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The effects of multiple team membership on networking online and offline: using multilevel multiple membership modeling

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ABSTRACT

When organizations use multiple team membership (MTM) to enhance efficient use of resources, workers in multiple teams develop networks that expand across team boundaries and are linked to teams at a higher level. On such complexity in multilevel networked organizations, we investigate how MTM and team characteristics shape individual-level networks both online and offline. We explain and use the relatively new approach of multilevel multimember modeling (MMMM) to consider how the diversity of teams is related to individual behaviors and networks. Studying a large trans-Canadian network of scholars making and studying digital media, we find that MTM and diversity in teams have a positive impact on the development of diverse ego networks online (email) rather than offline (in person). We also discuss the broader implications of MMMM for understanding the ways in which networked organizations operate.

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Email network; networked organization; multilevel multiple membership model; multiple team membership

Introduction

Organizations devoted to research and development often use short-term teams to perform knowledge-intensive tasks (Bertolotti, Mattarelli, Vignoli, & Macri, 2015). To leverage resources more effectively, these organizations often requires workers to be members of more than one team at a time (Bertolotti et al., 2015; Cummings & Haas, 2012; O'Leary, Mortsen, & Woolley, 2011). Due to the organizational use of multiple team membership (MTM), workers' networks are relatively multidimensional and multi-layered, as relationships develop and span the fuzzy boundaries between teams (Krebs, 2007; Larson & Starr, 1993; Rainie & Wellman, 2012).

In considering MTM, some analysts have started to use a social network perspective to approach the topic (Bertolotti et al., 2015). As MTM allows workers to develop interpersonal ties across team boundaries while being connected to multiple teams at a higher level, we adopt the concept of multilevel networked organizations to investigate MTM and its effects on workers. In multilevel networked organizations, team members form

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at least one type of tie such as product development or advice sharing. They are simultaneously affiliated with one or more higher-level teams. In other words, MTM forms cross-level ties.

To investigate the mechanisms in such organizations, social network analysts have developed various methods to study the relationships between individual and higher-level networks: team, division, or organizational levels (Lazega, Jourda, Mounier, & Stofer, 2008; Wang, Robins, Pattison, & Lazega, 2013). However, despite the importance of MTM and the relative attention it has gained in organizational studies, the effects of MTM and team characteristics on the development of networks are rarely discussed in the multilevel networks literature. To this end, we propose applying a multilevel multiple membership modeling approach (MMMM) (Hill & Goldstein, 1998), to examine multilevel networked organizations.

In multilevel networked organizations, workers use digital media to aid team work (Bertolotti et al., 2015). To maintain MTM while enhancing performance of individuals and teams, workers extensively use synchronous technologies, such as instant messaging and Skype, as well as asynchronous technologies, such as email, to maintain collaborative relationships that are collocated or dispersed (Bertolotti et al., 2015). Some research has shown that the use of synchronous technologies contributes to the development of online community by fostering a spirit of commitment and responsibility (Chamakiotis, Dekoninck, & Panteli, 2013). Meanwhile, asynchronous technologies, which provide the affordance of anonymity, reduce the fear of disagreement will increase team performance (Pissarra & Jesuino, 2005). However, some researchers argue that using digital media, either synchronous or asynchronous, increases opportunities for misunderstanding, slows down communication, decreases the incentive for participants to adapt, and makes building trust difficult (Dimitrova & Koku, 2010; Olson & Olson, 2000). In other words, the use of technology may not support the development of online community among workers and could decrease productivity and impairs individual and team performances.

To address the debate over digital media use in MTM, we aim to investigate how MTM affects the development of individual networks and how email plays a role during this process by using a case study of a large nation-wide research organization in Canada, the Graphics, Animation and New Media, Network of Centres of Excellence (GRAND). In this work, we employ a multilevel unit of analysis (individual, team, technology), use multiple data collection methods (survey, primarily used in this paper, interviews, and roster), and adopt a MMMM approach (Hill & Goldstein, 1998) to analyze the survey data. Our analysis indicates strong difference in the email and face-to-face communication networks. The findings provide implications for the development of online community: MTM fosters the development of online networks in terms of increasing the multidisciplinary diversity in individuals' ego networks, while it only casts insignificant impact on the development of offline networks.

This study makes four contributions to understanding teams in organizations. For the development of theory, it sheds light on the multilevel networks emerging from the organizational adoption of MTM and investigates the effects of MTM on networks developed online and offline. Focusing on online networks rather than individuals' use of email, this study provides insights into the formation of online community, which is directly associated with the collaborative processes within and across teams.

