we provided written descriptions of the networks such as "In our communication structure, one member could communicate with everyone" to which participants responded on a 5-point scale from "Strongly Agree" to "Strongly Disagree." This assessment was captured in the survey at the conclusion of the experiment.[7]

The second manipulation check was behaviorally assessed. We compared the extent to which members communicated along the available network paths. While all ties had some communication, some ties were heavily used and others were less so. In order to calculate network density and centralization on these behavioral networks, we dichotomized these weighted network ties as is common in research interested in overall network characteristics, such as density and centralization (Doreian 1969, Wasserman and Faust 1994). If the number of messages between a connected pair of members was

[7] These items were added later in data collection and thus, twenty groups did not receive these network manipulation checks. We also provide an additional manipulation check in the form of network accuracy.

greater than one standard deviation below the group's mean of number of messages, we code the tie as being active. We then calculated density and centralization for these networks based on the groups' communication usage. For this analysis, we used communication during the programming task.

Network Accuracy. We asked each participant, "Can member X speak to member Y?" for all six relationships that could exist within the group, and members responded "Yes," "No," or "I don't know."[8] We asked these questions in between the two tasks and at the end of the experiment; the two measures are highly correlated (r = .80, p < .001) thus we report the second measure here. We then scored these reports to determine the extent to which an individual accurately perceived his or her network. An accurate assessment of the presence or absence of a tie received a score of 1, an incorrect assessment received a score of -1, and reporting, "I don't know" received a score of 0. These 6 values were then averaged within individual and adjusted, by adding 1 and dividing by 2. These values then ranged from 0 to 1 and thus can be interpreted as percentage network accuracy.[9] This individual-level networks accuracy was then averaged to the group-level. To include this variable in regression analyses, we created a version that was standardized by centering and dividing by the standard deviation. More information on this measure is available in Appendix D.

Results (Study 1)

We begin with a discussion of the manipulation checks to determine whether the network conditions were recognized by the participants. Next, we present the primary hypothesis tests. We then present results indicating that support for our hypotheses depends on the group's network accuracy. We then discuss the individual-level features of the network that underpinned the group-level effects we demonstrated. Findings at the individual-level led to additional analysis of the group-level data. We conclude with a short discussion of potential alternative explanations of our findings.

[8] One group did not receive the network accuracy survey due to a technical error and thus are dropped from analyses using this variable.
[9] This assessment of accuracy is similar to Bondonio (1998). We also investigated Krackhardt's (1990) cognitive social structure accuracy score, but, as accuracy is zero if all possible ties are reported as present, this calculation appears to be inappropriate for small group networks.

Manipulation Checks. Investigating the first manipulation check, groups in Figure 1's Network 1 agreed that a written description of their network matched their perception of the structure of their network more than group members assigned to other networks (3.7 vs 3.1, t = -2.80, p = .008). We found the same finding for Network 2 (3.25 vs. 2.62, t = -2.90, p = .006), Network 3 (3.78 vs. 2.71, t = -3.59, p = .001) and Network 4 (3.71 vs. 2.68, t = -4.61, p < .001). These results suggest that individuals were able to distinguish the network structure they were in from other structures used in the study.

Investigating the second manipulation check using planned contrasts, groups in the high density condition had denser patterns of communication than those in low density conditions (.57 vs. .46, $t(62)$ = -4.085, p < .001).[10] Groups who were assigned to high centralization networks had communication patterns that were higher in degree centralization than those of groups assigned to low centralization networks (.45 vs. .25, $t(62)$ = -5.604, p < .001).[11]

Network Accuracy. For the perceived network accuracy calculation, individuals were 84 percent accurate in identifying the correct connections within their networks. Additionally, no significant differences were found in members' accuracy across the four network conditions. Thus, individuals were generally accurate in understanding their network, and accuracy did not vary by network condition.

Hypotheses Tests. Means, standard deviations, and correlations for our variables are provided in Table 1. Hypothesis 1 posits that the relationship between density and shared social identity depends on centralization, such that density's effect on shared social identity would be more negative when the network is high in centralization than when it is low in centralization. The model proposed in Hypothesis 2 is a moderated mediation where density's effect on performance is mediated by shared social identity and moderated by centralization. Hypothesis 2 was tested using PROCESS 3.0 (Hayes 2015, 2018), an OLS-based plugin for SPSS that allows for indirect effects tests to be performed using bootstrap

[10] It is important to note that members could drop ties in the behavioral network (not communicate along them) but members could not add ties. Thus, density in the behavioral network must be equal to or lower than the given network.

[11] The results of this manipulation check were not sensitive to other reasonable dichotomization choices. Dichotomizing the network at the mean minus two standard deviations also resulted in statistically different degree centralization for the high centralization versus low centralization groups (.49 vs. .17, $t(65)$ = -7.590, p < .001).

sampling. The bootstrapping test of mediation provides a high-power test of mediation (Preacher et al. 2007) and is superior to the causal steps approach established by Baron and Kenny (1986, MacKinnon et al. 2002). All confidence intervals (CI) are 95% CI based on 50,000 percentile bootstrap samples. As errors is a count variable, additional Negative Binomial regressions were used to confirm effects and in no cases were there any substantial differences from the linear regressions.

-Insert Table 1 about here-

Table 2 presents ordinary least squares regression estimates. From Model 1 in Table 2, we see that there was a significant interaction between density and centralization in predicting shared social identity, which we depict in Figure 3. We used planned contrasts to determine that, for low centralization groups, shared social identity did not differ significantly between conditions based on density (3.28 to 3.51, $t(32) = 1.635$, $p = .107$) but for high centralization groups, shared social identity was significantly higher in low versus high density groups (3.41 to 3.09, $t(30) = -2.163$, $p = .034$). These results provide support for Hypothesis 1.

-Insert Table 2 and Figure 3 about here-

Next, we tested the full model proposed in Hypothesis 2 and depicted in Figure 2. For low centralization groups, the indirect effect of density on errors through identity was negative but not significant at the 95% level (-1.606, 95% CI: -3.619, .169) though zero was not included in the 90% level (90% CI: -3.263, -.107), suggesting a marginally significant, negative mediated effect of density on errors. For high centralization groups, the indirect effect of density on errors through identity was significant and positive (2.159, 95% CI: .070, 4.754). The effect size, calculated as the partially standardized indirect effect, was .366 (95% CI: .012, .820), suggesting that errors increased by .366 standard deviations for low centralization vs. high centralization groups due to the effect of density on shared social identity, a medium to large sized effect (Cohen 1988). The index of moderated mediation, which tests if the size of the mediation differs in magnitude between low and high centralization groups, was significant (95% CI: .935, 7.273). Significant indirect effects can occur even when there is no total effect of an independent variable on the dependent variable of interest (Hayes 2018). Hence, these results support the moderated mediation predicted in Hypothesis 2.

Additional Analyses

Our theory proposes that the structure of the group's network affects members' shared social identity by introducing differences between members' network connections. First, we investigated whether these effects were conditional on the accuracy of members' perceptions of their networks. Secondly, we anticipated that individuals' positions within the network would affect their perceptions of themselves and their group members. We investigated which network variables affected individual's reports of the group's shared social identity. Third, findings at the individual-level led to a re-analysis of the main hypothesis tests in Study 1 with a new variable, positional equivalence, the number of group members with a similar pattern of connections. Lastly, we summarize two potential alternative explanations that are discussed in more detail in Appendix E.

Network accuracy analysis. Our arguments are contingent upon group members having reasonably accurate perceptions of their network. Hence, we first conducted analyses to determine if the effect of the network on group shared social identity as proposed in Hypothesis 1 was conditional based on perceptual network accuracy. Second, we investigated if the moderated mediation that supported Hypothesis 2 was conditional on whether the group was accurate in perceiving their network's structure. Neither density (β= -.12, p = .64), centralization (β = -.11, p = .68) nor their interaction (β = .10, p = 80) were significant predictors of network accuracy.

Table 2, Model 3 demonstrates that there is a significant three-way interaction between density, centralization, and network accuracy in predicting shared social identity. We probed this 3-way interaction in predicting shared social identity using the Johnson-Neyman technique (Johnson and Fay 1950). The cross-over point in network accuracy where the interaction between density and centralization on identity is significant at the .05 level is 79.76% accurate or higher. As can be seen in Figure 4, the interactive effect of density and centralization on shared social identity as identified in Hypothesis 1 is not significant in the left panel (Low Accuracy) but is in the center and right panel (Mean Accuracy and High

Accuracy). In forty-two of the sixty-five cases (63.6% of the sample) the average accuracy was above this threshold, which suggests that our effects hold for the majority of groups.

- Insert Figure 4 about here -

Model 7 in Table 2 indicates that there is a significant 3-way interaction between density, centralization, and accuracy in predicting errors. We probed this interaction and found the crossover point at which the interaction between density and centralization is significant in predicting errors is 86.5% accuracy. Within groups above that level of accuracy, for groups high in centralization, density had a positive effect on errors. Thirty-one of the sixty-five groups (47.7% of the sample) had this level of accuracy or higher. Notably, when the interaction of density and centralization is interacted with accuracy, the interaction of density and centralization has a direct effect on error for groups above 86.5% accuracy (47.8% of the sample). Consistent with the hypothesized mediating role of shared social identity, when shared social identity is added in Model 8 of Table 2, it is negative and significant in predicting errors whereas the 3-way interaction is no longer significant.

