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Teammate Invitation Networks: The Roles of Online Recommender Systems and Prior Collaboration in Team Assembly

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Abstract

Teammate invitation networks are foundational for team assembly, and recommender systems (similar to dating websites, but for selecting potential teammates) can aid the formation of such networks. This paper extends Hinds, Carley, Krackhardt, and Wholey's (2000) influential model of team member selection by incorporating online recommender systems. Exponential random graph modeling of two samples (overall $N = 410$; 63 teams; 1,048 invitations) shows the invitation network is predicted by online recommendations, beyond previously-established effects of prior collaboration/familiarity, skills/competence, and homophily. Importantly, online recommendations are less heeded when there is prior collaboration (effect replicates across samples). This study highlights technology-enabled team assembly from a network perspective.

Keywords: invitation networks; team formation; recommender systems; team assembly; exponential random graph models

Introduction

In large multinational organizations, distributed work arrangements among people without strong prior relationships are common (Hinds & Cramton, 2013). Relatedly, many individuals are first exposed to their new collaborators in virtual settings (J. Cummings & Dennis, 2018)—a trend likely to continue due to the explosion in virtual remote work. Before the widespread adoption of virtual collaboration, assembling teams in a co-located work context was reliant upon activating personal relationships, partnering with others who had positive reputations, and demographic homophily (Hinds et al., 2000b). We here extend Hinds et al.'s (2000) classic model of teammate selection by incorporating a new technology that can support the emergence of teammate invitation networks: automated recommender systems that suggest potential new teammates to invite.

The promise of teammate recommender systems, similar to the promise of recommender systems for online shopping, resides in their potential to help the decision maker filter a multitude of potential options quickly in a manner that satisfies user objectives (e.g., choosing team members who will enhance team effectiveness, team diversity, etc.). The current study answers the practical question of whether project team members will follow the advice of recommender systems while choosing teammates, and highlights boundary conditions for when online recommendations are more (versus less) likely to be heeded. At this point, we draw an important distinction between "online recommender systems" and "online reviews." An online review is a review, rating, or recommendation that is written by an individual and then posted online (e.g., Amazon product reviews and Yelp business reviews). In contrast, a recommender system in our study context refers to algorithmically-generated suggestions with the purpose of filtering down the number of options the decision-maker must consider (e.g., Amazon's "related to items you've viewed"), which are the output of traditional recommender systems (Resnick et al., 1994; Resnick & Varian, 1997). In general, online recommender systems (similar to dating websites) can play a role in helping people build meaningful relationships in the workplace too (Guy, 2015; Terveen & McDonald, 2005). According to Terveen and McDonald (2005), using online recommendations in social settings is "semi-automated matchmaking" (p. 402) and assists people in finding and making new connections. As such, in the remainder of the paper we use the terms online recommendations and recommender systems to refer specifically to the recommendations that are produced by algorithmic online recommender systems, and not to online reviews. We seek to understand the effect of such recommender systems on teammate invitation.

The importance of this topic lies in the fact that teammate invitation is often an early step in the process of team assembly. Team assembly comprises both the relationships and activities invoked as people organize into teams (Contractor, 2013; Humphrey & Aime, 2014). Teammate invitation is only one stage in the larger team formation process, with team formation stages including teammate search (e.g., matching individual attributes with individual preferences, as done by the recommender system), teammate invitation, teammate response (accepting or declining invitation), and team composition (Gómez-Zará et al., 2019). The current study focuses on teammate invitation, and inferences about downstream effects on team formation and team composition are therefore necessarily speculative. Overall, the team assembly process undergirds team composition, which influences a team's ability to accomplish organizational tasks and achieve desired performance (Mathieu et al., 2017; L. L. Thompson, 2018); as well as team diversity, which is also connected to team performance in particular contexts (Joshi & Roh, 2009). Whereas the main priority of modern team assembly is the formation of teams capable of solving complex and interdisciplinary problems (J. N. Cummings & Kiesler, 2005, 2007, 2008), the initial first step is inviting potential collaborators who can be expected to meet task demands. Indeed, by engaging with recommendations, users can directly control team diversity and average team member performance by influencing how individuals with particular attributes are distributed into teams (Gómez-Zará et al., 2019, 2020).

Additionally, current research integrates considerations of how technology usage and social networks co-exist during team formation processes, which has been a largely under-explored relationship in previous literature on team assembly (Twyman & Contractor, 2019). We presently extend research on team formation by modeling the teammate invitation networks that precipitate technology-enabled team assembly via an online recommender system. The current study investigates recommender systems as an aid to uncertainty reduction in the teammate invitation process, identifying boundaries for when recommendations are followed during the invitation of potential collaborators to a team. In the study, an online recommendation system creates an environment for team formation by providing interfaces to search for teammates, review matches to explicitly-stated preferences, and invite potential teammates.

Teammate invitations signal interest from one person to another and constitute an invitation network that directly results in team formation. By investigating the invitation network during technology-enabled team assembly, we observe the initial interaction between prospective teammates. When choosing team members, individuals use multiple types of information to reduce uncertainty around a collaboration. According to the theory underlying Hinds et al.'s

(2000) model of team member selection, several individual and relational attributes are proposed to serve as *uncertainty reduction mechanisms* (around a team's future performance): familiarity, competence, and homophily (p. 228). Whereas each of these antecedents of teammate invitations is theoretically and empirically supported, none of them considers the effects of online technology, which has noticeably shifted the nature of modern work (Colbert et al., 2016; Zammuto et al., 2007). For example, IBM is a global organization with over 100,000 employees. The size of the organization makes search and locating experts across the organization a non-trivial business challenge. To remedy the situation, IBM has developed numerous recommendation systems to help locate experts and replace team members, such as the SmallBlue project for social networking (Alkan et al., 2018; Li et al., 2015; C. Y. Lin et al., 2009). Additionally, business-oriented social media applications like LinkedIn have recently incorporated measures of bias and fairness to implement a framework that includes *fairness criteria* (e.g., regarding personal demographic data) when ranking LinkedIn users in LinkedIn Talent Search, which impacts professional hiring opportunities for over 630 million LinkedIn users (Geyik et al., 2019). In the current study, we extend understanding of teammate selection by investigating: (a) the role of recommender systems as an antecedent to teammate invitation networks, (b) the possibility that recommender systems operate beyond and interact with previously established mechanisms for teammate selection, and (c) endogenous network effects in teammate invitation networks (e.g., popularity, network closure).

Applying a social network perspective is key to our explanation of teammate invitations and the relevance of online recommendations. Previous research has established the importance of social networks when selecting team members. For example, teams of members with diverse network ties are able to access more varied information sources within an organization (Gao et al., 2013; Hinds et al., 2000b; Reagans et al., 2004). We here integrate considerations of individual attributes, relational attributes, social networks, and technology, to explain the process of teammate invitation. Therefore, we propose a multitheoretical, multilevel model for analyzing the emergent teammate invitation networks inherent to team assembly (Contractor, 2013; Contractor et al., 2006; Monge & Contractor, 2003), and we test this model using exponential random graph modeling (ERGM).

Theory and Hypotheses

Team assembly for project teams can often involve team members' selecting their own teammates (Contractor, 2013; Hackman, 1987). In the generative model of team member selection proposed by Hinds et al. (2000), they focused theoretically on uncertainty reduction in the choice of would-be teammates. This builds upon Thompson's (1967) and Kanter's (1977) work highlighting uncertainty reduction as a means of reducing threats to the organization's objectives and maintaining organizational control. For context, this theoretical perspective on uncertainty reduction as a basis for teammate selection thematically echoes classic research, which proposed uncertainty reduction in service of risk management while pursuing organizational profits (Knight, 1921), and as a mechanism underlying societal preference for hiring privileged workers (Piore, 1978). The particular instantiation of uncertainty reduction articulated by Hinds et al. (2000) entails choosing teammates with the goal of reducing uncertainty about how well the potential teammate will fit in the team, in terms of both task performance and social integration/coordination. This results in a focus on individual characteristics of the potential teammate that would improve confidence in that teammate's ability to contribute to the success of the group. Hinds and colleagues thus specify three distinct uncertainty reduction mechanisms in teammate choice, which rely upon increasing amounts of interpersonal interaction: (a) observing gender and race homophily (i.e., demographic similarity between the individual choosing teammates and their preferred teammates), (b) recognizing another individual's reputation for competence, and (c) having personal familiarity from a prior collaboration with an individual.