Second, rather than seeing individual workers as members of only one team, the research addresses the nature of partial involvement in multiple teams.

Third, by presenting the methodological use of multilevel models in social network context, this study explores an indirect way to link individual-level ego networks to whole networks of teams through the meso-level network or MTM. Specifically, we treat teams' network structure as a team-level variable, attach each meso-level ties to a team with a weight determined by the strength of each tie, and associate individuals' ego networks with the multiple teams with which they are affiliated.

Fourth, we contribute to the broad understanding of how networked individuals work in networked organizations that are a blossoming part of our networked society. To date, most such analysis has focused on households, friendship, and kinship; we add the important component of networked work to the literature.

MTM and multilevel networks in networked organizations

When workers collaborate on multiple teams, they develop not only formal networks within each team, but also informal networks across team boundaries in various domains, such as friendship and advice networks (Bertolotti et al., 2015; Dimitrova & Wellman, 2015). Therefore, MTM enables workers to develop multilevel networks: informal networks across the organization at the individual-level and formal networks that links individuals to teams.

A multilevel network usually refers to a form of network that consists of nodes and ties in two levels – the individual (micro) level and the group (macro) level. In 'The duality of persons and groups', Breiger (1974) proposed a framework that elaborates upon the dialectical relationships between individuals and groups: individuals are connected by the groups that they are affiliated with and groups are connected by their members in common. In this framework, he did not require ties among nodes within each level (see Figure 1(a)).

Social network analysts have recently shown interest in multilevel networks. Some scholars started to use hierarchical linear modeling (HLM) (Snijders, Spreen, & Zwaagstra,

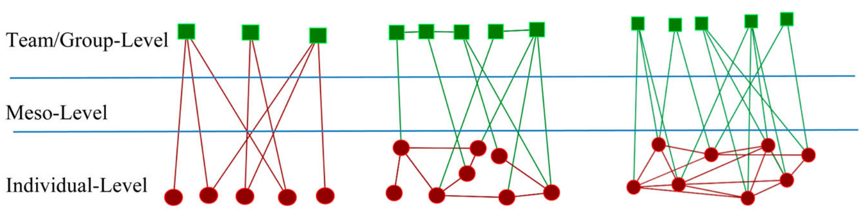

Fig. 1. 1. Two-mode network Fig. 1.2. A multilevel network* Fig.1.3. A multilevel networked organization

*Fig. 1.2. is adapted from Wang et al. 2013. Exponential random graph models for multilevel networks. Social Networks 35, 96-115, p.97.

Figure 1. Configurations of multilevel networks. (a) Two-mode network. (b) A multilevel network (adapted from Wang et al., 2013, p. 97). (c) A multilevel networked organization.

1995), but HLM assumes that individuals are members of only one team, neighborhood, or other higher-level unit. To understand complex social processes, some scholars analyze organizational structures by constructing a meso-level network from the individual and group-level networks. For instance, Lazega et al. (2008) analyzed multilevel networks among a group of cancer researchers and their laboratories in France. In this work, the authors provided a popular definition of multilevel networks, combining networks as micro-, meso-, and macro-levels (Figure 1(b)). The authors view macro- and micro-level networks as preconditions of the meso-level network because they have to construct the meso-level network from the micro- and macro-level networks.

However, in the case of MTM, meso-level networks are salient. When workers participate in one or multiple teams, membership represents a level-spanning relationship that links individuals to teams. This forms a meso-level or affiliation network (Wasserman & Faust, 1994). Taking the role of MTM into consideration, we define multilevel networks in networked organizations as including three basic components (Figure 1(c)):

(1) Two sets of nodes composed of individuals (a) and teams (b);
(2) Individuals' networks that can stretch across team boundaries;
(3) Each individual's membership in one or more teams (x) that in turn form the affiliation or meso-level network (X) (MTM).

As teams are work units that are organized to reaching a common goal (Weiss & Hoegl, 2015), the characteristics of teams often define individual members' behavior and shape their development of informal networks that expand beyond team boundaries (van Duijn, van Busschbach, & Snijders, 1999; de Miguel Luken & Tranmer, 2010; Snijders et al., 1995; Wellman & Frank, 2001).

In this study, we focus on diversity as key characteristics of teams (O'Leary et al., 2011), which refers to the extent to which team members have heterogeneous knowledge and expertise (Mo, in press) . When diversity in teams increases, workers can share diverse information and thus contribute to the development of skills and knowledge within teams (Cox, 2001; Herring, 2009; O'Leary et al., 2011). However, diversity may lead to distrust, conflicts, and communication barriers, impairing productivity (Anderson, 1998; Cummings & Haas, 2012; Cummings & Kiesler, 2005; Dimitrova & Koku, 2010). The existing literature mainly focus on diversity within the boundary of teams, the issue of how MTM and team diversity affect the individual-level networks beyond the team boundaries is unaddressed in the literature.