We repeated the moderated mediation analyses now accounting for the interactive effect of accuracy. The pattern of results was unchanged such that the indirect effect of density on errors through shared social identity was not significant for groups who were low in centralization, regardless of the group's accuracy in perceiving their network [Mean -1 SD Network Accuracy: (95% CI: -6.016, .816); Mean Accuracy: (95% CI: -3.911, .204); Mean + SD Accuracy: (95% CI: -3.796, 1.548)]. For groups high in centralization, shared social identity was not a significant mediator of density's effect on errors when groups were low in network accuracy [Mean – 1 SD Accuracy (95% CI: -5.314, .766)]. The mediation is significant, however for groups at the mean level of network accuracy (95% CI: .224, 4.342) and at the mean + 1 SD level of accuracy (95% CI: 2.345, 10.123). The index of moderated mediation is significant (95% CI: .290, 9.357) suggesting that the moderated mediation as tested in Hypothesis 2 was conditional on the group's accurate perception of their network (Hayes 2018). These analyses suggest that the moderated mediation as proposed in Hypothesis 2—density and centralization affect performance through their influence on shared social identity—was significant for groups who were relatively accurate in perceiving their network.

Individual-level analysis. In an effort to better understand the micro-underpinnings of our effects, we also explored individual-level perceptions. Although shared social identity is a group-level construct, it is first measured at the individual level which permits us to explore variation in individual members reported level of shared social identity. Our theory would suggest that individuals report a higher shared social identity in the group if they recognize similarities between themselves and others in the network. A common operationalization of similarity in networks is structural equivalence, the extent to which individuals have the exact same pattern of ties to the same people (Burt, 1987). In this paper, we discuss automorphic equivalence (which we label positional equivalence for clarity) which is the extent to which individuals have similar patterns of ties irrespective of to whom they are connected, as this operationalization better matches our proposed mechanism than structural equivalence (Michaelson and Contractor 1992).[12] For example, in Figure 1 Network 1, members A and D are positionally equivalent because they are each tied to one member who has two ties though they are not structurally equivalent because they are tied to different members. The shading in Figure 1 highlights which individuals are positionally equivalent with each other in their respective networks.

When members are positionally equivalent, they are more likely to seek out each other for information and knowledge due to their similarity in function within the organization (Shah 1998, Wei et al. 2011). Being positionally equivalent also leads to perceptions of similarity (Burkhardt 1994). Thus, especially when little information about others is known, similarity in network relationships, if they are observable, can be used to infer similarity and social referents (Festinger 1954, Shah 1998). For example, in Network 2 of Figure 1, all members in the group have the same number and pattern of ties, so all members are positionally equivalent. In Network 3, there is a central member and three peripheral

[12] The three members on the periphery in Figure 1, Network 3 (A, B, D) are structurally equivalent as they each have one tie all to the same member, C. In Network 1, however, no members are structurally equivalent because none have the exact same ties.

members. The three peripheral members each play a similar role in the communication network and thus may feel identified with their peripheral partners, even though they are not directly connected. Thus, we anticipated that the presence of more members with whom one is positionally equivalent in a network would increase one's likelihood of perceiving other group members as similar to oneself. As a shared social identity is largely driven by perceptions of individuals as occupying the same categories (Ashforth and Mael 1989), we investigated whether the presence of positionally equivalent members increased an individual's rating of their group's shared social identity.

To investigate if positional equivalence helps explain individual's reports of shared social identity, we calculated the number of positionally equivalent others each member of the group had in their network using the definition of automorphic equivalence from Hanneman and Riddle (2005). We regressed individuals' reports of their shared social identity on how many ties they had to other members and how many members were positionally equivalent to them. To account for nonindependence of individual responses we estimated robust standard errors clustering by group.

As can be seen in Table 3, there was a positive effect for the number of other members in the network who were positionally equivalent with the individual (see Model 1). Individuals who themselves had more ties also reported higher social identity with the group (see Model 2). When included together (see Model 3 for the full sample and Model 4 for the sample where the measure of network accuracy was available), the number of positionally equivalent others and the number of ties both remain significant. These results demonstrate that positional equivalence contributes to perceptions of social identity over and above the number of ties. The inclusion of network accuracy in Model 5 does not change the effects seen in Model 4. Number of ties appears to have an interactive relationship with network accuracy, see Model 6. This interaction suggests that the positive effect of the number of ties on social identity is reduced when members are accurate in perceiving their network than when they are less accurate. There is no interactive relationship between network accuracy and positionally equivalent members, suggesting that this variable does not vary in its positive effect on social identity as a function of network accuracy.

-Insert Table 3 Here-

These analyses demonstrate that individual-level differences in how members are connected in the group may drive the larger network-level effects. Networks where members have more individuals who are positionally equivalent may, therefore, lead members to perceive their group as having a stronger shared social identity. The network that had the highest average number of similar members is the high-density, low-centralization group with 3 whereas the high-density, high-centralization groups only have an average number of similar members of .5. The largest mean level difference in shared social identity was also between these two networks (3.51 vs. 3.09). Thus, the group-level effect of the network on shared social identity is due, in part, to the number of positionally equivalent members in the group. We provide a re-analysis of the group-level effects below.

Re-analysis of Study 1. The individual-level analyses above suggested that the extent to which individuals had positionally equivalent others in their network had a significant effect on their report of shared social identity. We investigated whether this concept of positional equivalence would have a similar effect at the group-level. We translated the individual-level variable, the number of other individuals who were positionally equivalent to the focal individual, to a group-level variable, the number of sets of equivalent members in the group. For example, in Network 3 in Figure 1, there is a central member and three peripheral members, which translates into two sets of equivalent members. We ran a set of additional analyses (see Table 4) to determine if the number of sets of equivalent members explained our results. As can be seen from Model 1, Table 4, the number of positionally equivalent sets was a significant predictor of shared social identity (β = -.21, p = .005).[13] We also found support for a significant mediation such that the effect of the number of positionally equivalent sets in a group on errors was due to the number of positionally equivalent sets having a negative effect on shared social identity and shared social identity in turn reducing errors (95% CI: .473, 2.640). The effect size of this mediation was .245 (95% CI: .083, .453), representing a small to medium sized effect. Thus, the number of positionally equivalent sets has a similar relationship to performance as the interaction of density and

[13] The results reported in the text are without controls for density and centralization. The results are not substantively changed if controls are added.

centralization in Study 1. Positional equivalence has the dual benefit of potentially being more closely related to individual's perceptions of member similarity and provides a more parsimonious explanation of effects than the density by centralization interaction.

-Insert Table 4 Here-

We next tested if the mediation of the number of positionally equivalent sets on performance by shared social identity was conditional on network accuracy as the interaction of density and centralization was. We found similar results such that this mediation was not significant for groups who reported low network accuracy (for Mean – 1SD, 95% CI: -.949, 2.160) but was for those at mean levels of network accuracy (95% CI: .368, 2.462) and high levels of accuracy (Mean + 1 SD, 95% CI: .575, 3.587). However, the strength of the mediation did not vary significantly based on network accuracy (95% CI: -.404, 2.543). Thus, positional equivalence may be more immune to individual's misperception of the network in influencing a group's shared social identity than the interaction of density and centralization.

Alternative Explanations. We investigated two alternative explanations for our findings: communication frequency and communication equality. The network is likely to affect group choices about how much to communicate or the equality of communication among members, and these factors might explain the network's effects on performance instead of shared social identity. We measured communication frequency and communication equality to assess the extent to which some members receive or send more communications than others. Both communication frequency and communication equality were positively related to shared social identity, but the inclusion of either variable did not change the significance of the interaction of density and centralization on shared social identity or identity on performance (see Appendix E for more details).

Study 1 Discussion

In this laboratory experiment, we demonstrated that density and centralization have an interactive effect on the shared social identity within a group. The effect of density on shared social identity was more negative for groups high in centralization compared to those low in centralization. Shared social identity mediated the effect of the interaction of density and centralization on group performance, a moderated mediation. Additional analyses demonstrated that the hypothesized effects were present only for groups that are relatively accurate in perceiving their network. We found in both the individual-level and group-level analyses that these effects are due, in part, to individuals reporting higher levels of shared social identity when there are more members in the network who are positionally equivalent to themselves.

Study 2

Motivation

In Study 1, we examined the interaction of density and centralization and demonstrated that this interaction determines the number of group members who have similar configurations of ties within the group or are positionally equivalent. Members who are positionally equivalent are more likely to perceive themselves as belonging to the same category than members who are not positionally equivalent (Michaelson and Contractor 1992, Wei et al. 2011, White et al. 1976). As such, we argued that being positionally equivalent increases member's shared social identity beyond simply being connected to other members. In Study 1, we inferred that individuals were determining the extent to which there were positionally equivalent members in the group, which had a positive influence on their shared social identity. We found this effect at both the individual and group level; however, we did not ask individuals explicitly with whom they identified or felt similarity. In Study 2, we directly investigated whether positional equivalence affected perceptions of group member similarity. We anticipated that individuals would rate members within a dyad as more similar if they were positionally equivalent to one another than if they were not.

