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Relational Mechanisms in Team Self-Assembly: A Network and Computational Approach

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ABSTRACT

Relational Mechanisms in Team Self-Assembly: A Network and Computational Approach

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This dissertation combines perspectives from social networks and teams research to advance understanding of team self-assembly. Across three substantive chapters, I explore team member search behaviors and invitation patterns in contexts where individuals exercise agency to select team members. First, I consider the search for team members in a social network and the resultant team characteristics. During team assembly, how does the prevalence of homophily in a network affect the search for team members and impact team diversity? Next, I investigate invitation patterns that emerge when people invite one another to teams in a technology platform developed to facilitate team assembly. From the investigation, the main question I answer is, "To what extent does the information contained in online recommendations affect teammate invitations when the potential target of a teammate invitation is someone whom you already know?" In other words, how do online recommendations influence whether an individual will invite a prior collaborator? Lastly, I study how invitation patterns impact the evolution of team relationships throughout the span of collaboration. Specifically, how do teammate invitation patterns affect the subsequent evolution of communication and leadership networks in teams?

The team self-assembly patterns under investigation exemplify the typically opaque invitation and search behaviors performed when people look for and select teammates. As such, I sharpen insights into the ways in which people engage with one another when deciding with whom to form teams—making social networks a helpful perspective to guide the research conducted in this thesis. The dissertation leverages social network analysis techniques such as exponential random graph modeling (ERGM) and stochastic actor-oriented models for network

dynamics (also known as SIENA models) to analyze empirical social networks related to invitations as well as agent-based modeling (ABM) and simulation of search behaviors in social networks.

In the first substantive chapter, ABMs are employed to generate insights regarding the search for team members and the effects on team diversity. By varying levels of homophily in networks and manipulating problem complexity, I investigate the effectiveness of two different search strategies in identifying team members and also the effect of search on the expertise that exists within teams. The advantages of enacting a more information-intensive search strategy increase as problems become more complex and difficult, while homophily in networks helps in identifying team members that closely match problem requirements.

In the next chapter, I observe two samples of students assembling interdisciplinary project teams by using a technology platform for team assembly. Using digital trace data from the platform, I conduct ERGM to explain the mechanisms responsible for generating the invitation networks that emerge as determine who to invite to their teams. Online recommendations are a notable feature of the platform's interface and positively influence the likelihood of sending an invitation to a potential teammate, but prior collaborations are a boundary condition for the effect of online recommendations; specifically, online recommendations are less likely to be heeded when there is prior collaboration.

Finally, the third substantive chapter extends the previous to investigate the implications of invitation patterns on dynamics of assembled teams. By investigating the longitudinal coevolution of communication and leadership within teams using SIENA modeling, there are new insights developed that explain how team self-assembly in a technology platform contributes to the emergence of team relationships. Leadership and communication influence the evolution of each other as project teams collaborate over time, and the invitation network that emerges during team self-assembly has a positive influence on communication but a negative effect on leadership within teams. However, teammate recommendations generated by the online platform do not have an effect on the coevolution of the team networks. Other important effects in explaining coevolution of the team relationships are endogenous network structures, such as popularity, reciprocity, and transitive closure. The study identifies the limits of employing technology-enabled team assembly as a tool to explain the coevolution of emergent team relationships. In its totality, this dissertation deepens understanding of invitation and search behaviors that occur during team self-assembly as well as the implications of such behaviors on team characteristics and dynamics.

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DEDICATION

I dedicate this work to the family that I have lost, who have served as motivation for me to live as full a life as possible.