Reducing uncertainty involves assessment of surface-level characteristics (i.e., demographic, or detectable attributes) and deep-level characteristics (i.e., personality, skills, or underlying attributes) deemed relevant for team performance goals (Bell, 2007; Harrison et al., 1998). Such individual attributes then aggregate to constitute a team's composition (Klein & Kozlowski, 2000). The skills and competence within a team are critical for determining the team's aggregate ability, configuration of skills, and member roles (Kozlowski & Ilgen, 2006). However, assessing characteristics from the surface to deep-level becomes progressively more challenging because observing deep-level characteristics (e.g., competence and personality) typically requires interpersonal interaction with the person, or at least interactions with others who know the person.

In the model proposed by Hinds et al. (2000), the three uncertainty reduction mechanisms relate to both surface and deep-level characteristics gleaned from increasing amounts of interpersonal interaction: observing demographic homophily (surface-level attributes), acknowledging another individual's reputation for competence (deep-level attributes), and having personal familiarity with another individual (deep-level attributes). Observing demographic homophily only requires that an individual judge the appearance of another person and then assess similarity to their own appearance; homophily can manifest in a desire to work with similar others or those who belong to the same social groups (Kossinets & Watts, 2009; McPherson et al., 2001; Ruef et al., 2003; Wimmer & Lewis, 2010). On the other hand, acknowledging another individual's reputation for competence is a more deliberative social process, in that it depends on "socially shared information as people signal their own value and search for indications of others' competence" (Hinds et al., 2000b, p. 233). Last, gaining familiarity with another individual is an even more demanding process because it requires building a relationship with another person and amassing direct experience working together. Overall, these considerations have implications for team performance because team member relationships, competence, and homophily in a team all affect task coordination, communication to external groups, and access to new ideas (Ancona & Caldwell, 1992; Harrison et al., 1998; Harrison & Klein, 2007; Reagans et al., 2004; Williams & O'Reilly, 1998).

Considering multiple attributes and combinations of attributes in potential teammates is a complex task. Relatedly, researchers have long understood that integrating technology into organizational work practices can help individuals manage complexity and meet task demands (Cherns, 1976; T. G. Cummings, 1978). In recent years, new technology has been designed to aid the teammate selection process by optimizing the fit between team members based on matching algorithms involving different combinations of attributes and relationships (Ding et al., 2017; Jahanbakhsh et al., 2017). For example, a technology platform developed by Bergey and King (2014) used a series of algorithms to generate teams that performed better than teams assembled by a subject matter expert. Additionally, the technology-generated teams were "balanced in terms of demographics, undergraduate degree, work experience, general intelligence, and personality"

(Bergey & King, 2014, p. 124). While this type of technology does not change whether people have attributes that are relevant or in-demand for teamwork, they do automate team member assignments by attempting to optimally fit people into teams. The introduction of such technology seeks to fulfill the purpose of reducing the uncertainty inherent in team assembly when there are many potential teammates from whom to choose.

Attending to Teammate Recommendations

When individuals are first introduced to one another, their interactions are guided in part by the motive to reduce uncertainty (Berger & Calabrese, 1975; Kramer, 1999). In this context, utilizing teammate recommender system technology opens up the possibility of more efficiently gaining access to some deep-level information about many potential teammates, without needing to directly engage with a large number of candidates. As such, the use of recommendation system technologies introduces a novel mechanism for reducing uncertainty when selecting potential teammates, which enables the decision maker to scale up, at minimal cost, the number of other individuals about whom one can access deep-level information. We next elaborate on how such technologies can serve as an uncertainty reduction mechanism.

In general, recommender systems calculate matches between a set of objects and a set of preferences, and then display the matches to a user who is searching for or wishes to be exposed to a specific kind of object (Resnick et al., 1994; Resnick & Varian, 1997). These systems have the capacity to transform, organize, and present complex information in ways that guide and suggest actions to people who need to make choices from a large set of options (e.g., potential teammates in this case; see Lazer, 2015; Xiao & Benbasat, 2007). Recommender systems vary in their degree of sophistication. One version helps individuals make their own choices about teammates by providing recommendations of potential teammates that match the individual's stated preferences, on both surface-level attributes such as demographics and deep-level characteristics such as personality types and skills sets (Guy, 2015; Jahanbakhsh et al., 2017; Terveen & McDonald, 2005). As such, it is akin to the result rankings one gets from a search engine in response to a query.

More sophisticated recommender systems use algorithms to autonomously match an individual with other individuals, products, and/or services based on rules and algorithms embedded in the technology, and they can either introduce a user to new people or help a user reinforce already-established relationships (Guy et al., 2009, 2011). Often these algorithms *learn* from the success of prior matches as well as surface and deep level characteristics of the individuals. Online recommender systems have further been used for personnel management to help differentiate and rank candidates for jobs and academic programs (e.g., LinkedIn, Geyik et al., 2019; Waters & Miikkulainen, 2014)—a practice that is mimicked by recommender systems designed for teammate selection. In the context of team assembly, a question prompted by the increasing popularity of these recommender systems is: to what extent does the information contained in online recommendations still affect the teammate invitation network, when the potential target of a teammate invitation is someone whom you already know?

The act of recommending another person is a common behavior in professional settings. When considering the labor market, workers often try to find jobs by engaging their social networks, including relatively weaker connections (Granovetter, 1973). Past research has dealt with old-fashioned interpersonal recommendations (not using recommender systems) in the context of job search (Fernandez et al., 2000; Montgomery, 1991; Smith, 2005, 2012). This research has shown that referrals are largely related to social relationships, perceptions of potential job match, and applicant reputations; and further claim that organizational productivity benefits from hiring recommended applicants. The current paper likewise assesses recommendations in an organizational context, but importantly involves recommendations generated by a computer algorithm (not interpersonal recommendations) and their consequences for teammate invitations (not job applications). So the current study addresses a phenomenon distinct from the job search recommendation literature.

Recommender systems compute social matches, initiate social relationships, and are commonly embedded in applications that leverage rich user data (e.g., dating and social network websites) (Finkel et al., 2012, 2016; Geyik et al., 2019; Kautz et al., 1997; K.-H. Lin & Lundquist, 2013; Maldeniya et al., 2017; Pizzato et al., 2013, 2010). Social matches are produced when recommender systems perform two functions: finding a user's current contacts, and introducing a user to strangers (Chen et al., 2009; Guy et al., 2009, 2011). In the organizational environment, there is often a need to find people who have specific expertise or experience, and recommender systems include techniques for finding available expertise (Guy, 2015; C. Y. Lin et al., 2009; Shami et al., 2008). Leveraging large quantities of information to recommend new team members helps people efficiently replace team members or find new members within geographically distributed settings (Brocco & Groh, 2009; Li et al., 2015). Because recommender systems are designed to aggregate user preferences in the context of numerous alternatives, we believe they will demonstrate some utility for guiding teammate selection in online project teams.

H1. Individuals are more likely to send a teammate invitation to potential teammates who have been more highly recommended by the online recommender system.

Although this hypothesis is intuitive, it provides a simple assessment of whether the teammate recommender system meets its baseline goal of influencing teammate choice. The counterfactual would be a nil effect, where the online recommendations are not used much in teammate selection. Next, this main effect of online recommendations is evaluated in light of its potential boundary condition—to determine whether online recommendations are still utilized even when uncertainty has already been reduced via prior collaboration with the would-be teammate.