Methods (Study 2)

Two-hundred and fifty-six individuals from a northeastern US university participated in this experiment in partial fulfillment of a course research requirement. The participants were 38.7 percent female. The participants were fifty-five percent Caucasian, seventeen percent African or African American, ten percent Asian or Asian American, seven percent Hispanic, and eleven percent mixed or "other" ethnicity. The average age of the participants was 21.4 years old with a standard deviation of 3.8.

Participants were randomly assigned into one of the four networks used in Study 1, see Figure 1. Participants were told that they should think about being a member of a group completing a collaborative task. They were then shown a picture of their network and told that the ties represented pathways of communication between group members. Our analysis in Study 1 showed that groups with low perceptual network accuracy were less affected by the network manipulations. To mitigate such issues, in Study 2, participants were provided with complete information of the network. Participants were then asked a series of questions about how similar each pair of members were as well as basic demographic information. As each participant provided six similarity assessments, there were 1,536 observations. This experiment took approximately 5 minutes to complete.

Measures

Perceived Member Similarity. Participants were shown the image of one of the networks in Figure 1 with each circle labelled with an identifier. Participants first responded to the prompt: “After the group has worked together for a while, which members do you think would feel most similar to each other? By this I mean that they might feel like they are playing the same role in the group. Write your thoughts below.” This prompt served to focus the participants and have them think carefully about the dynamics within the group. Participants were then asked to respond to the question: “Rate how similar you think each listed pair would feel toward each other” on a three-point scale with the options as “Not Similar”, “Similar” and “Very Similar” for each pairing of an individual in the image.

Connected. If individuals are connected, they may be seen as more similar to one another. We created a dummy variable such that if the two members being assessed on similarity had a direct connection (a path length of 1) they were coded as connected. If the members being assessed were not directly connected (having a path length of 2 or greater) this variable was 0.

Positional Equivalence. As in Study 1, we operationalize positionally equivalent members based on Hanneman and Riddle’s (2005) definition of automorphic equivalence. This was a dummy variable such that individuals who were positionally equivalent had a value of 1 and members who were not positionally equivalent had a value of 0. In Figure 1, if the shading of members within a network match, they are positionally equivalent.

Results (Study 2)

Means, standard deviations, and correlations are available in Table 5.

-Insert Table 5 about here-

We used OLS regressions on perceived member similarity with robust standard errors clustered by participant to account for each rater providing six ratings. As shown in Table 6, members were perceived as more similar both if they were positionally equivalent (see Model 1) and if they were directly connected by a tie (see Model 2). These effects persisted in Model 3 when both variables are entered together. The interaction of both variables shown in Model 4 was not statistically significant suggesting that members were not perceived to be more similar if they were both positionally equivalent and connected. Thus, these variables had independent effects on perceived similarity.

-Insert Table 6 about here-

Study 2 Discussion

The results of Study 2 indicate that an individual's configuration of ties within a network affects perceptions of similarity. Individuals who were positionally equivalent were perceived to be more similar than individuals who were not positionally equivalent. Additionally, individuals who were connected were seen as more similar than individuals who were not connected. These results parallel and complement the individual-level analysis in Study 1. As we gave full information to participants in Study 2 about the connections in the network, difference in network accuracy were not present here. In Study 2, group members did not interact with a group thus their similarity judgments between individuals would primarily be affected by network differences. This study provides evidence that both the number of ties and similarity in the pattern of network connections increase perceptions of similarity.

Overall Discussion

One goal of this paper was to investigate whether having more available ties (higher network density) would negatively affect a group's identity if that additional network density increased differences between members. We found that density and centralization interacted to affect the group's shared social identity: increasing density had a more negative effect on sharing a social identity when communication networks were high in centralization than when they were low in centralization. The additional analyses at the individual level suggested that the number of positionally equivalent members in the group operated similarly to the interaction of density and centralization in predicting shared social identity. A re-analysis of Study 1's group-level data based on those findings demonstrated that groups with more positionally equivalent members were more likely to feel a shared social identity than groups with fewer positionally equivalent members. Study 2 demonstrated that positionally equivalent individuals are perceived as more similar than non-positionally equivalent individuals in a group, reinforcing the earlier findings. Importantly, both Study 1 and Study 2 demonstrated that members need not be connected to feel similar if they are positionally equivalent, and both being connected and being positionally equivalent have independent and positive effects on members sharing a social identity.

Further, we found that shared social identity mediated the effect of the interaction between density and centralization on group performance. That is, we found support for the moderated mediation model proposed in Figure 2: the size of the mediation was significantly different for high versus low centralization groups in support of Hypothesis 2. When we probed the mediating effect of identity on the relationship between density and performance separately for high and low centralization groups, we found that the relationship was significant for groups high in centralization. We did not find that the mediation was statistically significant ($p < .05$) for groups low in centralization, though the effect was in the anticipated direction and zero was not within the 90% confidence interval, suggesting marginal significance.

The re-analysis of data from Study 1 using the number of positionally equivalent members suggested that this variable could be a parsimonious explanation for the relationship of network configurations on performance through shared social identity. In our networks, the number of positionally equivalent sets was perfectly correlated with the interaction between density and centralization. Thus, we could not analyze positional equivalence and density in the same model to directly compare their effects. In Appendix F, we present two simulations showing that the interaction of network density and centralization remain highly correlated with the number of positionally equivalent sets across a range of small group networks.

Future Directions, Boundary Conditions, and Limitations

While this paper serves as a step forward, the study of networks in small groups and the relationship of network structure to group and psychological processes provides many opportunities for future research. In the current experiment, we focused primarily on the relationship of density, centralization, and positional equivalence on shared social identity in communication networks. Focusing on other types of ties, such as advice, may further refine understandings of the effect of networks on group processes.

Other work on centralization within small groups has often examined it in conjunction with leadership or hierarchy (Bunderson et al. 2016) and, in field settings, power and status are often seen as the source of network centralization (Cook and Emerson 1978, Gould 2002, Mizruchi 1994). Given the random assignment of individuals to positions, differences in power and status between individuals would not have contributed to the degree of network centralization in our study. Although the central member in the centralized groups had greater access to other members and could be thought of as being higher in the hierarchy, their position was not due to internal characteristics and provided them no personal advantage as the task was to create a collective product. Thus, we were able to assess the effects of the network independent of power and status. Future work could manipulate power or status in addition to network characteristics to determine the independent and interactive effect of the network characteristics and power or status on emergent states such as identity and group performance.

A finding in our experiment was that only when groups recognized their network did the network have an effect on their shared social identity. Further, the predicted mediation of identity on the relationship between density and performance as moderated by centralization only occurred for groups who were relatively accurate in perceiving their network. Though most of the group members were relatively accurate in perceiving their networks in Study 1, accurate perception may be less likely in larger groups (Krackhardt and Kilduff 1999). Thus, our results are most likely to generalize to relatively small groups.

Although we included two measures of performance in our study, errors and innovation, we found significant relationships only for one variable: errors. From observing the groups and reading transcripts of group conversations, it appeared that the innovation task was not as interdependent as we had expected, which might explain why it was not affected by group-level variables such as the extent to which members shared a social identity. Further work is needed to characterize the tasks that would be sensitive to the effects of positional equivalence and shared social identity.

Conclusion

Our study addresses recent calls for organizational and groups research to bridge social network and social psychology literatures (Casciaro et al. 2015, Katz et al. 2004, Park et al. 2020). We demonstrated that the addition of a tie can hurt shared social identity if it increases differences between members. The present study also extends prior research on networks by demonstrating that the effect of the network on performance was due to shared social identity. Moreover, our findings underscore that communication networks not only alter the means by which group members can share information but also the degree to which members identify as a group due to network effects on social categorization. By investigating positionally equivalent sets as a determinant of group dynamics, this study provides a greater understanding of processes that inform group emergent states and outcomes.

The studies presented here advance knowledge of small groups and networks in three primary ways. First, the majority of prior work has examined the group's network density or centralization independently and not in combination (Balkundi and Harrison 2006, Cummings and Cross 2003, Lee et al. 2014, Reagans, et al. 2004, Shaw 1964, Sparrowe et al. 2001). No experiments, to our understanding, have examined the interactive effect of density and centralization on group emergent states or outcomes. Our experimental design allowed us to study the independent and interactive effects in a systematic way not possible in field settings. The laboratory setting allows the present experiment to have high internal validity through experimental manipulation of network density and centralization. Although studies on group networks are increasingly employing random assignment to condition or group (e.g. Brands et al.

2015, Lee et al. 2014, Tröster et al. 2014), in most studies, the groups' networks and their properties are emergent. In emergent networks, other factors besides the network could contribute to the groups' success, such as individual member's access to different sources of information, and these factors could also have affected the emergence of the network (Cummings 2004, Reagans et al. 2004). As such, allowing group members to form their networks and choose their individual positions within that network introduces concerns about endogeneity (Manski 1993). Our study randomly assigned participants to both the network and their positions within the structures. Therefore, endogeneity issues do not arise in our study and we are able to establish causality. We find a causal effect of network density and centralization on shared social identity and group performance.