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CHAPTER 1. INTRODUCTION

Teams have been a foundational aspect of organizations for many years (Ilgen, 1999; Kozlowski & Bell, 2013; Mathieu, Hollenbeck, van Knippenberg, & Ilgen, 2017). As such, assembling teams that meet specific criteria and have high performance potential is a focus for many managers and organizations. While managers can choose to assemble teams using demographic characteristics or social networks, there is no clear advantage to selecting one type of information over the other when assembling teams (Reagans, Zuckerman, & McEvily, 2004). Over time, people have become more sophisticated in the criteria, tools, and technologies they use to support team assembly activities. It is now common to consider many types of factors when selecting teammates, including task requirements, individual abilities and traits, interpersonal relationships, and the broader ecosystem and work context (Hackman, 1987; Harrison & Humphrey, 2010; Mathieu, Maynard, Rapp, & Gilson, 2008; L. L. Thompson, 2018). All of these factors have increased the complexity of the information available to those who select team members and assemble teams.

In response to this increased complexity, individuals look for collaborators and teammates by using countless types of technology. From professional networking platforms to enterprise social media platforms, many of these technologies use software algorithms and other affordances to connect people and facilitate social interaction in organizations (Colbert, Yee, & George, 2016; Leonardi & Vaast, 2017; Treem & Leonardi, 2012). In recent years, technology platforms and algorithms have demonstrated value in helping people find replacement team members and assemble teams within large organizations (Alkan, Daly, & Vejsbjerg, 2018; Li et al., 2017, 2015). In general, social media platforms in organizations offer promise in helping people more effectively understand “who knows what” within an organization and coordinate as needed for an array of tasks (Leonardi, 2018).

This dissertation builds knowledge of team self-assembly practices that occur through technological interfaces, such as online recommender systems and networking platforms. Team self-assembly is a process where people exercise agency and self-organize into teams by selecting or being selected by their own teammates (Contractor, 2013; Hackman, 1987; Pelesko, 2007; Wax, DeChurch, & Contractor, 2017; Zhu, Huang, & Contractor, 2013). It is a subset of team assembly, which broadly refers to the relationships and activities responsible for organizing groups of people (Humphrey & Aime, 2014). While not common in many organizational settings, self-assembled teams are a dominate form of organizing collaboration in domains requiring innovative solutions, such as scientific research (Guimerà, Uzzi, Spiro, & Amaral, 2005; Hagstrom, 1964; Wang & Hicks, 2015).

Often, research on team self-assembly excludes the behaviors that were conducted in order to bring individual members into a team. There are two team self-assembly practices of interest in this dissertation, teammate search and teammate invitation. Because individuals conducting knowledge intensive work commonly need to rely on the contributions of multiple teammates and collaborators as they continue to encounter complex problems that require diverse expertise, these two team self-assembly practices inform the main research question guiding this dissertation, “What mechanisms describe team self-assembly—specifically teammate search and invitation practices—and how does team self-assembly affect the characteristics and relationships of the teams that assemble?”

I define teammate search as the series of behaviors that an individual enacts when looking for teammates, i.e. the information processing and social interactions that a person employs to find teammates. Teammate invitation is the action of signaling interest to collaborate, i.e. expressing a desire to work with another person by explicitly sending a message. Both of these practices are fundamentally a part of finding teammates and assembling teams, but both have often been overlooked. The lack of investigation is at least partly due to the difficulty that exist in observing both practices. Search, in particular, is difficult to study because it is unclear what information people attend to when making choices regarding which people to collaborate with in a team. For instance, people can focus on individual attributes that are or are not relevant for a task, social relationships that exist, or any combination of factors. Meanwhile, invitations have another issue in that it is difficult to capture the moment when people make contact to offer an opportunity to collaborate. This dissertation focuses on team self-assembly and benefits from the use of online platforms because such platforms alleviate challenges in observing invitations. Therefore, the main contribution of this dissertation is the development and presentation of three substantive chapters investigating different aspects of team self-assembly that occurs within a technologically saturated context.

The focus of Chapter 2 is teammate search and uses agent-based modeling (ABM) to investigate search behavior to find problems solvers for problems of varying complexity. While search does not strictly require the use of a technology platform, two search strategies are developed that correspond to differential amounts of information available to a searcher. One strategy only relies on an agent's personal perceptions of their direct contacts, but the other strategy provides access to contacts of direct contacts as well as information about those contacts in a fashion that is analogous to common functionality found in technology platforms to facilitate search and information retrieval (i.e., viewing profiles of others without being directly connected).