To improve individual and team productivity and performance, digital media is often used to aid communication within or across collocated and dispersed teams (Bertolotti et al., 2015; Chamakiotis et al., 2013; Chen & McDonald, 2014; Olson et al., 2008). Although studies have identified several benefits of using digital media for MTM (e.g., productivity, flexibility, connection) (Chamakiotis et al., 2013; Chen & McDonald, 2014), some drawbacks are also repeatedly reported (e.g., stress, long working hours, distraction). Bertolotti et al. (2015) found that when workers are at high levels of MTM, the intensive use of instant messaging is associated with poorer team performance. Nevertheless, it is not enough to only look at the use of digital media in the scenario of MTM because when workers are using technology to exchange advice, coordinate, and collaborate, they may develop trust, a sense of belongying, and thus form an online community whose network structure does not necessarily overlap with the formal team boundaries. Instead of viewing technology use as a factor that affects team performance, we consider the use of digital media a part of the work processes that is embedded in MTM. Therefore, we distinguish communication networks established online and offline from the means of communication (technology or in-person) and focus on MTM's impact on the former.

Communication through digital media could be less efficient than face-to-face communication. Comparing these two forms of communication, Kerr and Murthy (2004) found that although workers may generate more ideas from online than offline communication, the use of digital media may be less efficient as it produces more irrelevant ideas. Since workers, especially those with higher level of MTM, are developing various ties both online and offline, the relationships between MTM, team characteristics, and the development of online community became important issues that are associated with team performance and the development of skills and knowledge.

To address the gaps in the literature of MTM, we ask two research questions:

(1) How does diversity in teams influence diversity of individuals' ego networks that expand beyond team boundaries?
(2) Does diversity in teams cast differential effects on individuals' ego networks online and offline?

Multiple membership multilevel modeling

To investigate how MTM affects individual's behavior, Hill and Goldstein proposed multiple membership multilevel modeling in 1998. They developed multiple membership multilevel modeling (which we abbreviate as MMMM) to examine the relationships between group-level units and individual-level units that are affiliated with one or multiple groups (Hill & Goldstein, 1998). In this approach, the primary sampling unit of a team member is included as an individual-level unit of analysis, but team-level characteristics also come into play.

MMMM gives complexity in meso-level networks more consideration than the HLM on which it is based (Hill & Goldstein, 1998; Leckie, 2013; Rasbash & Browne, 2001). MMMM supports analysis of non-hierarchically structured data in which individuals are affiliated with one or multiple groups, and it also enables the examination of interactions at various levels. The groups being analyzed can be composed of a variety of entities such as teams, departments, organizations, locations, families, or networks (Reed & Dongarra, 2015; Rosenfeld, 2015). When individuals are affiliated with a variable number of groups, MMMM can analyze how the characteristics of these groups jointly shape individuals' network composition (e.g., diversity or heterogeneity), positions in their network (e.g., centrality), and their behaviors (e.g., reciprocity).

These characteristics make MMMM useful for examining the impact on individual academic performance of the configuration of multilevel networks constructed from meso-level networks of multiple memberships in friendship cliques (Tranmer, Steel, & Browne, 2014). By examining relationships between membership in friendship networks and individual-level variables, such as health status and educational attainment, Tranmer et al. (2014) found that adolescents' involvement in friendship cliques has an impact on their individual academic performance.

While Tranmer et al.'s study provided a pioneering heuristic example that uses network composition to construct a team-level variable, it did not utilize MMMM's strength in estimating the impact of group characteristics on individual-level variables. The network at the individual level was absent.

In our own study, we follow Hill and Goldstein (1998) in assigning a proportional weight according to each individual's memberships within each unit, and within the group as a whole, summing to 1. As suggested by Cummings and Haas (2012), time allocation into teams can be viewed as an indicator of the strength of the tie linking members and their teams. Therefore, we use as the weight the percentage of time allocation on each team. In a networked organization, membership weights are denoted by w_{ij} for individual i in group j, adding up to 1 for every member in the organization: $\sum_{j=1}^{J} w_{ij} = 1$.