Second, the design of this study provides high external validity as the complex, interdependent programming task maps directly to work commonly done in organizations (Bunderson 2003, Faraj and Sproull 2000), and the distributed communication was similar to groups that are geographically distributed and exclusively communicate through technological channels (Cummings 2004, Hinds and Mortensen 2005). Even though accruing evidence does not find consistent differences between managers and student samples for a variety of experimental tasks (Fréchette 2016), the sample of Study 1 was drawn from a public pool that included a range of participants, not only college students. The programming task in Study 1 would fall into the conceptual-cooperative quadrant of McGrath's (1984) circumplex model. Thus, the findings from this study may be most relevant to groups doing conceptual and cooperative tasks that have some level of complexity or difficulty. Although this is a boundary condition of the study, many groups in modern organizations primarily work on difficult and interdependent tasks (Faraj and Sproull 2000, Hinds and Mortensen 2005).

Lastly, by accounting for social psychological processes in predicting group performance, this study enhances our understanding of how various network characteristics influence group processes. Considering that ties may affect feelings of identity rather than just act as channels of information presents a rich avenue by which to understand groups processes that is uncommon in research on small group networks. Although prior work has examined the effects of positional equivalence on individual outcomes (Michaelson and Contractor 1992), to our knowledge, our study is the first to examine its effects on a group-level outcome. Most commonly, prior research has analyzed the similarity of firms or individuals' behaviors, such as in their donation decisions or jobs, based on role equivalence (Mizruchi 1993, Winship 1988). The effect of positionally equivalent sets on shared social identity highlights how structural characteristics of the communication network might influence how members view themselves and others. Variations in networks affect the number of positionally equivalent sets, which becomes another factor by which members can differentiate or integrate themselves (Hogg and Turner 1985). The incorporation of positional equivalence into future studies of small groups could advance research for other group-level outcomes or emergent states.

Using the findings from these studies, group leaders and managers may be better equipped to improve group performance by changing the network structure of a group to one that is more conducive to strong group performance (Methot et al. 2018). The findings from this experiment suggest that simply increasing the number of communication ties within a group may not be effective in improving performance if the additional ties increase differences between members. Ties that increase differences are likely to decrease the extent to which members share a social identity and harm their performance. Thus, before adding a tie to a communication network, a group should assess whether the tie is likely to bind group members together (as in the example of B in Figure 1) or tear them apart (as in the example of D in Figure 1). Not all ties are equal in increasing group performance.

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TABLES

Table 1

Means and Correlations for Study 1 (N = 66)

	Mean	SD	1	2	3	4	5
1. Density (Dummy Coded)	.52	.50					
2. Centralization (Dummy Coded)	.48	.50	.03				
3. Shared Social Identity	3.32	.43	-.04	-.17			
4. Errors	6.56	5.88	.06	.10	-.50***		
5. Linguistic Similarity	3.38	0.67	.10	-.14	.27*	-.08	
6. Network Accuracy	0.84	0.12	-.05	-.04	.09	-.18	.60***

* $p < .05$, ** $p < .01$, *** $p < .001$

Table 2

Predicting Shared Social Identity and Errors in Study 1

	Shared Social Identity			Errors				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dense Network	0.23	0.24	0.24	-0.97	0.64	-1.15	-1.18	0.50
	(0.14)	(0.14)	(0.13)	(2.01)	(1.81)	(1.99)	(1.89)	(1.71)
Centralized Network	0.13	0.12	0.13	-0.84	0.08	-1.22	-1.23	-0.33
	(0.15)	(0.15)	(0.14)	(2.08)	(1.84)	(2.09)	(1.98)	(1.76)
Dense * Centralized	-0.55**	-0.53*	-0.56**	3.69	-0.08	3.99	4.27	0.40
	(0.20)	(0.21)	(0.19)	(2.89)	(2.69)	(2.88)	(2.73)	(2.58)
Shared Social Identity					-6.88***			-6.92***
					(1.59)			(1.68)
Network Accuracy		0.05	0.11			-1.95	-1.58	-0.80
		(0.07)	(0.13)			(1.02)	(1.92)	(1.71)
Dense * Network Accuracy			-0.12				-3.96	-4.82*
			(0.18)				(2.63)	(2.33)
Centralized * Network Accuracy			0.28				-1.04	0.90
			(0.19)				(2.69)	(2.42)
Dense * Centralized * Network Accuracy			-0.58*				9.23*	5.20
			(0.27)				(3.79)	(3.48)
Constant	3.24***	3.26***	3.24***	4.41*	26.69***	3.83	3.08	25.51***
	(0.15)	(0.15)	(0.14)	(2.10)	(5.48)	(2.09)	(2.04)	(5.73)
Observations	66	65	65	66	66	65	65	65
R^2	0.13	0.14	0.31	0.07	0.29	0.12	0.26	0.43
Adjusted R^2	0.08	0.06	0.21	0.01	0.23	0.05	0.15	0.34

Note 1: Models 4-8 were replicated using Negative Binomial regression but results were similar.
Note 2: Values in parentheses are standard errors.
Note 3: All models include a control for the groups that received less time.
Note 4: Models 1, 4, and 5 are identical if the sample of 65 for which the accuracy measure is available are used for the OLS or Negative Binomial regression.
* $p < .05$, ** $p < .01$, *** $p < .001$

Table 3

Individual Network Characteristics Predicting Report of Shared Social Identity

	Shared Social Identity					
	(1)	(2)	(3)	(4)	(5)	(6)
Number of Positionally Equivalent Members	0.64*		0.76*	.73*	0.73*	0.67*
	(0.31)		(0.30)	(.30)	(0.30)	(0.31)
Number of Ties		1.03*	1.21*	1.32**	1.33**	1.34**
		(0.50)	(0.49)	(.49)	(0.49)	(0.45)
Network Accuracy					-0.02	1.34
					(0.33)	(0.84)
Net Accuracy * Positionally Equivalent						0.03
						(0.26)
Net Accuracy * Number of Ties						-0.79*
						(0.37)
Constant	22.02***	21.23***	19.66***	19.50***	19.49***	19.50***
	(0.79)	(1.21)	(1.14)	(1.14)	(1.13)	(1.11)
Observations	263	263	263	259	259	259
R^2	0.02	0.02	0.04	.04	0.04	0.05
Adj. R^2	0.01	0.01	0.03	.03	0.03	0.03
Log Likelihood	-803.24	-803.36	-800.15	-786.69	-786.69	-785.23

Note 1: Values in parentheses are robust standard errors clustered by group.
Note 2: All models include a control for the groups that received less time.
Note 3: If Model 4 includes the same variables as Model 3 but performed on only the sample where network accuracy was available.
* $p < .05$, ** $p < .01$, *** $p < .001$

Table 4

Predicting Shared Social Identity and Errors using Positionally Equivalent Sets

	Shared Social Identity		Errors		
	(1)	(2)	(3)	(4)	(5)
Number of Positionally Equivalent Sets	-0.21**	-0.21**	1.43	-0.004	0.23
	(0.07)	(0.07)	(0.99)	(0.93)	(0.87)
Network Accuracy		0.30			-8.02**
		(0.21)			(2.41)
Number of Positionally Equivalent Sets * Network Accuracy		-0.13			3.26**
		(0.10)			(1.15)
Shared Social Identity				-6.90***	-6.11***
				(1.56)	(1.49)
Constant	3.69***	3.74***	1.68	27.16***	22.86***
	(0.18)	(0.18)	(2.53)	(6.16)	(5.95)
Observations	66	65	66	66	65
R^2	0.12	0.15	0.06	0.29	0.41
Adjusted R^2	0.09	0.10	0.03	0.25	0.36

Note 1: Values in parentheses are standard errors.
Note 2: Models 3-5 are substantially the same when performed with negative binomial regression.
* $p < .05$, ** $p < .01$, *** $p < .001$

Table 5

Descriptive Statistics and Correlation Matrix for Study 2 (N = 1536)

	Mean	SD	1	2	3	4
1. Similarity Rating (1-3)	1.90	.79				
2. Positionally Equivalent	.51	.50	.20***			
3. Connected	.59	.49	.44***	-.13***		
4. Density (Dummy)	.52	.50	.09***	.20***	.17**	
5. Centralization (Dummy)	.46	.50	-.04†	-.35***	.00	.02

† p <.1, * p < .05, ** p < .01, *** p <.001

Table 6

Study 2 Predicting Perceived Member Similarity from Positional Equivalence and the Number of Connections