Re-Engaging Prior Collaborators

Having experience working with a given individual on a past project team can be beneficial for future collaboration with that individual, because there is a level of familiarity that reduces the uncertainty associated within the newly-formed team (Hinds et al., 2000b). Familiarity enhances teamwork because it gives team members, "information about others, such as their preferences, routines, values, and expertise" (Okhuysen, 2001, p. 796). Once familiarity develops, it suggests that team members can be attracted to one another, have an established set of norms, and can resolve task and social conflicts more effectively (Gruenfeld et al., 1996; Okhuysen, 2001; Shah & Jehn, 1993; Van Zelst, 1952). A team that possesses a shared and accurate understanding of the expertise that exists within that team will benefit from member's ability to access relevant expertise and experience related to positive team performance (Faraj & Sproull, 2000; Reagans et al., 2005; Ren & Argote, 2011; Wegner, 1987, 1995). In addition, prior collaborations allow members of a team to devote time to orienting themselves to the task and the current capabilities of others, while not spending as much time establishing new social norms, which were already partly developed via past collaboration. Familiarity among team members has been shown to improve team performance, such that even modest degrees of familiarity (i.e., working together on a team task once or twice before) can produce the same team performance benefits as high degrees of familiarity (i.e., living in the same house; (Harrison et al., 2003). Thus, inviting teammates by relying on the prior collaboration network helps a person establish more accurate expectations for future collaboration. Given that the robust effect of prior collaboration on teammate selection has been previously established (Hinds et al., 2000b), we do not advance this as a novel hypothesis in the current paper. Nonetheless, we do expect the effect of prior collaboration on teammate invitation to replicate in the current study.

The Interplay between Prior Collaborations and Teammate Recommendations

Thus far, we have hypothesized main effects of both online recommender systems (recommendations) and interpersonal familiarity (priori collaboration) on the teammate invitation network, extending the work of Hinds et al. (2000). We note that recommendations in general serve as endorsements to help a person who is choosing among a pool of candidates (Fernandez et al., 2000; Fernandez & Weinberg, 1997). When inviting teammates, online recommendations expose the invitation sender to potential teammates, if those teammates meet some specified criteria. What is unknown is how online recommendations influence the teammate invitation network, both alone and in the presence of prior collaborations. Because both online recommendations and prior collaborations commonly serve to reduce uncertainty about a team's future performance, the two might be conceptualized as functionally redundant sources of information.

As such, we posit that the effect of online recommendations depends upon whether one has engaged in prior collaboration with a potential teammate. In particular, when the potential teammate is someone who is unknown and who has not worked (zero contact or zero acquaintance) with the inviter before (Albright et al., 1988; Amir, 1969; Harrison et al., 1998), then online recommendations might be the only source of information available about the target individual. In such information-impoverished circumstances, one is especially likely to follow advice provided by the recommender system.

H2. The relationship between online recommendations and teammate invitation is moderated (buffered) by prior collaboration, such that online recommendations have a weaker effect on the likelihood of sending a teammate invitation when the potential teammate is a prior collaborator.

It is important to clarify that we are proposing an interactive effect (i.e., a multiplicative effect, or more specifically a substitution effect) between online recommendations and prior collaboration. When there has been a prior collaboration, the value of the online recommendation for uncertainty reduction becomes smaller, because the invitation sender already possesses a great deal of information about the prior collaborator. Familiarity removes the value of a recommendation. Hypotheses 1 and 2 are depicted in Figure 1, which summarizes the proposed effects of online recommendations and prior collaboration on teammate invitation.

—Insert Figure 1 about here.—

Method

Data and Sample

Data were collected from student project teams using a teammate recommender system that provides online recommendations. The system also included functionality for exchanging teammate invitations. Students from two universities were enrolled in an interdisciplinary, dual-university course; social psychology students at one university were linked to environmental ecology students at another university. The course was offered in two consecutive years (2014 and 2015) generating two independent samples of participants (labeled Samples 1 and 2, which serve as exact replications of each other). Over a period of twelve weeks, participants in each sample were required to collaborate in dual-university (geographically distributed) teams to complete a term project simulating an advertising campaign to mitigate an environmental sustainability issue. Sample 1 includes 213 participants (47 percent female; mean age = 20.8 years, SD = 2.79 years) in 32 interdisciplinary, dual-university teams (mean team size = 6.65; SD = 0.48); Sample 2 includes 197 participants (54 percent female; mean age = 21.1 years, SD = 2.57 years) in 31 interdisciplinary, dual-university teams (mean team size = 6.35; SD = 1.25). There were no significant differences between samples with respect to team size, gender representation, or age.

Procedure

Participants selected their own teammates using a teammate recommender system. Over a five-day period, participants used the system to form teams of five to seven members. Individual-level data were collected through an online survey administered during registration in the system prior to team assembly. Participants answered survey questions about different attributes, including demographics, pre-existing relationships, competence, and other characteristics. Then, participants performed searches based on the survey responses by explicitly entering their teammate preferences into the teammate recommender system. For each attribute, the system included options for the attribute's importance (from one to four stars) and the number of desired teammates with the attribute (one, some, or all). The searches serve as input data for a ranking algorithm that returns an ordered list of potential teammates based on the degree to which they match the stated teammate preferences. After receiving the online recommendations from the ranking algorithm embedded in the platform, participants reviewed other participants' profiles and exchanged invitation messages to form the teammate invitation network for the purpose of self-assembling into teams.

Measures

Teammate Invitation Network (Dependent Variable). Invitation messages to potential teammates were exchanged between participants over five days and collected using digital trace data generated by the teammate recommender system. The traces are a complete record of all invitations, including the sender and receiver. From these data, a binary directed social network was constructed, where nodes are the participants and links are the invitations sent from one participant to another.

Online Recommendations. The teammate recommender system rank-ordered a list of potential teammates matched to a searcher's stated preferences. These matches are recommendations from the ranking algorithm. The system recommended potential teammates by calculating a cumulative score for potential teammates based on their self-reported survey responses (attributes) collected during registration, and the searcher's stated preferences. For each stated preference, the corresponding potential teammate's attribute was scored by multiplying the attribute's value by the searcher's selected importance. Then, all attribute scores were summed together to create the cumulative score for each potential teammate. Because not all attributes were required to be selected as preferences, the cumulative score was then divided by the number of selected attributes in the search. These scores were calculated for all participants except for the searcher, and they were automatically converted by the algorithm into a rank-order from one to the sample size N-1 (excluding the searcher).

When a searcher performed multiple searches, only the single highest recommendation ranking achieved by a potential teammate was used for analysis. Therefore, in the dataset, each searcher has one list of potential teammates with each potential teammate's best ranking. The online recommendations are then transformed into a directed social network where the nodes are the participants, and a tie is directed from a searcher to a potential teammate. The online recommendations network (e.g., containing ranks from 1 to 212 in Sample 1 and ranks from 1 to 196 in Sample 2) is dichotomized, with a value of 1 assigned to the top-ten ranked potential teammates, and a value of 0 assigned otherwise. We also investigated other dichotomization cutoffs, as described in the Results section.

Prior Collaborations. A network roster survey was administered online during participant registration in the system, with the roster including names of all other people in the course across both universities. Participants responded to the relationship question, "With whom have you previously worked?" by checking the names of prior collaborators. The general nature of the survey question was designed to encapsulate any prior work experiences among participants without overburdening participants by requesting that they recall specific information about past experiences (Marsden, 1990). Responses were used to construct a binary directed network (coded 1 if the respondent selected a prior collaborator, and 0 otherwise).