There are two types of outcomes of interest in the study: team diversity and teammate search performance. Team diversity is measured by determining the breadth of expertise coverage within a team and how well the team matches the problem being solved; both measures assess the expertise profiles of teams that assembled from search. Teammate search performance captures how often search successfully finds problem solvers while also capturing the social network distance covered during a search. Exploring search to assemble teams relies on ABM simulations because, while there are countless criteria that people can potentially use when searching for teammates, empirical challenges exist in measuring whether a given criterion was taken into consideration. The models simplify such considerations by defining search strategies that provide differing levels of information that are used during the course of search. The study of teammate search clarifies the influences that problem complexity and difficulty, network structure, and type of search strategy have on team diversity and search performance when assembling teams.

In Chapter 3 of the dissertation, attention shifts to teammate invitation behaviors that are empirically observed as groups of people self-assemble into project teams. From teammate invitations, a network emerges that encapsulates social interactions among those who are assembling teams. Observations of invitations are made from digital trace data that are collected from an online platform facilitated team self-assembly. The platform also leveraged user preferences to provide algorithmic recommendations for potential teammates, which help explain the network structure of teammate invitations. The study uses exponential random graph modeling (ERGM) as the statistical modeling approach to generate insights about invitation patterns in the network and draw linkages between invitations and external factors, specifically recommendations and familiarity. The study identifies a boundary condition for the impact of recommendations on whether individuals will invite others to teams; having familiarity with another person through prior collaboration reduces the informational value of recommendations. In summary, by interrogating a network of invitations, the utility of technology platforms in team self-assembly is notable, but also limited based on the social relationships that exist among those who are assembling the teams.

Chapter 4 builds on the research conducted in Chapter 3 by investigating the coevolution of two relationships within the teams that assembled. The two relationships are leadership and communication within the team. Communication networks are the backbone of collaboration because people must coordinate and share information (Cataldo & Ehrlich, 2012; Contractor, 2013; Mesmer-Magnus & DeChurch, 2009), and leadership influences the actions and priorities of members when working within a team (Lord, Day, Zaccaro, Avolio, & Eagly, 2017; Yukl, 2010; Zaccaro, Rittman, & Marks, 2001). Assessing how these two relationships affect one another over the course of a collaboration helps describe the dynamics that exist among team members. There are additional benefits that accrue when considering both relationships in terms of the behaviors that contributed to team assembly. The study focuses on the impact that recommendations and invitations have on coevolution of leadership and communication. The approach for this study relies on stochastic actor-oriented modeling (SOAM or SIENA) to describe the longitudinal changes that occur in both team relationships over the collaborations.

Newly developed insights explain how team self-assembly in a technology platform contributes to the emergence of team relationships. Leadership and communication influence the evolution of each other as project teams collaborate over time, and the invitation network that emerges during team self-assembly has a positive influence on communication but a negative effect on leadership within teams. However, teammate recommendations generated by the online platform do not have an effect on the coevolution of the team networks. Other important effects in explaining coevolution of the team relationships are endogenous network structures, such as popularity, reciprocity, and transitive closure. The study identifies the limits of employing technology-enabled team assembly as tool to explain the coevolution of emergent team relationships. From the modeling, both team relationships influence one another and the invitation network that emerges during team self-assembly has a positive influence on communication but a negative effect on leadership within teams. Meanwhile, teammate recommendations generated by the online platform do not exert much influence on the studied relationships. Other important explanatory mechanisms include tie patterns endogenous to the observed network, such as popularity, reciprocity, and transitive closure.

Taken all together, the contribution of this dissertation is to increase knowledge surrounding the relational mechanisms that describe team self-assembly behaviors. Towards this end, the three substantive chapters focus on the search for teammates, the network of invitations that emerges when people are self-assembling teams, and the coevolution of team relationships within the assembled teams. By studying different aspects of team self-assembly, this dissertation illustrates how social networks underpin the choices that people make when forming teams.