Note that some individuals are only involved in one group, so there is only one meso-level tie for them and the strength of this tie is 1. To indicate the missed ties with other units at the group level, we use 0 to express the strength of ties. For example, the equation for Individual 33 in the example used above is:

$$\begin{aligned} Y_{33} &= \beta_0 + w_{33,1}u_1 + w_{33,2}u_2 + w_{33,2}u_3 + w_{33,4}u_4 + w_{33,5}u_5 + w_{33,6}u_6 + e_{33}, \\ &= \beta_0 + 0.5u_1 + 0.2u_2 + 0.2u_3 + 0.05u_5 + 0.05u_6 + e_{33}. \end{aligned}$$

This hierarchical, crossed, and multiple membership structure is thus modeled as:

$$Y_{ij} = \beta_0 + \sum_{j \in J} w_{ij}u_j + e_{ij},\ u_j \sim N(0,\ \sigma_u^2),\ e_{ij} \sim N(0,\ \sigma_e^2).$$

The subscript j denotes that a micro-level node does not necessarily connect to one unique macro-level node, while e_{ij} is the random error at the micro-level, stating the individual's deviation from the group mean, and u_j is the random error at the macro-level. Therefore, the macro-level random effect u_j is weighted by w_{ij}. An individual i, who is not connected with group j, has $w_{ij} = 0$, so it does not contribute to the meso-level network.

If there are independent variables at the micro- or macro-level, then the same kind of weighting is used for these variables (Leckie, 2013). The model, where we include one micro-level independent variable and one macro-level independent variable, is:

$$Y_{ij} = \beta_0 + \beta_1 X_{1ij} + \beta_2 \sum_{j \in J} w_{ij}X_{2j} + \sum_{j \in J} w_{ij}u_j + e_{ij},$$

$$\text{where: } u_j \sim N(0,\ \sigma_u^2),\quad e_{ij} \sim N(0,\ \sigma_e^2).$$

In the fixed part of the model, $\sum_{j \in J} w_{ij}X_{2j}$ is the weighted sum of the macro-level independent variable with slope coefficient β_2. $\sum_{j \in J} w_{ij}u_j$ is the weighted sum of the random effects at the macro-level. $\beta_0 + \sum_{j \in J} w_{ij}u_j + e_{ij}$ determines the intercept of each regression line.

For example, in a networked organization where members are affiliated with one or multiple teams, we examine the relationship across teams between dependent variables – such as diversity in individuals' face-to-face and email networks; a macro-level independent variable – such as the composition of disciplines in teams; and a micro-level independent variable – such as individuals' motivation to collaborate with others. We can write this model as:

$$\begin{aligned}\text{Diversity in communication network}_{ij} &= \beta_0 + \beta_1 \text{ Motivation}_{ij} \\ &+ \beta_2 \sum_{j \in \text{Project}} w_{ij} \text{ Composition of disciplines}_j \\ &+ \sum_{j \in \text{Project}} w_{ij} u_j + e_{ij}, \quad u_j \sim N(0,\ \sigma_u^2),\ e_{ij} \sim N(0,\ \sigma_e^2).\end{aligned}$$

This is the first use of multilevel multimember models in a social network context, linking individual-level networks to team-level whole networks through meso-level ties. Specifically, we treat teams' network structure as a team-level variable; attach each meso-level tie to a team with a weight determined by the strength of each tie; and associate individuals' ego networks to all the teams that they are affiliated with. As a result, we incorporate the informal networks at the individual-level and the affiliation networks across the individual and the team-levels into the same model. This allows us to discuss the relationships between these two types of networks.

The GRAND network of scholars

To serve as an example of MTM, we studied the GRAND networked research organization formed by a Canadian government grant in 2010 to support research and innovation for new media and information technologies. It was funded by the program of 'Network of Centre of Excellence' which encouraged researchers to belong to more than one project team. GRAND had a flexible, networked organizational form, based more on permeable and boundary-spanning flows and less on formal ties. We use the past tense, as GRAND has dissolved in 2015.

At the time of our data gathering in 2010, GRAND comprised 144 faculty researchers: 60 (42%) were Network Investigator (NIs) team leaders while the remaining 84 (58%) were Collaborating Researchers (CRs). GRAND encouraged NIs, the primary researchers in project teams, to be involved in at least two teams and CRs to be involved in at least one. All researchers were expected to work in networks and to collaborate across teams. While the practice was less than perfect, half (52%) of the researchers participated in multiple teams, becoming bridges between them.