Controls. Participant competence is included as a control in the analyses. The competence measure was created from self-ratings on a 3-item project skills inventory. Participants were asked to, “Please indicate your level of skill in the following areas” (ratings from “1 = Not at all skilled” to “5 = Extremely Skilled”), and the rated project skills were: “Using communication technology,” “Writing and preparing professional reports,” and “Publishing, print media, and/or design” (Cronbach’s $\alpha = 0.64$ in Sample 1, $\alpha = 0.63$ in Sample 2). These project skills items were generated by consensus of the course instructors to capture the skills needed for success on the project. Participant gender was self-reported using the item, “What is your gender? (male, female, other);” every participant in the current samples was coded as male or female. The university affiliation for the participants was captured to assess differences between locations. From gender and university affiliation, we assessed two types of homophily. Responses to the gender item were used to create dyadic gender homophily variables for women who invite other women (adjacency matrix coded as “1” when both individuals are female, and “0” otherwise) and men who invite other men (coded as “1” when both individuals are male, and “0” otherwise), respectively. The same university affiliation is a shared dyadic attribute for participants who attend the same university.

Analytic Approach

Hypothesis testing in the teammate invitation network is conducted using the p*/exponential random graph modeling (ERGM) approach (Lusher et al., 2013; Robins, Pattison, et al., 2007; Robins, Snijders, et al., 2007; Snijders et al., 2006). ERGMs are capable of simultaneously modeling the effects of endogenous network structure, individual attributes, shared attributes between individuals (e.g., homophily), and relationships between networks (e.g., H1 and H2). The conceptual framework that accompanies ERGM has delivered useful insights in recent organizational and strategy scholarship by allowing researchers to broaden their explanation of relationships in organizations while accounting for mechanisms that influence network structure (Contractor et al., 2006; Kim et al., 2016; Monge & Contractor, 2003). With ERGM, multiple types of relationships have been explained in recent years, e.g., communication in online communities (Faraj & Johnson, 2011), information, support, friendship, and advice networks (Lomi et al., 2013; Rank et al., 2010); and product team communication based on technical design interdependencies (Sosa et al., 2015). In the current study, measures at the individual, dyadic, and network levels of analysis including endogenous network structure are described in Table 1. Table 1 is derived from Kim et al. (2016) and Lusher et al. (2013).

—Insert Table 1 about here.—

Because teammate invitations are a social network, it is essential to account for several endogenous network structures that may be responsible for its formation (Lusher et al., 2013). Accounting for these structural interdependencies allows for a more accurate specification of the hypothesized effects (Snijders et al., 2006). When specifying exponential random graph models (ERGM), several network effects can be estimated (see Table 1 for a summary). The *arc* pattern refers to the likelihood that a link will be randomly created from one person to another (e.g., sending a teammate invitation). Another common endogenous network structure in social interactions is *reciprocity*, which refers to the likelihood that a person will create a link to a person from whom they received a link (e.g., inviting an inviter). *Activity* and *popularity* refer to tendencies for individuals to have more outgoing or incoming links than are expected by chance (e.g., active inviters, popular invitees). The calculation of these hub structure statistics produces positive estimates when actors have the same amount of activity or popularity in the distribution of invitations and produces negative estimations when there is a skewed distribution of invitations. Clustering in social networks is also common when people belong to invitation chains and send invitations to the same others (*multiple 2-paths*; e.g., common invitation). Triadic closure occurs when sending an invitation to a person who is already indirectly tied with the sender via an intermediary (*generalized transitive closure*). Each of these endogenous network structures is potentially theoretically interesting in the context of team assembly, but the current study uses them as controls to avoid biased estimates when testing the hypothesized effects (Lusher et al., 2013).

ERGM is similar to logistic regression, except that the log-odds for each parameter estimate must be calculated conditional on the rest of the network. Therefore, the size and direction of an effect is *conditional* on the other effects in the model when interpreting the parameter estimate (Lomi et al., 2014). The model for the teammate invitation network predicts whether an invitation has been sent or not (1 or 0). For example, if the predictor variable is prior collaborations and its coefficient B from the ERGM model is $B = 0.69$, then it suggests a positive relationship between having a prior collaboration with a person and sending a teammate invitation to that same person, conditional on the other effects modeling the network. The exponent of the coefficient [e^B] is the odds ratio. In the current example, $e^{0.69} = 2.0$, which means that the odds of sending a teammate invitation are twice as high if there was a prior collaboration between the sender and recipient. The parameter estimates and odds ratios for this study were calculated from maximum likelihood estimation (MLE) of a Monte Carlo Markov Chain

(MCMC) simulation process, using the "statnet" package in the open software R (Handcock et al., 2014; Hunter et al., 2008).

Results

Results are presented in three components: (a) descriptive statistics and correlations among individual-level variables, (b) descriptive statistics and correlations among network-level variables, and (c) ERGM model estimates predicting teammate invitations, which are used to test the hypotheses. As shown in Table 2, the individual-level measures (gender, university affiliation, and competence) are not significantly correlated. Table 3 displays descriptive statistics and correlations among network-level variables (teammate invitations, online recommendations from the recommender system, and prior collaborations), revealing that quadratic assignment procedure (QAP) correlations among all three network-level variables are positive and statistically significant: teammate invitations are correlated with both online recommendations ($r = 0.10$, $p < .05$, Sample 1; $r = 0.10$, $p < .05$, Sample 2), and prior collaborations ($r = 0.14$, $p < .05$, Sample 1; $r = 0.21$, $p < 0.05$, Sample 2).

—Insert Tables 2 and 3 about here.—

See Table 4 for the ERGM analyses that test the hypotheses regarding teammate invitations while controlling for the endogenous network effects, individual effects, and dyadic effects. Model 1 is a baseline model estimating the likelihood of an invitation using only endogenous network effects, sender and recipient competence, gender homophily (female and male), and university affiliation. Interpreting this baseline model supports inferences regarding the emergence of the teammate invitation network.

In the baseline model (Model 1, Table 4), several effects are significant and replicate across both samples. Sending a teammate invitation (arc effect in Table 1) is negative and significant ($p < 0.001$) meaning it is not likely for people to send a teammate invitation to a random person. The effect reflects the observed sparsity of the teammate invitation networks. In both samples, invitation senders appear to be selective and exercise discretion when selecting potential teammates to invite. Inviting an inviter (reciprocity effect in Table 1) was positive in both samples, but only significant in Sample 1 ($p < 0.01$). Reciprocity appears as an artifact of the social technology interface design; participants did not have to review their "received invitations"' before deciding to invite a person, which made it possible for a person to invite someone who already invited them. Therefore, the positive effect captures reciprocity in teammate invitations when members of a dyad both invite one another. In the "statnet" software package, the "activity" and "popularity" parameters are calculated such that a positive estimate indicates a uniform distribution of ties among actors whereas a negative estimate indicates an inequitable distribution (Hunter, 2007). The presence of popular recipients is indicated by a negative and significant popularity effect ($p < 0.001$). Therefore, the interpretation of a negative estimate in this model signals popular recipients exist and are more likely to receive teammate invitations. On the other hand, the presence of active inviters was not statistically significant, meaning no inviters were especially more active than other inviters (in terms of sending invitations). The higher-order endogenous network effects of common inviters ($p < 0.001$) and closure of invitations ($p < 0.001$) were significant in both samples. Common inviters (i.e., multiple connectivity/multiple two-paths) had a negative effect in both samples, while closure had a positive effect in both samples. As explained by (Quintane, 2013, p. 277), the combination of a substantial closure parameter with a small negative multiple connectivity parameter suggests a key feature of the network structure is the closure process, or "tendency for individuals to interact in denser grouplike structures."