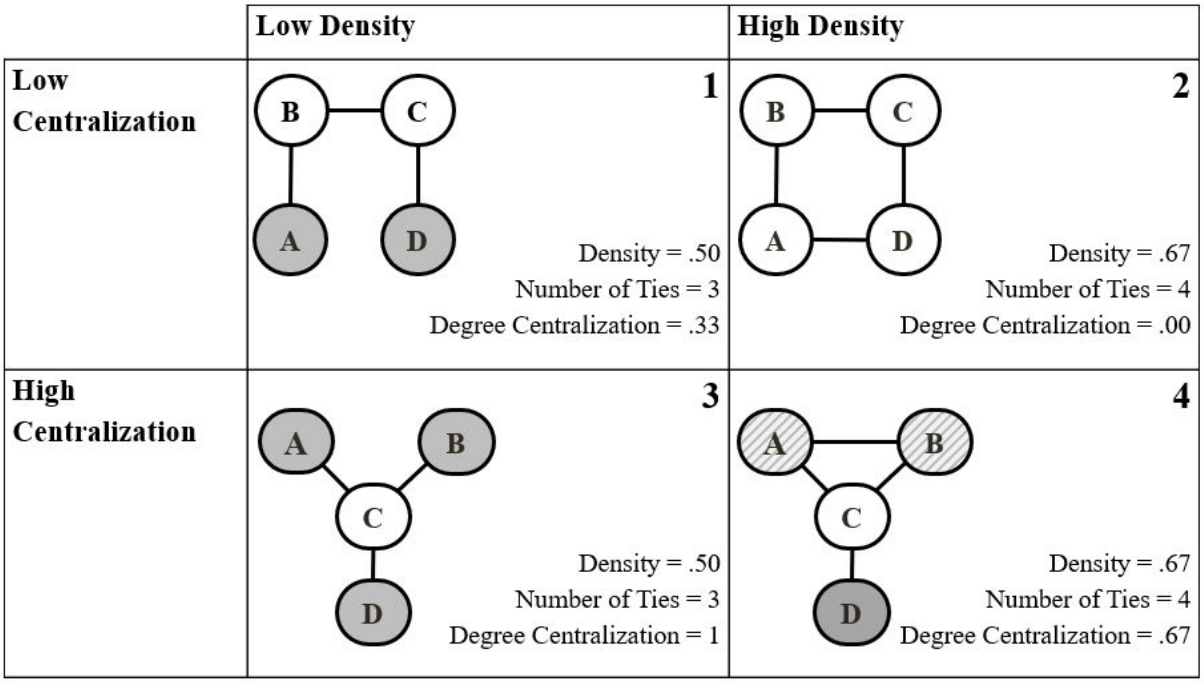
	Perceived Member Similarity			
	(1)	(2)	(3)	(4)
Positionally Equivalent	.32***		0.42***	.47***
	(.05)		(0.05)	(.07)
Connected		.70***	0.76***	.81***
		(.06)	(0.06)	(.05)
Positionally Equivalent * Connected				-.09
				(.08)
Constant	1.73***	1.48***	1.24***	1.20***
	(.03)	(.04)	(0.04)	(.03)
Observations	1536	1536	1536	1536
R^2	.04	.19	0.26	.26
Adjusted R^2	.04	.19	0.26	.26
Log Likelihood	-1793.98	-1662.22	-1595.41	-1594.58

Note 1: Values in parentheses are robust standard errors clustered by rater id.
* $p < .05$, ** $p < .01$, *** $p < .001$

FIGURES

Figure 1

Communication Networks



Note: The circles represent members and the lines represent bidirectional communication relationships. Circles A, B, C, and D represent individual members Alice, Bob, Candace, and Daivik, respectively, as they are discussed in examples in the text. Members with the same shading share similar connections within the network and thus are positionally equivalent.

Figure 2

Theoretical Framework of Paper

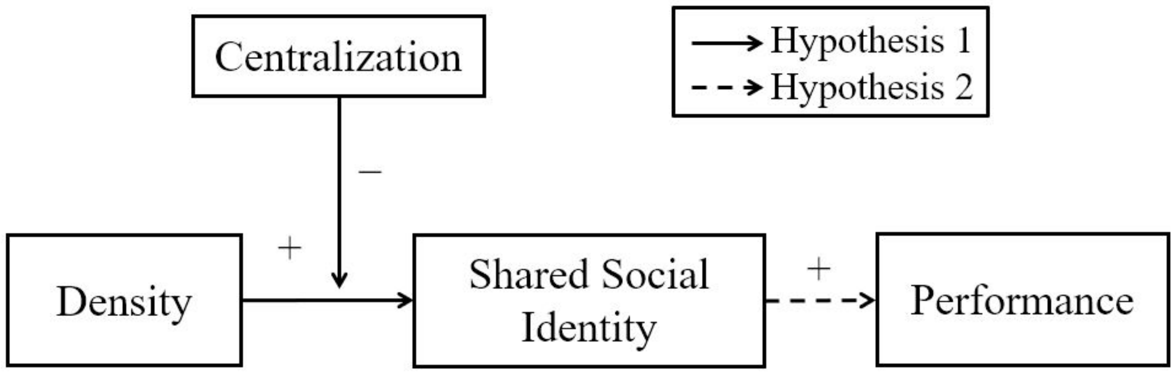
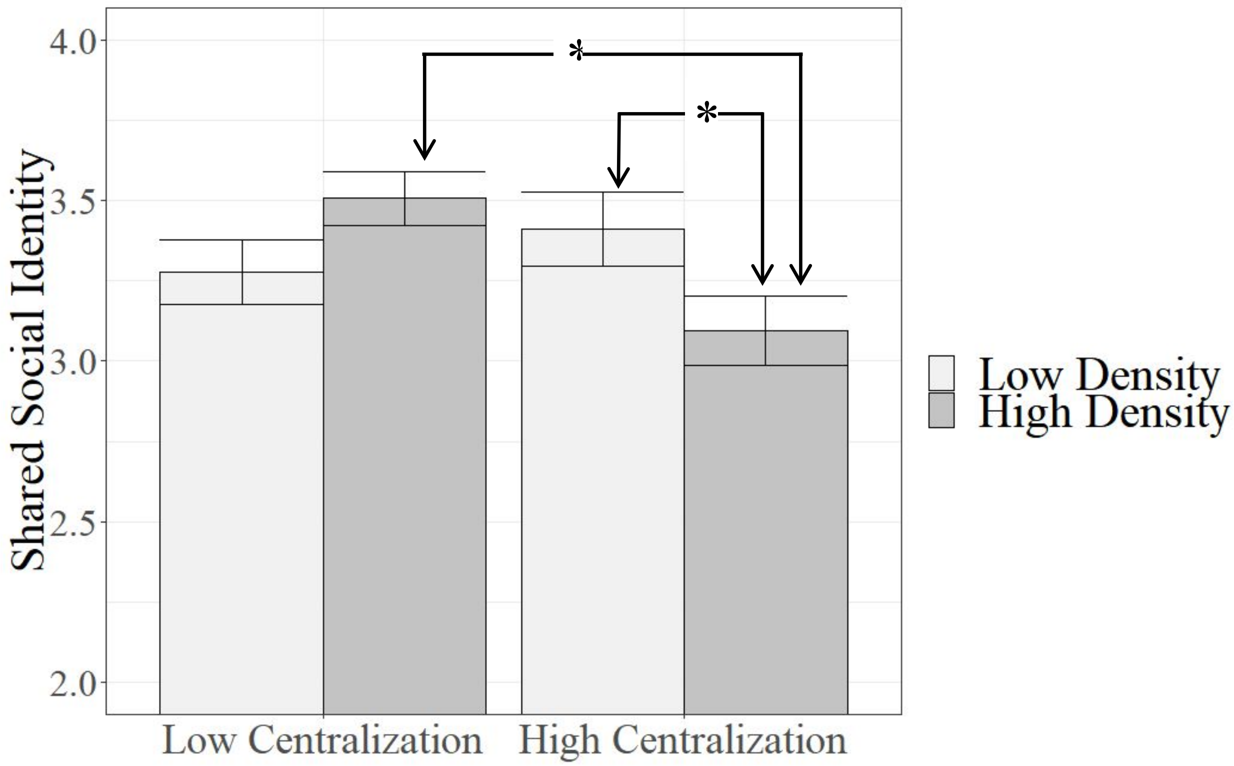