GRAND embraced the notion that diversity leads to better performance and encouraged multidisciplinary collaborations. Among GRAND researchers, coming from 26 universities dispersed across Canada in seven provinces, almost half (46%) were computer scientists; while others came from Information Science, Media, and Design (15%); Communication and Management (14%); Social Sciences (8%); Engineering (6%); Humanities (3%); and other professions such as Medicine and Journalism (9%). In general, these were high-performing individuals who volunteered to be in GRAND for the excitement and opportunities to network, with federal funding, albeit at the cost of having to navigate relationships with different disciplines and norms (Dimitrova et al., 2013).

Two-thirds of the 34 projects involved 3 or 4 disciplines, with a mean of 3.34 disciplines per project (ranging from 1 to 6). Within projects, a majority of GRAND teams had members from various disciplines with a mean diversity within teams of 0.51 disciplines (SD = 0.27). The opportunities for networking and collaborating with researchers in diverse fields encouraged many members to be involved in several project teams.

GRAND's nature was an interesting case study for using MMMM to study MTM because it was designed to be a networked organization, and it had a key goal of promoting the development of cross-disciplinary networks among researchers and institutions that spanned large geographical distances. Both digital and face-to-face communications were intertwined. Everyone can contact each other by email, and almost everyone had face-to-face contact opportunities.

GRAND was a combination of hierarchical and network structures. Its Director and Research Management Committee hierarchically provided central administration, while team-leading NIs administered teams that included multiple CRs. Yet GRAND's hierarchy was flatter than most traditional bureaucracies of similar size, and it was networked at each level. At the organizational level, all members were funded by GRAND and had access to all other members. At the team level, all teams were connected via the researchers' memberships in multiple teams, affording opportunities for exchanging diverse information between teams (Mo, 2015). Moreover, each individual scholar had multiple interpersonal advice and friendship networks.

Data and measurement

To examine the mechanisms between networks at various levels, we conduct MMMM using two datasets collected from GRAND members. One is a roster containing the demographic details of each GRAND member – such as age, gender, and professional data – such as their discipline, university, and department affiliation, and membership in GRAND projects.

The second dataset is composed of social networks constructed from data our team collected in an online survey, September to November 2010. All 144 of GRAND's members were invited to participate, and 101 did so (70%). Males, NIs, professors and assistant professor, and computer scientists are under-represented in the non-respondents, while females, CRs, associate professors, researchers from the disciplines of engineering, information, management, and communication, social science, and other professions are over-represented. As a result, the network data does not include some active individuals with more diverse ties, situated in larger networks. Those who did not participate in the survey are still included in the constructed networks when they are identified as contacts by the respondents. In email and face-to-face communication networks, the ties are non-directional. Therefore, we symmetrized the ties to compensate for the missing values. While all social network parameters are calculated based on matrices of 144 members, the other statistical analyses use the completed surveys ($N = 101$).

Our online survey provided the respondents with a roster of GRAND members and asked them to identify with whom they collaborated, exchanged help and advice, were friends, or would like to meet. In addition, the survey also asked about the communication channels the respondents used to interact with collaborators, such as face-to-face, phone calls, email, and social media. The approach of starting with a roster of members allowed us to capture the GRAND network in various domains, such as its networks of advice and collaboration.

In this paper, we also use some illustrative quotes to provide the context of technology use in the GRAND. However, this does not form the base of the MMMM analysis.

Dependent variables

As our primary interest is in differences between scholars' use of email and face-to-face networks, we analyzed two individual-level variables: disciplinary diversity in each member's email and face-to-face communication networks. Using the social network data, we created matrices of the email and face-to-face networks across GRAND. We used Blau's (1977) heterogeneity index to measure diversity in cross-disciplinary communication in the above networks, calculated with the formula $1-\sum_{i}^{p} 2$ where p is the proportion of the group in the ith category. A higher index score indicates greater diversity among GRAND members.

Independent variables at the individual level

Our evidence for the researchers' motivations for participating in multidisciplinary collaborations was generated from a matrix indicating who wanted to meet each other in which discipline. Blau's heterogeneity index (1977) indicated the extent to which researchers wanted to meet more collaborators from diverse disciplines or only from their own.

We used a variety of measures to indicate hierarchy in this scholarly network. Academic status is measured along four dimensions: age, g-index citation index (Egghe, 2006), seniority, and the researcher's role in GRAND. Both age and g-index citation index are continuous variables. Two other variables, academic ranking and role in GRAND, are ordinal and ranked by value. Academic rank has three values: assistant professor, associate professor, and professor. Role in GRAND has two values: NI and CR (details in Dimitrova et. al., 2013)

Control variables at the individual level

We use gender as a control variable because of its importance in influencing people's structural positions in their networks (Moore, 1990), shaping the structure of their networks (Erickson, 2004), and affecting with whom people are connected (McPherson, Smith-Lovin, & Cook, 2001).