CHAPTER 2. TO SEARCH AND ASSEMBLE: FORMING TEAMS WITH DIVERSE EXPERTISE IN SOCIAL NETWORKS

Abstract

Searching for team members is a necessary activity when assembling teams to solve complex problems that require interdisciplinary solutions. Previous research has repeatedly demonstrated the role that social network structure plays in the effectiveness of network search. The current paper extends prior research on network search by considering cases where the goal is assembling a team by finding multiple targets. Towards this end, the study uses agent-based modeling to explore the effects of problem difficulty and complexity, the preference for homophily in a network, and search strategy on team expertise coverage—maximum differences among teammates, the match between a team and problem, search success, and the network distance of search. Three insights emerge from the analysis of search under various conditions: problem difficulty heightens the importance of the selected search strategy in terms of success, problem complexity has a curvilinear relationship with team expertise coverage while shortening the network distance of a search and diminishing the match between a team and problem, and the preference for homophily increases the network distance of a search while decreasing the team expertise coverage. These findings detail the significance of network search, problem requirements, and social network structure on team assembly and the expertise diversity of assembled teams.

Introduction

The problems commonly encountered in scientific and knowledge intensive industries require interdisciplinary solutions, and teams capable of solving such problems need diverse expertise (Hagstrom, 1964; Page, 2017; Savage, 2018; Wuchty, Jones, & Uzzi, 2007). Searching for diverse sources of expertise and knowledge promotes innovation, but requires that a person navigates the broader social network to look for potential team members with desirable expertise (Siciliano, Welch, & Feeney, 2017). When an individual searches within an organization or community, a key challenge lies in navigating social networks in order to understand where specific knowledge is located and who possesses such knowledge and expertise (Contractor & Monge, 2002; Leonardi, 2015). Indeed, accessing new information and transferring knowledge through different units of an organization has long been recognized as a challenge to developing innovative solutions (Hansen, 1999, 2002; Kleinbaum & Tushman, 2007; Reagans & McEvily, 2003; Singh, Hansen, & Podolny, 2010; Tsai, 2001). Likewise, accessing new information and knowledge has consequences for team assembly and the characteristics of the team being assembled.

The expertise diversity within a team becomes more important as problems increase in complexity and become more complicated. As an example of increasing complexity, the contemporary scientific enterprise has advanced to the point where teams composed of multiple types of expertise are now needed to conduct interdisciplinary science. Resultantly, new areas of inquiry are created to define problem-solving that is situated in multiple intellectual spaces. For example, the medical research field of oncofertility emerged from a set of problems requiring expertise combining reproductive health and fertility with cancer diagnosis and treatment (Jeruss & Woodruff, 2009; Lungeanu & Contractor, 2015; Woodruff, 2007). The shift towards team collaboration among disciplines has implications for the modern scientific enterprise and makes understanding teams—and their assembly—meaningful for understanding complex-problem solving in general (Falk-Krzesinski et al., 2010; Ledford, 2015; Wuchty et al., 2007). This shift is especially important as society moves towards a more open model of collaboration where technology enables the recruitment of a highly-skilled and on-demand labor force that contribute across an array of projects (Kittur et al., 2013; Retelny et al., 2014; Salehi, McCabe, Valentine, & Bernstein, 2017). Investigating the role of social networks and how people navigate them to find team members helps increase knowledge surrounding how people find team members in fluid collaborative environments.