Figure 3

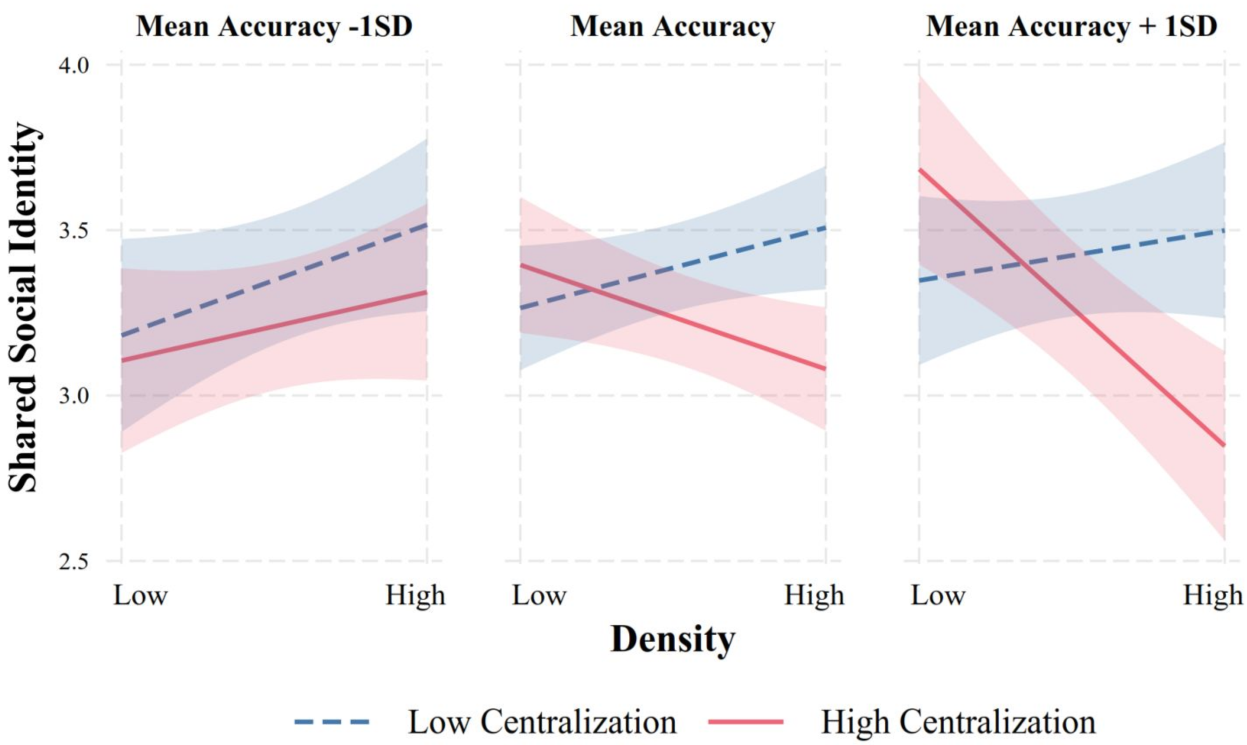
Interaction of Density and Centralization on Shared Social Identity (Study 1)



Note 1: Differences between bars were tested using planned contrasts. Significant at the $p < .05$ level.
Note 2: Error bars are 95% percentile-based confidence intervals.

Figure 4

Three-way Interaction of Density, Centralization, and Accuracy on Shared Social Identity



Note 1: The confidence intervals along the lines are at the 95% level.
Note 2: Density is a dichotomous variable for the low and high density manipulation.
Note 3: Fitted lines are based on regression coefficients presented in Table 2, Model 3. The left panel contains 35.4% of the sample and the center and right panel each represent 32.3% of the sample.

Appendix A: Innovative Ideas Dependent Measure

In the manuscript, we found a mediated effect of the network on errors on the programming task. Groups also completed a brainstorming task where they had 15 minutes to generate alternative uses for the programming tool. Groups proposed ideas about different types of useful programs that could be constructed using the graphical programming interface. As is customary in this type of brainstorming task (Woolley et al. 2010) we used counts of the number of ideas as the dependent variable of interest. Two coders determined the number of innovative ideas each group generated. The list of ideas generated was cleaned so that ideas that were verbatim repeats or not responsive to the prompt were deleted. The two coders reached substantial agreement (Landis and Koch 1977) on what constituted a creative idea with a Cohen's Kappa of .64 ($p < .001$). An average of the two coders' ratings was used in the analyses. We performed identical analyses as those in predicting errors using innovative ideas, including analyses that tested whether results depended on network accuracy. No effects, however, were significant (see Appendix A, Table 1) nor were mediation analyses significant.

This brainstorming task turned out to be much lower in interdependence than the programming task. Instead of discussing ideas, individuals often developed ideas and used the instant messenger to send their ideas to one member or took turns placing their ideas on the shared screen. Thus, the task was in many ways an individual task which might explain why the number of innovative ideas was not affected by group-level variables such as the extent to which members shared a social identity.

Appendix B: Structure's Effect on Agreement in Shared Social Identity Measures

We used the Luhtanen and Crocker (1992) measure of identity in the analyses presented in our manuscript for conceptual and empirical reasons. The questions in this scale are provided at the bottom of this section. Two other common measures of shared social identity were considered. The Doosje, Ellemers, and Spears (1995) scale assesses the extent to which individuals feel that they are members of their group, these questions are also provided at the bottom of this section. The Hinds and Mortensen (2005) measure asked participants to choose the level of overlap of circles that represents how they feel about being part of a group. The two circles (labeled "self" and "other") vary between being totally separate to mostly overlapping. Group members did not have acceptable agreement to justify group aggregation on the Doosje et al. (1995) scale [rwg(j) = .78, ICC(1) =.07, ICC(2) = .22, p = .097.] or the Hinds and Mortensen (2005) measure [ICC(1) = -.02, ICC(2) = -.08, n.s.].

We conducted additional analyses to explore why the Doosje et al. (1995) and the Hinds and Mortensen (2005) measures did not reach acceptable within-group agreement. As a member's interactions with others affects their development of a shared social identity, we investigated whether members' structural positions influenced their perceptions of identity. As discussed in the methods section, group members generally agreed on their level of shared social identity using the Luhtanen and Crocker (1992) measure. For this measure, the central members within high centralization groups were marginally significantly higher in their reports of shared social identity than non-central members (3.46 vs. 3.17, $t(125) = 1.818$, $p = .071$). The member with only one tie in groups high in density and high in centralization (Member D in Figure 1, Panel 4) did not report different levels of shared social identity than the other two non-central peers (2.98 vs. 3.05, $t(49) = .365$, $p = .717$). Thus, the differences in shared social identity between high centralization groups that were low or high in density were not driven by the member with only one tie in dense groups identifying less with their group than other non-central members.

The structural position of members had a larger influence on the other two measures of shared social identity than on the Luhtanen and Crocker (1992) measure and could explain why members did not reach within-group agreement on these measures. Although members agreed about their level of reported identity using the Doosje et al. (1995) scale in the two low centralization networks, members did not agree in the two high centralization networks. Within the high centralization, low density network (Figure 1, Panel 3), central members typically reported higher levels of identity than the peripheral members (3.38 vs. 2.85, $t(57) = -2.412$, $p = .019$). This same difference was also significant (3.44 vs. 2.91, $t(66) = -2.390$, $p = .020$) in the high centralization, high density network (Figure 1, Panel 4). The Hinds and Mortensen (2005) measure had similar results: central members reported higher levels of overlap in their self-identity with that of the group than the other members did in both low density groups (4.00 vs. 2.90, $p = .011$) and high density groups (3.93 vs. 3.10, $p = .024$). Thus, there is some evidence that group disagreement on these two measures of shared social identity was driven by members' structural positions influencing the extent to which they saw themselves as members of the group. Thus, both the Doosje et al. (1995) and Hinds and Mortensen (2005) measures do not appear to assess a group-level construct in our empirical context.

Shared Social Identity: adapted from Luhtanen & Crocker (1992)

1. I often regretted being part of this group (reversed)
2. Being a part of this group has little to do with how I feel about myself. (reversed)
3. In general, I am glad I was part of this group.
4. Overall, I feel that my group was not worthwhile. (reversed)
5. I feel good about the group I belonged to.

Note. All items use a 7-point strongly disagree– strongly agree response format, in which -3 = strongly disagree, 0 = neutral, 3 = strongly agree

Identity (Doosje, Ellemers, & Spears, 1995)

1. I identify with the other members of this group.
2. I see myself as a member of this group.
3. I am glad I am a member of this group.
4. I feel strong ties with the other members of this group.

Note. All items use a 5-point disagree–agree response format, in which 1 = strongly disagree, 2 = disagree, 3 = neutral, 4 = agree, and 5 = strongly agree

Appendix C: Communication Measure of Shared Social Identity

The measure of shared social identity used in the paper is the survey-based measure developed by Luhtanen and Crocker (1992). This survey was given at the conclusion of the experiment. In order to validate this measure, we investigated communication-based measures of shared social identity. These assessments have the benefit of being behavioral and of being collected during performance instead of afterward. To our knowledge, there are no established measures of shared social identity based on communication in the literature. Because group members are more likely to feel that they share an identity when they are similar to each other (Ashforth and Mael 1989), we assessed the extent to which the language an individual used was similar to the language of other group members, using a measure previously developed by Srivastava and colleagues (2016).

Following Srivastava's et. al. (2016) method, we use Linguistic Inquiry and Word Count (LIWC) to code all individual communications into different semantic categories (Pennebaker et al. 2015). LIWC counts a variety of categories of language such as the number of verbs, affect words, tenses, articles of speech, etc. The communication that each individual sent during the performance periods via instant messenger to other members was assessed to create a vector of the percentage of the text that was in each of the 93 categories in LIWC 2015's default dictionary. Once each individual's communication was assessed, it was compared to the three other members of their group using the J-S distance which was then reversed (to turn it into a similarity score) by taking the negative log. This score assesses the similarity of each individual's vector of communication categories to the average of the other group members. If an individual has a high similarity score, it means that he or she used similar language to his or her groupmates'. The four similarity scores, one for each individual, was averaged to the group level.

This linguistic similarity score was positively correlated with the survey-based measure of shared social identity (r = .27, p = .020) and remains correlated when accounting for the network variables in a partial correlation (r = .26, p = 039). Thus, a measure of group similarity based on behavior before the survey was administered was moderately correlated with the survey assessment of shared social identity, which provides some evidence for the validity of the survey measure.