To better understand diversity, we control for the percentage of team members from the same department. Collaborators who can meet and discuss issues in person are able to communicate more efficiently compared to those at a distance. GRAND collaborators in the same department tend to meet face-to-face more often and collaborate more closely.

Independent variable at the team level and MTM

The diversity of disciplines in teams is calculated using roster data that provides information about GRAND members' disciplines and affiliation with one or more projects. We use Blau's heterogeneity index to calculate the multidisciplinary diversity of the teams.

For the membership weights denoted by w_{ij} for individual i in team j, we use self-reported time spent in proportion on each project to calculate the proportional weight.

For instance, researcher A reported that she spent 50% of her time on Team A, 20% of her time on Team B, and 30% of her time on Team C. The proportional weights add up to 1 and can be considered as the strength of ties to corresponding teams.

Comparing email and face-to-face networks

Although we had expected to find much use of new forms of digital media (e.g., Facebook, Twitter, etc.) among these scholars who were themselves so immersed in making and analyzing digital media, we found instead that they only used old-fashioned email with only minimal use of other forms of digital media such as *Facebook* (Table 1). We probed with the question 'why' and were told 'email is so easy because we're online working all the time and it is just there'. By contrast, they would have to switch mental gears for getting involved with the more immersive *Facebook*. They saw email as a tool – an extension of their existing thoughts –while *Facebook* and Skype were more destinations in their own right. As a result, our analysis in the rest of this paper compares only email and face-to-face communication.

Although GRAND researchers had developed more ties through email than in person (Table 1), Blau's heterogeneity index (1977) showed that their face-to-face networks were more diverse than their email networks, with a mean diversity of 0.39 vs. 0.29.

We used MMMM to fit multiple membership variance components to individuals' diversity scores in their email media and face-to-face networks (Table 2). Model 1 shows that the mean researcher is predicted to have a diversity score of 0.005 in their email network, and 0.011 in their face-to-face network, with an intercept not significantly different from zero ($z = 0.05$, $p = .96$ in the email network and $z = 0.09$, $p = .93$ in the face-to-face network). This is expected as the response variable has been standardized to have both a mean of zero and a constant variance. The between-group variance is estimated at 0.061 in the email network, and 0.0231 in the face-to-face network. The estimated individual-level residual error variance is 0.945 in the email network and 0.989 in the face-to-face network.

Although individual-level variables have stronger effects on the dependent variables, MMMM is preferable to single-level (individual-only) modeling because its team-level variance provides a significantly better fit for the analysis. Further steps of modeling to include team-level variables can better explain the individual-level dependent variables of email and face-to-face contact.

Having fit Model 1 to the data, we also predict empirical Bayesian estimates of the team effects together with their associated standard errors in order to check whether the random effects are normally distributed. The test reveals that the predicted team effects

Table 1. Scholars' use of communication media.

Network	Ties	Percentage
Frequent email	2280	79.4%
Frequent face-to-face	512	17.8%
Conference	51	1.8%
Online (chat, listserve, etc.)	16	0.6%
Social networking sites	12	0.4%
Total	2871	100.0%

Table 2. MMMM: teams' disciplinary diversity and individuals' diversity in email and face-to-face networks.

	Model 1		Model 2		Model 3	
	Email	Face-to-face	Email	Face-to-face	Email	Face-to-face
Intercept	0.005	0.011	−0.309	0.024	−0.855***	−0.605
Individual-level variables						
Motivations for diversity			0.320**	0.346**	0.289***	0.313
Age			0.109	0.134	0.102	0.141
Role in GRAND			0.278**	0.248*	0.293**	0.260
Academic rank			0.007	0.049	0.029	0.055
G-Index			0.149	0.141	0.191*	0.173
Gender			0.432*	0.248	0.451*	0.262
% of researchers in same department			1.738	1.620	1.559	1.734
Team-level variable						
Disciplinary diversity					1.176*	0.589
Variance estimates						
Team variance	0.061**	0.023**	0.066**	0.024**	0.002**	0.011**
Individual variance	0.945**	0.989**	0.594**	0.675**	0.567**	0.66**

Note: Individual $N = 101$, team $N = 34$.
$^{*}p < .05$.
$^{**}p < .01$.
$^{***}p < .001$.

range from 0.301 to 0.223, with a difference of 0.524 between the highest and the lowest scoring team. This is large, given that the dependent variable is standardized. This test further suggests that we should incorporate team-level variables into the model.