The other control variables in Model 1 were competence, gender homophily, and sharing the same university affiliation (see Table 4). Because Table 4 presents conditional log odds, it is possible to convert these effect sizes into odds ratios (*OR*) by exponentiating (i.e., $e^{(\text{log odds})} = OR$), which helps with interpretation of results. While it could be expected that competence of a recipient would positively predict teammate invitations, surprisingly this effect is only significant in Sample 1 ($OR_{S1} = e^{0.10} = 1.11$; $p < 0.05$; $OR_{S2} = e^{0.01} = 1.01$; $p > 0.05$, n.s.). However, the competence of a sender is positive and significant ($p < 0.001$) in both samples. Competent people are more likely to send an invitation; $OR_{S1} = 1.55$ times more likely in Sample 1, and $OR_{S2} = 1.82$ times more likely in Sample 2. Participants with higher competence demonstrated greater agency by exerting control over team assembly and initiating teammate selection instead of passively waiting for invitations. Gender homophily was also a positive predictor of teammate invitations. Female homophily showed significant effects in both samples ($p < 0.05$ in Sample 1, $p < 0.01$ in Sample 2). Women were more likely to invite another woman to a team; $OR_{S1} = 1.22$ times more likely in Sample 1, and $OR_{S2} = 1.32$ times more likely in Sample 2. Male homophily was not significant in either sample. For university affiliation, there was also no evidence that being from the same university influenced the likelihood of sending or receiving teammate invitations.

Beyond the control variables, the models in Table 4 also test our two hypotheses. Model 2 tests Hypothesis 1. Hypothesis 1 stated that online recommendations positively predict teammate invitations. Using the online recommendations, the results support this hypothesis in both samples. People who are recommended by the online system are 5.29 times (Sample 1) and 4.15 times (Sample 2) more likely to receive teammate invitations ($p < 0.001$ in both samples; supporting *H1*). Meanwhile prior collaborations positively predict teammate invitations. Prior collaborations are statistically significant ($p < 0.001$) and exhibit the largest positive effect in both samples ($OR_{S1} = 17.21$, $OR_{S2} = 47.48$). People were much more likely to invite their prior collaborators to join a team. With the effects replicated across both samples, the ERGM models established the relationship between both online recommendations and prior collaboration predicting teammate invitations.

We next test Hypothesis 2, which states that prior collaborations dampen the positive effect of online recommendations on the teammate invitation network. Model 3 (Table 4) includes the interaction term between online recommendations and prior collaborations. As expected, the effect is negative and significant in both samples ($OR_{S1} = 0.36$; $p < 0.01$ in Sample 1; $OR_{S2} = 0.33$; $p < 0.05$ in Sample 2). This means that the relationship between online recommendation and teammate invitation is weaker when potential teammates already have a prior collaboration. The interaction effects are plotted in Figure 2. Figure 2 shows that when there is *not* a prior collaboration (dashed lines), the relationship between an online recommendation and sending a teammate invitation becomes more positive. However, when there is a prior collaboration (solid lines), the online recommendation has a weaker effect on teammate invitation. These results and plots show prior collaborations moderate the effect of online recommendations on teammate invitations, supporting Hypothesis 2 in both samples.[1]

[1] We conducted supplemental analyses to assess the sensitivity of the current results to the dichotomization point chosen for the recommendations ranking variable. We converted recommendations into binary "Top 1", "Top 2", "Top 3", through "Top 10" variables, and then reran Model 3 of Table 4 in both Samples 1 and 2. Across these 20 analyses, results of the supplemental

—Insert Table 4 and Figure 2 about here.—

Next, we conducted a goodness of fit assessment to clarify the consistency between the observed network and simulated networks from each ERGM (Hunter et al., 2008; Robins et al., 2009). For Models 2 and 3 (which are the basis of the hypothesis tests), plots for the goodness of fit (see Figures 3 and 4) demonstrate reasonable fits for all statistics. In each sample, there were one or two values in this distribution that were either over- or underestimated, but all other values followed the observed network. Using the Bayesian Information Criteria (BIC), both Model 2 and Model 3 exhibited significantly better fits than Model 1, which only included endogenous network effects and other control variables.

—Insert Figures 3 and 4 about here.—

Post Hoc Analyses

At the request of a helpful reviewer, we present cross-tabulations of the core variables to further show how teammate invitations, pooled across both samples, were distributed (Table 5). From the perspective of the hypothesized variables, a higher portion of prior collaborator dyads resulted in an invitation (29%; 105 out of 362), compared to the portion of system-recommended dyads that resulted in an invitation (8%; 309 out of 3,842). Regarding gender, among invitations sent to recommended targets, and also among invitations sent to prior collaborators, women sent more of these invitations than men (gender proportion is 0.63 and 0.61, respectively). Also, for invitations sent to recommended targets, sender competence was relatively high; in comparison to invitations sent to prior collaborators, for which sender competence was lower (4.20 compared

analysis showed that H1 (recommendations predicting invitations) was supported in all conditions regardless of the recommendation cutoff. However, H2 (recommendation × collaboration interaction predicts invitations): (a) was consistently supported in "Top 8" through "Top 10" recommendation cutoffs, (b) was supported in Sample 1 only for "Top 6" and "Top 7" recommendation cutoffs, and (c) was not supported or not estimable (due to linear dependence involving the interaction term and other model terms) for "Top 5" recommendation cutoffs and below.

to 3.60 on average out of 5). We additionally specified ERGM models to test the following interaction effects predicting teammate invitations: (a) competence $\times$ recommendation, (b) female homophily $\times$ recommendation, and (c) male homophily $\times$ recommendation. None of these effects was statistically significant across both samples.

—Insert Table 5 about here.—

Discussion

The current study extends Hinds et al.'s (2000) classic model of teammate selection by incorporating an online recommender system, while also leveraging contemporary ERGM analyses to explain the process of teammate invitation. Online recommendations from a social technology platform (similar to an online dating website for team assembly) have incremental effects on the teammate invitation network. Additionally, these technology effects are subject to the boundary condition that recommendations are only heeded in the absence of information from prior collaborations. That is, recommender systems can facilitate team assembly when the recommendations provide new information.

Results also lend some insight into the effect of gender homophily on teammate invitations. Women were more likely to invite other women to join a team. Inviting other women onto one's team can be an act indicative of self-categorization, where individuals attribute positive qualities to members of their in-group (Tajfel, 1981; Tajfel & Turner, 1979). However, from the ERGM results, the observed effects of female homophily disappeared once online recommendations and prior collaborations were added to the model (Table 4). These results suggest that homophily effects in teammate selection do not operate above and beyond the effects of online recommendation and prior collaboration, which implies in part that homophily/similarity processes may take effect through the familiarity mechanism because similarity breeds more frequent communication and cohesion (Harrison et al., 1998; van Knippenberg et al., 2004; Williams & O'Reilly, 1998). To formally confirm this idea, we ran additional ERGM analyses, which revealed both female homophily effects ($B = 0.58$, $p < .001$; and $B = 0.62$, $p < 0.001$) and male homophily effects ($B = 0.66$, $p < .001$; and $B = 0.40$, $p < 0.05$) in the prior collaboration network, in both samples.

Familiarity possesses information value in collaborative settings, because prior collaboration can be thought of as an uncertainty reduction mechanism (Crozier, 2009; Hinds et al., 2000a; J. D. Thompson, 1967) during teammate invitation. One proposed origin of familiarity is that people become attracted to others as they have more interaction (Akşin et al., 2020; Bornstein, 1989; Reis et al., 2011; Zajonc, 1968). When people choose to invite a prior collaborator to join a team, they are relying on their knowledge of the capabilities and attributes of that person based on direct past experience (Okhuysen, 2001). Having awareness of the abilities and limitations of teammates is necessary as teams develop their transactive memory system, which is the shared understanding of a team's expertise and knowledge as it contributes to team performance (Argote et al., 2018; Reagans et al., 2005; Ren & Argote, 2011). Therefore, inviting prior collaborators serves the goal of establishing a team in which members possess shared information and knowledge about team structures and dynamics (Mohammed & Dumville, 2001).