Appendix D: Perceived network Accuracy

Group members were each asked, "Can member X speak to member Y?" for all six relationships that could exist within the group, and members responded "yes," "no," or "I don't know." These 6 questions represent every tie that could exist between a group of 4 individuals and thus these questions allow for the report of every possible tie structure possible between 4 individuals. This survey was given once in between the tasks and once at the end of the experiment; all values reported here and used in the paper are from the second data collection point though the correlation between the two assessments is very high ($r = .80$, $p < .001$).

In calculating members' accuracy in recognizing their network we scored each individual's report based on whether they were correct in reporting that a tie existed or not. If an individual was correct in reporting that a tie existed (or was absent) this assessment was given a score of 1. If an individual was wrong, the score was -1. Instead of treating an "I don't know" as a missing value (which could inflate or deflate an individual's accuracy score artificially) we gave all such reports a value of 0. These 6 values were then averaged within individual to create an accuracy score that could theoretically value from -1 to 1. This value had an average of .682 with a minimum of -.667, a maximum of 1, and a standard deviation of .337. In order to convert this score into a percentage, we added 1 and divided by 2 to compress the range of scores to 0 to 1 so that this score could be treated as a percentage. For this variable, the mean was 84%, the minimum was 17%, the maximum was 100% and the standard deviation was 17%.[1] For regression analyses, a separate variable was calculated which was centered and standardized by dividing by the standard deviation.

As reported in the main text, there were no significant differences between the average accuracy in perceived networks based on network condition. The planned contrasts presented here at the individual level also demonstrate that. The accuracy of individuals in the low-density, low-centralization network was not significantly different from the accuracy of individuals in the low-density, high-centralization

[1] In the first assessment of network accuracy, the mean was 81%, the minimum was 0%, the maximum was 100%, and the standard deviation was 16%. As mentioned earlier the correlation between these two measures was .80.

networks (85.7% vs. 83.8%, t(256) = .615, p = .539), individuals in the high-density, low-centralization networks (85.7% vs. 83.6%, t(256) = .717, p = .474), or individuals in the high-density, high-centralization networks (85.7% vs. 83.3%, t(256) = .801, p = .424). The network accuracy of individuals in the low-density, high-centralization networks was also not significantly different than the network accuracy of individuals in the high-density, low-centralization networks (83.8% vs. 83.6%, t(256) = .066, p = .948) or individuals in the high-density, high-centralization networks (83.8% vs 83.3%, t(256) = .146, p = .884). The network accuracy of individuals in the high-density, low centralization networks was also not significantly different from individuals in the high-density, high-centralization networks (83.6% vs. 83.3%, t(256) = .084, p = .933). Lastly, individuals in groups that were low in centralization were not more accurate than individuals in groups that were high in centralization (84.6% vs. 83.5%, t(256) = .504, p = .615) nor were individuals in groups low in density more accurate than those in groups high in density (84.8% vs. 83.5%, t(256) = .600, p = .549).

Appendix E: Communication and Communication Equality as Alternative Explanations

In our experimental study, we manipulated the communication network and controlled the opportunities members had to communicate with each other. The amount of communication that group members engaged in, however, could have varied with this manipulation. Hence, we investigated whether the frequency of dyadic communication was an alternative explanation for our findings. These results are shown in Appendix E, Table 1. Dyadic communication frequency was measured as the total number of instant messages sent during the tasks, divided by the amount of time the group took and the number of ties available within the group.

As can be seen in Appendix E, Table 1, groups high in centralization communicated somewhat less than groups low in centralization.[2] Communication frequency was positively related to shared social identity (β = .23, p < .001), but the effect of the interaction of density and centralization on shared social identity does not differ before and after communication frequency is added to the model (compare Models 2 and 3 in Appendix E, Table 1). Communication frequency measured during the programming period did not significantly predict errors or change the significance of any variable (see Model 4 in Appendix E, Table 1). Similarly, communication frequency measured during the innovative task did not significantly predict or change the significance level of other predictors of innovative ideas when added (see Models 5 and 6 in Appendix E, Table 1). The moderated mediation identified in support of Hypothesis 2 also did not change with the inclusion of communication frequency. Lastly, the effects above do not change significantly with the inclusion of network accuracy in models. Thus, there is no evidence that communication frequency among the members explained our results.

Communication Equality

Another alternative explanation of the effects we found in the experiment could be that certain network conditions led to an unequal distribution of communication among group members, which in turn

[2] Though the version of communication we use is, in part, corrected for variations in network density, the uncorrected raw count of communication showed similar results with a marginal, negative effect of centralization (β = -48.28, p = 081) but no effect of density (β = 15.58, p = .557) nor its interaction with centralization (β = 37.00, p = .332).

led to the reduced shared social identity. We used the group's dyadic communication to calculate a Herfindahl–Hirschman Index (HHI) that assessed the extent to which individuals sent or received communications in differing frequencies. We used the inverse of the measure to indicate communication equality instead of concentration in the calculations below.

Appendix E, Table 2 replicates the analyses in Table 2 but with equality of communications sent and received included. As can be seen in Models 1 and 2, there was some influence of the network structure on the equality of group member's communications. The main effect of density was significant in predicting equality in sending communication (β = .05, p = .027). For equality in receiving communication, there was a main effect of centralization (β = -.15, p < .001) and an interactive effect with density (β = .11, p = .039). When added to Model 1 of Table 2, communication equality in sending communications was marginally positively related to shared social identity (β = 1.69, p = .061), but the effect of the interaction of density and centralization on shared social identity changed little when the equality of inward communication was or was not in the model (β = -.52, p = .012 to β = -.55, p = .010). Similarly, communication equality in receiving communications was significantly related to shared social identity (β = 1.00, p = .037) but the size of the interaction of density and centralization is not diminished (β = -.66, p = .002). Thus, neither equality in sending or receiving communications explained the effect of the interaction of density and centralization on shared social identity. Also, neither variable was significantly related to either of our outcome variables or significantly changed the relationships of the other variables. The inclusion of either communication equality measure does not change the significance of the moderated mediation analysis that supports Hypothesis 2. If we control for communication frequency in all models, neither equality measure remains significantly related to shared social identity. Lastly, models are similar if network accuracy is accounted for with coefficients decreasing and standard errors increasing slightly for models predicting shared social identity. Thus, there is no evidence that communication equality accounts for the effect of the network on shared social identity or the mediation.

Appendix F: Simulation

In Study 1, we examined groups of four members with two levels of each density and centralization. We demonstrated that the interaction of density and centralization affected the degree to which individuals shared an identity, which in turn affected the number of errors groups made. We argued that the effect of network configurations on shared social identity was due to members' perceptions of similarity. The individual level analyses suggested that positional equivalence could be a more parsimonious explanation of the effect of the network on the group through its influence on individual's reports of their shared social identity. Study 2 showed that the number of positionally equivalent sets affected individuals' ratings of the similarity of individuals, validating the similarity mechanism we proposed in Study 1. For the four networks we investigated in Studies 1 and 2, the amount of positional equivalence in the network is determined by the interaction of density and centralization.

We present here the results of a simulation to demonstrate that the positive interactive effect of network density and centralization on the number of positionally equivalent sets holds for both larger groups and for different values of density and centralization.

Network Construction

We created two unique sets of simulated networks using different methods. In the first dataset of networks, we simulated 40,000 networks at random (10,000 networks for groups of each size, 4 through 7) as is common in network studies (Friedkin 1981). For the second dataset of networks, we simulated all the possible configurations of unique non-isomorphic networks for groups of 4 to 7 members. Thus, this dataset includes one of each network configuration possible for each group size. This simulation method allows us to ensure that all the configurations are present in the data and thus, represents the entire population of possible networks. As the first simulation method randomly simulates networks, not every unique version of the possible networks might be represented in this dataset while other configurations might be overrepresented.

In both sets of simulated networks, we excluded networks that had any isolated members or groups fractioned into disconnected subgroups, as we are only interested in connected groups. Networks in which density equaled one were also dropped. Both the randomly generated networks (N = 40,000) and the unique networks (N = 988) had similar distributions of our variables of interest. Within the randomly generated networks, density had a mean of .67 (SD = .17), centralization had a mean of .35 (SD = .20), and the number of positionally equivalent sets had a mean of 3.44 (SD = 1.51). Within the unique networks, density had a mean of .54 (SD = .12), centralization had a mean of .35 (SD = .17), and the number of positionally equivalent sets had a mean of 4.84 (SD = 1.43).

Results

We regressed the number of positionally equivalent sets on density, centralization, and their interaction controlling for group size as a series of dummy variables (four-member groups served as the reference category). We present the results for the ordinary least squares regressions in Table 5. The interaction of density and centralization was significant and positive for both the randomly generated networks and the unique networks (β = 14.41, p <.001 and β = 12.09, p < .001 respectively).[3] The direction of the interaction indicates that for low centralization groups, increasing density decreased the number of positionally equivalent sets whereas for high centralization groups, increasing density in a network increased the number of positionally equivalent sets, see Figure 4. In additional analyses, we separated the data by network size. These results reveal that the interaction of density and centralization was significant and positive, as predicted, for the number of positionally equivalent sets in both the unique and the random network samples for all group sizes, except for networks of size 5 in the unique network sample. For these networks, the interaction was in the predicted direction but not significant. Therefore, the interaction of density and centralization on the number of positionally equivalent sets is reasonably robust across various group sizes.