Model 2 includes individual-level independent variables and shows that individual motivations for participating in multidisciplinary collaborations have stronger effects on diversity than other independent variables – in both the email and face-to-face networks. Model 2 also shows that researchers in high hierarchical positions in GRAND are apt to have more diverse networks, both email and face-to-face. This is consistent with Lin and Dumin's finding (1986) that lower-status people are more apt to turn to higher-status people because of the latter's more diversified networks and greater power.

In comparison to Model 1, Model 2 (that includes the individual-level variables) leads to an increase of 8.2% in the team-level variance in the email network and 4.3% in the face-to-face network. It also leads to a drop in individual-level variance of 40% in the email network and 32% in the face-to-face network. The large decline in the individual-level variance suggests that in both the email and face-to-face networks, GRAND members' communications are affected more by their individual motivations and roles and less by the structure of multidisciplinary teams.

The usefulness of MMMM becomes clearer when Model 3 shows that team-level effects of diversity on dependent variables are not as strong as the effects of individual-level variables. The final Model 3 adds the team-level variable of multidisciplinary diversity. A Likelihood Ratio Goodness-of-Fit Test shows that variance in the teams' multidisciplinary diversity is positively related to diversity in the email network at the individual level, but is not related to diversity in the face-to-face network.

Model 3 shows that an increase of one standard deviation of multidisciplinary diversity within teams is associated with a 1.176 standard deviation of diversity in the email network. Team diversity is about four times stronger than individual motivations to participate in multidisciplinary collaboration on participation in the email network. The composition of disciplines in the research teams more powerfully affects the email networks than the face-to-face networks. We believe this is because email contact is more voluntary than face-to-face contact as much face-to-face contact in the spatially dispersed teams comes from occasional specially organized team or GRAND-wide meetings.

MMMMs also elaborate upon the relationships between the individual-levels under the team context. The findings show that diversity in the GRAND members' email networks, in comparison to that in their face-to-face networks, is more significantly associated with other factors: affiliation with more diverse teams, motivation for participating in diverse networks, role in GRAND as NIs, visible academic productivity (G-index), and being male.

Discussion

Our study contributes to the current scholarly conversation that organizations should adopt structural and technological changes such as MTMs and technologies to foster the development of networks among workers and build better communication bridges among them (Bertolotti et al., 2015).

We show that MTM and the use of technology matter for the development of diverse networks among workers, especially in research settings. Focusing on diversity as a main element of MTM, we asked (1) how diversity in teams is associated with diversity of individuals' own networks that expand beyond team boundaries, and (2) how such impacts vary on both online and offline networks. Using a social network approach, we show strong differences in the email networks of the GRAND scholars, with email networks being more affected by the nature of the research teams in which the scholars were embedded. We also show that diversity in teams is positively associated with diversity in individuals' email networks rather than face-to-face communication networks.

Our findings are consistent with O'Leary et al.'s (2011) theoretical model proposing that MTM diversity has positive effects on individual and team learning. When researchers established a diverse communication network that consists of members from various disciplines, they are engaged in learning and developing knowledge. MTM as a unique structural characteristic in networked organizations is able to help researchers develop diverse online networks, and thus enables individual and team learning online. Our findings use a social network perspective to help understand relationships between MTM and individual and team learning.

In communication studies, scholars have been debating whether technology or face-to-face communication can improve team performance and productivity. Although strategic use of digital media is able to facilitate and better communication of dispersed teams (Olson et al., 2008), research has identified problems with heavy reliance on technology (Chamakiotis et al., 2013; Chen & McDonald, 2014). Our study supports the idea that technology use is beneficial for teamwork and collaboration. Team members can use email to diversify their networks in networked organizations and thus faciliate their learning and boundary-spanning knowledge exchange.

Our results further expand our knowledge about the relationship between MTM, email, and dispersed teams. Researchers assume that MTM is more likely to see dispersed teams that are often pulled together from various disciplines (Chamakiotis et al., 2013; Cummings & Haas, 2012). However, GRAND researchers' face-to-face network is more diverse than their email networks. This occurs because such networks are formed beyond formal team boundaries thanks to GRAND's adoption of MTM and its organizational promotion of networking among members. Nevertheless, our findings show that using email significantly allows researchers to diversify their networks online. In other words, MTM provides the members with a network structure to develop diverse networks and technology use reinforces such practices online.