Nonetheless, in the absence of prior collaboration, online recommendations serve as a medium for exposing people to new information about potential teammates, and about how these potential teammates might match stated preferences. The recommender system thus served as a tool to aid uncertainty management (Brashers, 2001; Solomon & Vangelisti, 2010). On the other hand, in terms of team creativity, teams have sometimes been able to innovate by blending teams of prior collaborators with newcomers (Perretti & Negro, 2006; Taylor & Greve, 2006; Uzzi & Spiro, 2005). Nonetheless, newcomers—due to the lack of shared experiences—increase uncertainty when invited to join a team. For those instances in which newcomers or unfamiliar people must be invited to a team (e.g., when available previous collaborators do not possess the required expertise, or when fresh ideas are desired), online recommendations have utility for managing uncertainty in teammate selection.

Future Directions

Teammate invitation is only one stage in the larger team formation process, with team formation stages including teammate search (e.g., matching individual attributes with individual preferences, as done by the recommender system), teammate invitation, teammate response (accepting or declining invitation), and team composition (Gómez-Zará et al., 2019). The current study focuses on teammate invitation, and inferences about downstream effects on team formation and team composition are therefore necessarily speculative. There are two streams of future research that follow directly from the current research: (a) investigation into the influence of the teammate invitation network on team processes, team performance outcomes, and team composition (including diversity), and (b) investigation into technology features that govern and support digital interactions to produce social networks during team assembly. Despite the long tradition of team composition research linking individual attributes to team processes and outcomes (Bell, 2007; Kozlowski & Ilgen, 2006; Mathieu et al., 2008, 2017), extending the current study there is an opportunity to understand how teammate invitation behaviors influence team outcomes. For example, the stated preferences and interactions during teammate invitation can directly impact team composition, and potentially lead to settings where teams are segregated with respect to relevant project skills (i.e., highly skilled people only work with other highly skilled people) or other individual attributes (demographic diversity) (Gómez-Zará et al., 2019).

The other stream of future research involves the technology platform for team assembly. Online recommendations within an organization are available for numerous applications (e.g., networking, expertise finding, and knowledge sharing), and there are multiple design considerations that determine both the effectiveness and fairness of recommendations (Chen et al., 2009; Geyik et al., 2019; Guy et al., 2009, 2011; Shami et al., 2008). Better understanding the types of social interactions that take place within technology platforms, and then tying their use to team assembly, is critical for understanding how platforms influence team collaboration downstream. For example, social technology platforms commonly serve as the first place in which teams interact and where members begin to form impressions of one another (J. Cummings & Dennis, 2018). This also opens a frontier for future research in which features of the recommendation system are manipulated with the goal of balancing team expertise, diversity, and team viability.

Lastly, there are questions related to whether individuals should trust online recommendations to help reduce the uncertainty involved in establishing collaborations. When selecting prior collaborators, individuals rely on their familiarity and have expectations surrounding the future experience (Hinds et al., 2000a). Forgoing a familiar option would require an individual to trust information about the alternatives. In the case of the current study, a recommendation system presented the alternatives. The value of recommendations in social settings is contingent upon whether users are willing to trust generated results and recommendations as representations of desired information (Deng et al., 2017; Golbeck, 2009). There is opportunity to further explore the extent to which people trust the system to match their preferences to their needs. Additionally, such an investigation leads to questions related to determinations of trustworthiness, perceptions of teammate contributions, and the resultant team processes that emerge.

Limitations

There are several limitations of the current study. First, future work needs to be conducted to determine the relationship between social technology platform features (i.e., the nature of the interface, timing of messages, and a host of other platform design choices) and user behavior during team assembly. Second, there are also questions of generalizability and external validity, stemming from the use of student samples. The samples nonetheless have the advantage of being interdisciplinary, virtual, and geographically dispersed, which reflect contemporary modalities of collaboration. Also, the use of two samples provides the great advantage of allowing for a direct replication of effects. Another limitation stems from the fact that there are multiple enterprise technology platforms used for expert- and expertise-finding within corporations (C. Y. Lin et al., 2009), but relatively little data are available about the extent to which such platforms are used to support team assembly. Another limitation of this study relates to its scope. The investigation focuses on the networks that emerge through the use of technology to support team assembly, which is an area of inquiry adjacent to the subsequent formation of teams and does not directly address questions of team performance.

Conclusion

In conclusion, the current study contributes to social network scholarship by extending a theoretical model of teammate selection (via the teammate invitation network; Hinds et al., 2000) to incorporate an online recommender system (similar to a dating website for choosing teammates). Results signaled the value of online recommendations during teammate invitation, while clarifying that the utility of such recommendations might be limited to conditions where prior collaboration is absent. That is, online recommendations are useful when they provide novel information. By giving insight into the formation of teammate invitation networks within a technology-supported work environment, the current findings offer a bridge between research on teammate choice via social networks and research on social technology platforms.

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Figures

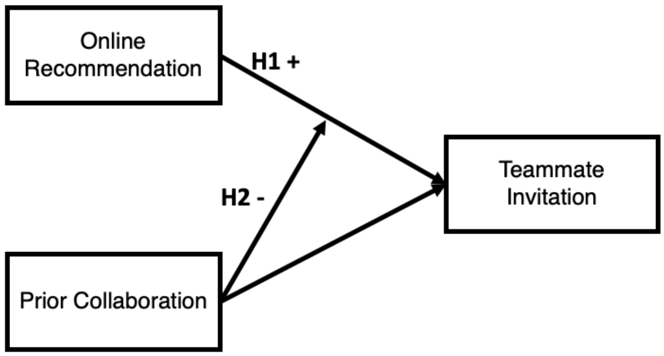


Figure 1: Model of Teammate Invitation Network

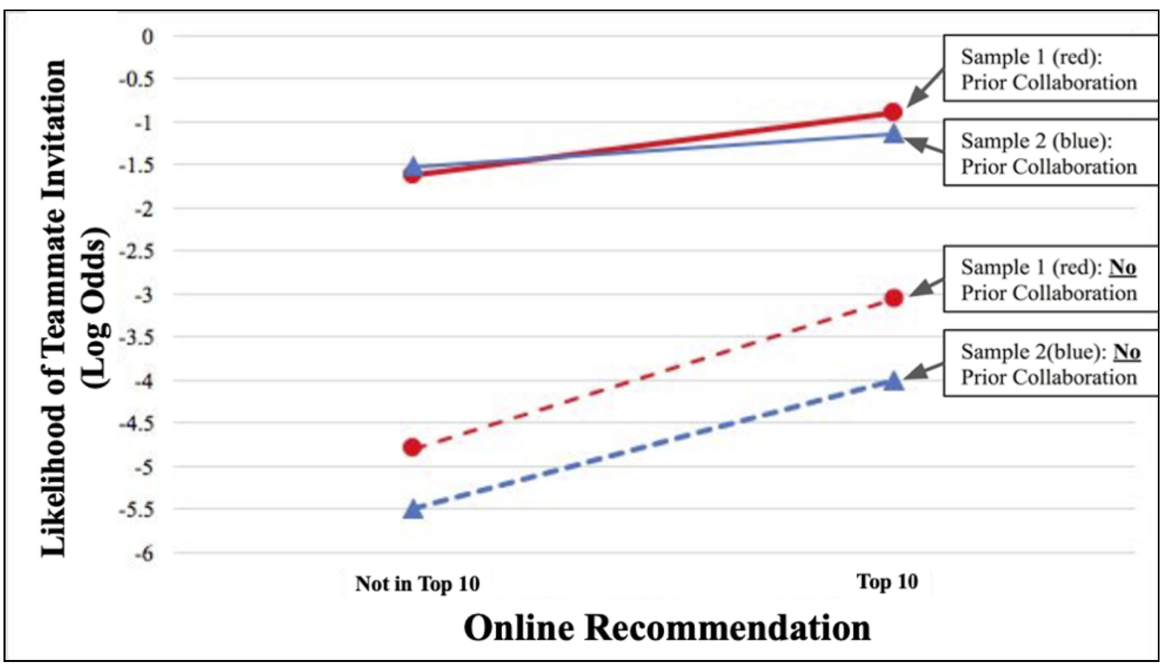


Figure 2: Online Recommendations × Prior Collaboration predicting Likelihood of Teammate Invitation (H2: Table 5, Model 3)