-Insert Table 5 and Figure 4 about here-

Discussion

Paralleling the findings in Study 1, the relationship between density and the number of

[3] These analyses are identical when repeated using Poisson or Negative Binomial regressions.

positionally equivalent sets in the group flips direction based on the level of centralization. For groups with low levels of centralization, increases in density reduced the number of positionally equivalent sets in the network. Whereas for groups high in centralization, increased density had a small positive effect on the number of positionally equivalent sets. These results suggest that the networks that we chose in the laboratory study are not unique in demonstrating this interactive relationship of density and centralization on the number of positionally equivalent sets. These results suggest that the results presented in the test generalize to groups larger than the ones we assessed in these experiments.

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Appendix A: Table 1

Density, Centralization, Accuracy, and Shared Social Identity Predicting Number of Ideas Generated

	Innovative Ideas			
	(1)	(2)	(3)	(4)
Dense Network	0.42	0.10	0.51	0.11
	(1.01)	(1.02)	(1.02)	(1.03)
Centralized Network	0.41	0.23	0.45	0.24
	(1.04)	(1.04)	(1.07)	(1.06)
Dense * Centralized	-0.04	0.71	-0.15	0.76
	(1.45)	(1.52)	(1.47)	(1.56)
Shared Social Identity		1.36		1.63
		(0.90)		(1.01)
Network Accuracy			0.69	0.51
			(1.04)	(1.03)
Dense * Network Accuracy			0.91	1.11
			(1.42)	(1.41)
Centralized * Network Accuracy			-1.35	-1.81
			(1.46)	(1.46)
Dense * Centralized * Network Accuracy			-1.29	-0.34
			(2.04)	(2.10)
Observations	66	66	65	65
R^2	0.03	0.07	0.11	0.15
Adjusted R^2	-0.03	-0.01	-0.02	0.01

Note 1: Values in parentheses are standard errors.
* $p < .05$, ** $p < .01$, *** $p <.001$

Appendix E: Table 1

Dyadic Communication Frequency as a Predictor of Shared Social Identity, Errors, and Innovation

	Communication	Shared Social Identity	Shared Social Identity	Errors	Innovative Ideas
Variable	Model 1	Model 2	Model 3	Model 4	Model 5
Dense Network	-.31	0.23	.31*	.26	-.10
	(.27)	(0.14)	(.13)	(1.88)	(1.05)
Centralized Network	-.57*	0.13	.26†	-.27	-.13
	(.27)	(0.15)	(.14)	(1.90)	(1.12)
Dense * Centralized	.50	-0.55**	-.66***	.43	1.19
	(.38)	(0.20)	(.19)	(2.78)	(1.62)
Shared Social Identity				-6.24***	1.66†
				(1.79)	(.96)
Communication			.23***	-.68	-.45
			(.06)	(.87)	(.50)
Observations	66	66	66	66	66
R^2	.10	0.13	.29	.30	.08
Adj. R^2	.04	0.08	.24	.23	-.01

Note 1: All models include a control for groups who received less time.
Note 2: Model 3 was replicated using Negative Binomial regression but results were largely the same.
Note 3: Values in parentheses are standard errors.
Note 4: In models 1 and 2 all dyadic communication during both the programming and innovation tasks is used. In model 3, communication during the programming task is used. In model 4, the communication during the innovation task is used. The results are not sensitive to which communication measure is used.
† p <.1, * p < .05, ** p < .01, *** p <.001

Appendix E: Table 2

Dyadic Communication Equality as a Predictor of Shared Social Identity, Errors, and Innovation

	Equality (Sent)	Equality (Received)	Shared Social Identity	Shared Social Identity	Errors	Errors	Innovative Ideas	Innovative Ideas
Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Dense Network	.05*	.04	.16	.20	.51	.54	-.06	.13
	(.02)	(.04)	(.15)	(.14)	(1.88)	(1.82)	(1.06)	(1.03)
Centralized Network	-.01	-.15***	.15	.28†	.12	.78	.29	.00
	(.02)	(.04)	(.14)	(.16)	(1.86)	(2.10)	(1.05)	(1.19)
Dense * Centralized	-.01	.11*	-.52*	-.66**	-.09	-.75	.69	.93
	(.03)	(.05)	(.20)	(.21)	(2.71)	(2.87)	(1.53)	(1.62)
Shared Social Identity					-6.99***	-7.19***	1.21	1.46
					(1.65)	(1.66)	(.93)	(.94)
Equality (Sent)			1.69†		3.42		4.28	
			(.88)		(11.63)		(6.55)	
Equality (Received)				1.00*		4.41		-1.45
				(.47)		(6.25)		(3.54)
Observations	66	66	66	66	66	66	66	66
R^2	.13	.31	.18	.20	.29	.30	.07	.07
Adj. R^2	.08	.27	.12	.13	.22	.22	-.02	-.02

Note 1: All models include a control for the groups who were given less time.
Note 2: Models 5 and 6 were replicated using Negative Binomial regression but results were very similar.
Note 3: Values in parentheses are standard errors.
† p <.1, * p < .05, ** p < .01, *** p <.001

Appendix F: Table 1

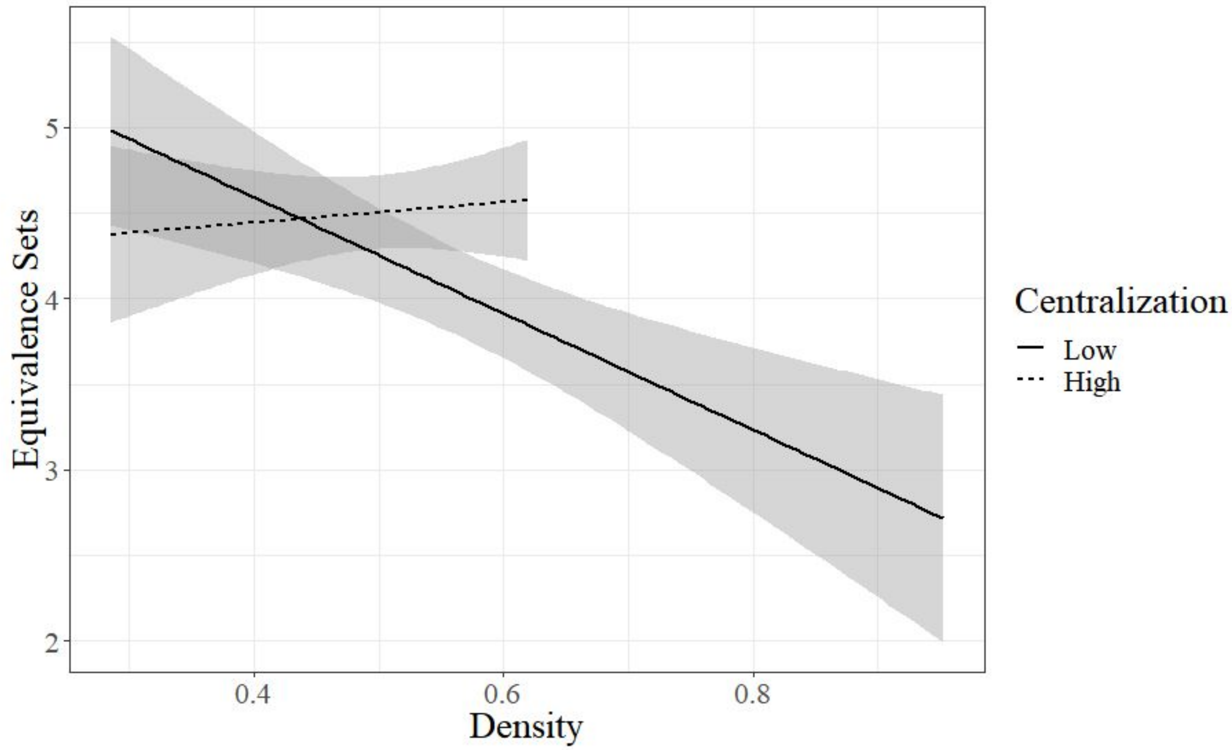
OLS Estimates Predicting Positionally Equivalent Sets for Simulated Networks

Sample	Randomly Generated Networks	Unique Networks
Variable	Model 1	Model 2
Density	-6.99***	-6.08***
	(.05)	(.73)
Centralization	-6.84***	-5.78***
	(.10)	(1.07)
Density * Centralization	14.41***	12.09***
	(.16)	(2.06)
Five Members	1.05***	.83
	(.01)	(.63)
Six Members	1.98***	1.61**
	(.01)	(.58)
Seven Members	3.13***	2.92***
	(.01)	(.57)
Observations	40000	988
R^2	.71	.22

Note 1: These analyses were repeated with Poisson and Negative Binomial regressions as the number of positionally equivalent sets is a count variable. There were no significant differences in the interpretation of either model.
Note 2: Values in parentheses are standard errors.
* $p < .05$, ** $p < .01$, *** $p <.001$

Appendix F: Figure 1

Interaction of Network Density and Centralization on the Number of Positionally Equivalent Sets for Simulated Unique Networks of Groups with Four to Seven Members



Note: Low and high centralization are based on one standard deviation above and below the mean within each network size. The shading represents the 95% confidence interval.