Methodologically, this study is the first to use MMMMs to compare email and face-to-face networks developed through MTM. Fitting MMMM to multilevel networked organization data achieves several goals. First, it has enabled us to elaborate how the composition of multiple teams jointly influences individuals' networks in these teams. MMMM is particularly useful when individuals are affiliated with a variable number of groups so that a nested hierarchical analysis is not possible. Additionally, analyzing the joint characteristics of teams and individuals can provide powerful information about individuals' networking behavior. In this case, we have seen how email networks have a quite different nature than face-to-face networks.

Second, our findings show that MMMM can investigate multiplexity by comparing the impact of team characteristics on different types of ties at the individual level (Boase, 2008). For example, we found that the disciplinary diversity of teams affects the characteristics of email networks more than it affects face-to-face networks.

Third, we have shown that MMMM affords the examination of the relationships among individual-level variables with the nuances of the combined contexts of multiple teams. Our example revealed that cross-level effects, though treated more as an inherent structure in the form of affiliation networks, provide a good fit to the data as well as simplifying the complexity of understanding meso-level data. Importantly, we show that team characteristics affect individual workers' behavior.

Implications for understanding networked organizations

Although our research focuses on scholars' email and face-to-face networks scholars, it has broader implications for understanding the dynamics of networked organizations. The networked society has fostered more need for people who can bridge multiple realms, bringing information from one realm to others (Burt, 1993; Rainie & Wellman, 2012). In such milieus, networked organizations flourish where workers bring knowledge that goes beyond specific tasks to be applicable to a range of activities. There has been a major growth of such organizations, where, like GRAND, employees are members of multiple teams that are often spatially dispersed across cities and continents. As early as 2008, 41% of American workers belonged to multiple teams (Madden & Jones, 2008). Like GRAND, the composition and structure of networked organizations are complex. Team members are only partially committed, as they often work in multiple teams almost simultaneously. Networks are multidimensional and multilayered, as relationships develop and span fuzzy boundaries between new forms of work units. With the growth of digital media, many teams connect members in far-flung locations (Krebs, 2007; Larson & Starr, 1993; Rainie & Wellman, 2012).

Some researchers have examined if online is inferior to offline communication since it may cause misunderstanding, distrust, and conflicts, which make it difficult to develop online community among workers (see the reviews in Dimitrova & Koku, 2010; Olson & Olson, 2000). However, our study shows that using email, GRAND researchers can develop networks beyond team boundaries and disciplinary boundaries. This finding implies that workers in networked organizations can use email to diversify their networks. By being constantly connected and available on email, workers can gradually develop a sense of online community.

The MMMM approach usefully conceptualizes multilevel networks in networked organizations by shedding light on the cross-level role of MTM or affiliation ties. Developed from Breiger's theory of duality of persons and groups (1974), the MMMM approach captures the inherent network structures of teams, the static affiliation networks at the meso-level, and rather dynamic and flexible networks at the individual level. It also acknowledges the important role of the affiliation ties that link each individual to multiple teams: they channel the features of each team generated from its unique formal structure to members and affect the development of individuals' ego networks beyond formal team boundaries. The approach is also useful for revealing complex mechanisms operating in multilevel networked organizations. MMMM can be used to evaluate how MTM can foster more flexible work, efficient information flows, better use of resources, and greater opportunities for the creation of innovation.

We have shown that the MMMM approach can to address key questions in relation to MTM and multilevel networked organizations, where higher-level work units still define members' practice to some degree, but members can develop their networks across work units. Such a modeling approach is important in the switch from nested, hierarchical organizations to networked organizations where individuals are affiliated with multiple teams.

MMMM can provide insight into cross-level interactions within multilevel networked organizations. For example, we are able to show how the composition of team networks jointly affect individuals' position in their ego networks (e.g., centrality), or their networking behavior (e.g., reciprocity), as well as compositional features of their ego networks (e.g., diversity) (Mo, 2015).

Limitations

While we are pleased with the usefulness of MMMM, we, however, note several limitations. First, MMMM does not permit us to specify which particular teams are affecting multiply affiliated individuals. We can only know about the overall effects of team characteristics. Second, rather than examining the patterns of ties at the team level or the relationships between ties, MMMM analyzes the relationships between team- and individual-level networks. It does not elaborate on group-level dynamics. Third, MMMM in its current form is not able to examine random slopes. It would be informative to explore ways for MMMM to incorporate random slopes to understand relationships between individual-level variables that vary across team-level units. Fourth, MMMM cannot be applied to multiteam situations where teams are interdependent with each other because it assumes the independence of teams (Shuffler, Jimenez-Rodriguez, & Kramer, 2015). We look forward to further work discovering how MMMM works within the context of MTM in networked organizations.

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