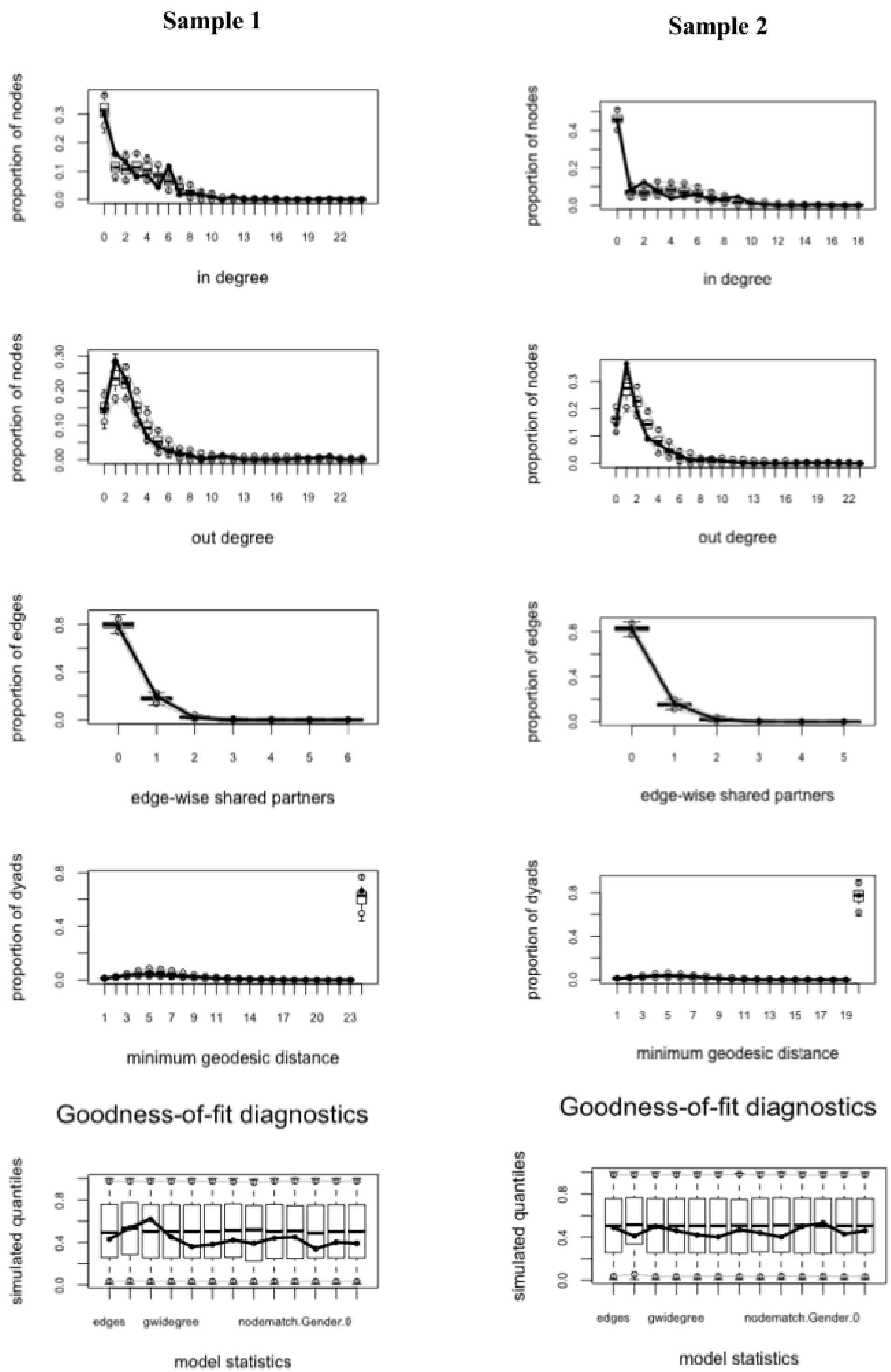


Figure 3: Goodness of Fit plots of model statistics for Model 2.

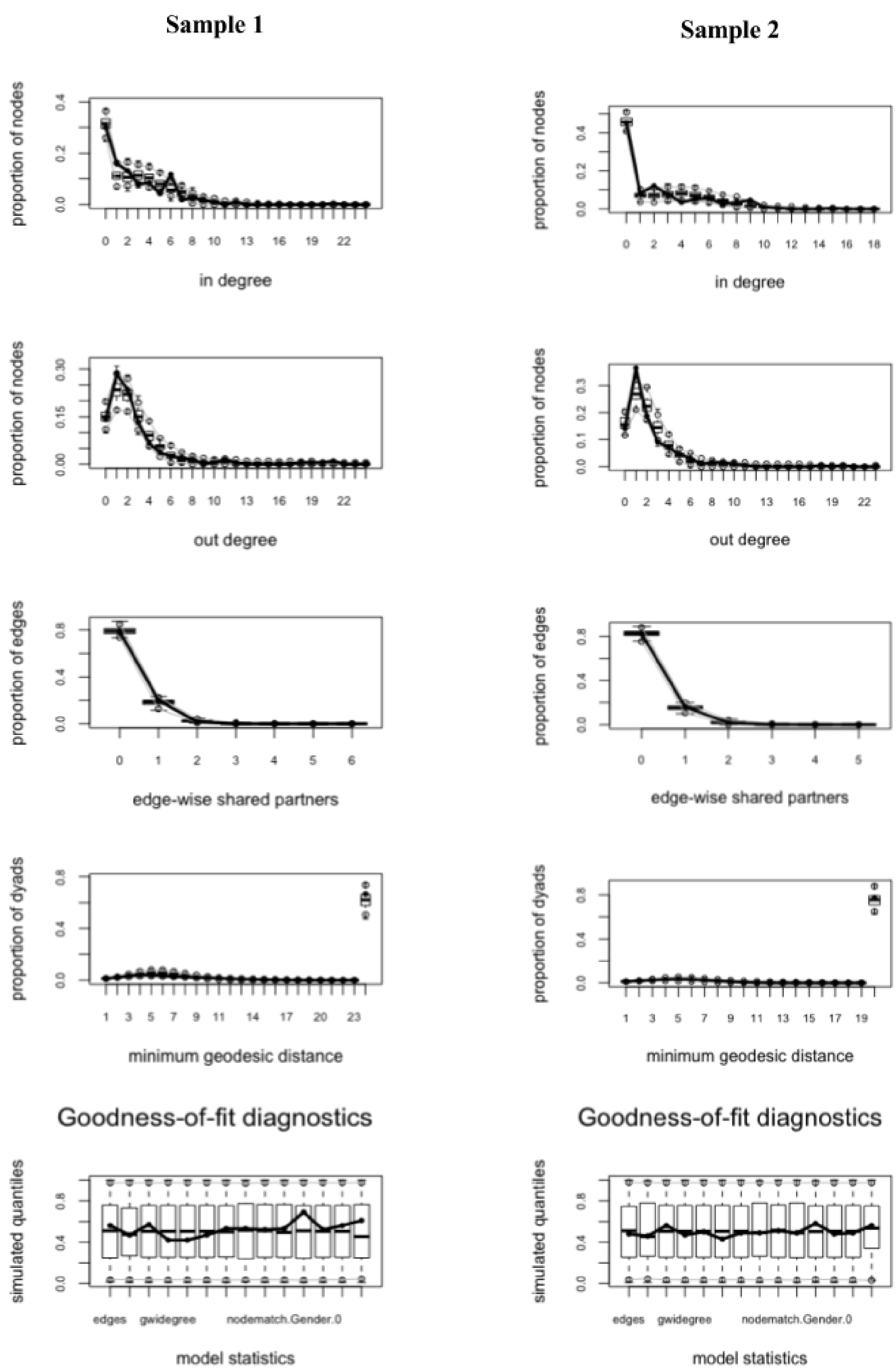


Figure 4: Goodness of Fit plots of model statistics for Model 3.

Tables

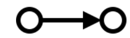
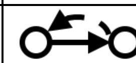
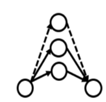
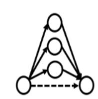
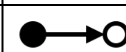
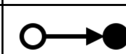
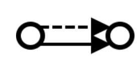
Parameter	Social Process	Variable	Diagram
Purely structural effects			
Arc	The likelihood of an individual randomly inviting another individual to a team	Sending a teammate invitation	
Reciprocity	The likelihood of two individuals inviting each other	Inviting an Inviter	
Activity (out-degree)	The likelihood of one or a few individuals sending many more invites than others, causing variance in the distribution of sent invitations	Active Inviters	
Popularity (in-degree)	The likelihood of one or a few individuals receiving many more invites than others, causing variance in the distribution of received invitations	Popular Recipients	
Multiple 2-paths	The likelihood that individuals invited by a common person will, in turn, converge on whom they invite (many people who share an inviter, inviting the same other person)	Common Inviters	
Generalized transitive closure	The likelihood that individuals indirectly connected through an intermediary will form a direct tie (sends an invite to a third party who is invited by other recipients of one's invitations)	Closure of Invitations	
Exogenous actor effects (black nodes indicate actors with attribute)			
Shared dyadic attribute	An invitation being sent when two individuals have the same gender, or are from the same university	Gender homophily Same university affiliation	
Nodal attribute (sender)	An invitation being sent when the sender has high competence	Competence (continuous)	
Nodal attribute (recipient)	An invitation being received when the recipient has high competence	Competence (continuous)	
Exogenous network effects			
Entrainment	An invitation being sent to someone who was recommended, or to someone with whom sender has a prior collaboration	Recommendation, Prior Collaboration	

Table 1: Summary of Network Effects used in ERGM Analysis

		Mean	SD	Pearson Correlations		
				1	2	3
	Sample 1 (*N* = 213; 32 teams)					
1.	Competence	3.59	0.70	1		
2.	Gender (m=0, f=1)	0.47	0.50	0.09	1	
3.	University affiliation (0 or 1)	0.45	0.50	-0.12	-0.06	1
	Sample 2 (*N* = 197; 31 teams)					
1.	Competence	3.51	0.77	1		
2.	Gender (m=0, f=1)	0.54	0.50	0.11	1	
3.	University affiliation (0 or 1)	0.44	0.50	-0.11	0.09	1

Table 2: Individual-Level Variables: Descriptive Statistics and Correlations

	Networks	Number of Ties	Average Out-Degree	Max	Min	Density	QAP Correlations 1	2	3
	Sample 1 (*N* = 45,156 potential ties)								
1.	Teammate Invitations (sent)	577	2.71	21	0	0.013	1		
2.	Online Recommendation (1 = Top 10, 0 = not Top 10)	2,174	10.2	145	0	0.050	0.10*	1	
3.	Prior Collaboration	181	0.85	8	0	0.004	0.14*	0.01*	1
	Sample 2 (*N* = 38,612 potential ties)								
1.	Teammate Invitations (sent)	471	2.40	20	0	0.012	1		
2.	Online Recommendation (1 = Top 10, 0 = not Top 10)	1,668	8.45	101	0	0.040	0.10*	1	
3.	Prior Collaboration	181	0.92	5	0	0.010	0.21*	0.04*	1

Note. Quadratic assignment procedure (QAP) correlations between two social networks measured on the same set of people reveals the associations between relationships (Krackhardt, 1987).

Table 3: Network-Level Variables: Descriptive Statistics and QAP Correlations

	Model 1 (Log Odds)		Model 2 (Log Odds)		Model 3 (Log Odds)	
	Sample 1	Sample 2	Sample 1	Sample 2	Sample 1	Sample 2
Control Variables						
Endogenous Network Effects						
Sending a Teammate Invitation	-5.68*** (0.33)	-6.02*** (0.34)	-4.80*** (0.29)	-5.53*** (0.37)	-4.80*** (0.30)	-5.50*** (0.36)
Inviting an Inviter	0.90** (0.33)	0.49 (0.41)	0.66* (0.31)	-0.74 (0.53)	0.74* (0.32)	-0.69 (0.51)
Active Inviters	-0.28 (0.24)	0.15 (0.26)	-0.07 (0.23)	0.26 (0.26)	-0.05 (0.23)	0.25 (0.25)
Popular Recipients	-2.02*** (0.20)	-3.09*** (0.21)	-2.04*** (0.19)	-3.08*** (0.21)	-2.05*** (0.19)	-3.09*** (0.21)
Common Inviters	-0.16*** (0.02)	-0.13*** (0.02)	-0.13*** (0.02)	-0.11*** (0.02)	-0.13*** (0.02)	-0.11*** (0.02)
Closure of Invitations	1.43*** (0.09)	1.30*** (0.10)	1.16*** (0.07)	0.99*** (0.12)	1.14*** (0.07)	0.97*** (0.11)
Attributes (Individual and Shared Dyadic)						
Competence (recipient)	0.10* (0.04)	0.01 (0.04)	0.09* (0.04)	0.00 (0.04)	0.08 (0.04)	0.00 (0.04)
Competence (sender)	0.44*** (0.07)	0.60*** (0.07)	0.14* (0.06)	0.46*** (0.08)	0.14* (0.06)	0.45*** (0.08)
Female Homophily (woman inviting woman)	0.20* (0.09)	0.28** (0.08)	0.10 (0.09)	0.13 (0.10)	0.09 (0.09)	0.15 (0.10)
Male Homophily (man inviting man)	0.07 (0.09)	0.21 (0.11)	0.00 (0.10)	0.18 (0.12)	0.02 (0.10)	0.19 (0.12)
Same University Affiliation	-0.05 (0.08)	-0.06 (0.09)	-0.22** (0.08)	-0.35*** (0.10)	-0.22** (0.08)	-0.35*** (0.10)
Hypothesized Variables						
Main Effects						
Online Recommendation (recipient)			1.67*** (0.09)	1.42*** (0.11)	1.74*** (0.10)	1.49*** (0.11)
Prior Collaboration			2.85*** (0.18)	3.86*** (0.20)	3.18*** (0.20)	3.98*** (0.21)
Interaction Effect						
Online Recommendation (recipient) X Prior Collaboration					-1.03** (0.39)	-1.11* (0.50)
Akaike Information Criteria	5,672	4,548	5,228	4,125	5,223	4,124
Bayesian Information Criteria	5,768	4,643	5,341	4,236	5,345	4,244
Note. SE in parentheses. *** 0.001, ** 0.01, * 0.05						

Table 4: ERGM Estimates predicting Teammate Invitation Network (Hypotheses 1 and 2)

		Recommendations		Prior Collaboration	
Counts		Yes	No	Yes	No
Invitation	Yes	309	739	105	943
	No	3,533	79,597	257	82,873
Sender Gender (m=0, f=1)					
Invitation	Yes	0.63	0.58	0.61	0.59
	No	0.58	0.49	0.48	0.50
Receiver Gender (m=0, f=1)					
Invitation	Yes	0.49	0.47	0.53	0.47
	No	0.53	0.50	0.52	0.50
Sender Competence					
Invitation	Yes	4.20	3.71	3.60	3.89
	No	4.12	3.52	3.54	3.55
Receiver Competence					
Invitation	Yes	3.54	3.53	3.35	3.55
	No	3.54	3.55	3.60	3.55

Table 5: Cross-tabulations for the variables of interest.