Social networks do not necessarily reflect formal structures—such as those assigned as part of traditional organizations. Instead, a network's underlying structure is often explained by the presence of homophily that exists among actors in the network (Kleinbaum, Stuart, & Tushman, 2013). Homophily—the tendency to connect with similar others—explains social relations in terms of personal attributes and assumes that people are more likely to connect with others in the same social group (Kandel, 1978; Kossinets & Watts, 2009; McPherson & Smith-Lovin, 1987; McPherson, Smith-Lovin, & Cook, 2001). By definition, homophily is at odds with diversity because people are more likely to connect to others comparable to themselves (at least along certain dimensions). In terms of expertise, homophily is present when people belong to intellectual domains where they interact with similar others (e.g., disciplinary silos resulting in echo chambers). Because of the resultant network structure, finding teammates with diverse expertise must be a focused and intentional activity where effort needs to be expended to find someone who contributes complementary expertise. Contrast this scenario with one where there is not as much homophily present in the network and a person has a diverse set of contacts. In such a case, multiple options exist for finding potential teammates with different types of expertise, which suggests that needed expertise is more readily reachable when a diverse team must assemble to solve a problem.

The goal of the current study is understanding team diversity as the outcome of search that occurs in a social network where homophily is a mechanism governing network tie creation. Considering the constraints that a social network imposes on search provides insights into how team assembly is affected by the surrounding social context. To broaden understanding of search in the pursuit of diversity, the current study develops and evaluates two search strategies that differentially support access to portions of a social network in which potential team members reside. The two strategies differ in the amount of information available to a searcher, *Local Search* is a strategy where actors search exclusively through their direct contacts and *Broker Search* extends search beyond direct contacts to include contacts two steps away in the network. Evaluating the two strategies helps distill whether any limits caused by homophily in the network can be displaced by using a more extensive search strategy accessing more information. By employing computational modeling and virtual experiments, team diversity and search are investigated with respect to various levels of homophily in a social network and by the complexity of the problems for which teams are assembled to solve. The current study pursues the following research question: When assembling teams, how does the prevalence of homophily in networks affect team diversity and the search to find team members?

The rest of the study is organized as follows. First, the literature review integrates the team diversity and network search literatures to situate the contribution of the current study. Then, I describe the computational approach along with a summary of related computational models relevant for investigating team assembly. Next, the developed search strategies and assumptions of the associated computational models are detailed, including information about search rules, network generation mechanisms, and variable parameters manipulated in virtual experiments. From the experiments, the models are evaluated and the observed patterns that emerge with respect to team diversity and search are analyzed. Finally, the paper closes with a discussion of the implications from the study findings.

Team Diversity and Network Search

The current study is conceptually grounded in two distinct literatures: team diversity and network search. Both areas have generated separate bodies of research that have rarely been integrated to explain how search promotes diversity within a team. Social networks are the patterns of people's connections to others, and assembling a team requires using such connections to find people that satisfy the demands of a given task. Searching a network to assemble a diverse team relates to both *how* one navigates the structure of a network to find valuable resources and—equally important—*what* resources are available in the network. Due to the complexity of problems typically encountered in knowledge intensive enterprises, diversity is often desired to ensure that a team has access to a wide variety of knowledge and functional skills (Ancona & Caldwell, 1992; Bunderson & Sutcliffe, 2002; Harrison & Humphrey, 2010; Page, 2008). Therefore, diversity relies on being able to find and connect with different types of people who offer unique contributions.

Assembling teams with the expertise necessary to solve interdisciplinary problems requires the current study to restrict its focus to expertise diversity. While there is a vast amount of research prioritizing different types of diversity that range from demographic attributes, resources, and network connections (Harrison & Klein, 2007; Williams & O'Reilly, 1998), focusing on expertise diversity makes it possible to consider the different knowledge that a team must integrate in order to accomplish its goals (Barley, Treem, & Kuhn, 2017; Milliken, Bartel, & Kurtzberg, 2003). In general, integrating diverse expertise within teams is a common method for solving complex problems instead of relying on individual contributors situated in specialized knowledge domains (Leahey, 2016; Leahey, Beckman, & Stanko, 2016). Before integrating knowledge in a team, individuals need to identify and access multiple perspectives to pursue expertise diversity; typically, individuals engage with their social networks to accomplish this goal.

Fundamentally, the connections that comprise a social network provide resources to people situated within the network. Having a team with members who are able to access diverse resources through their social network connections at least partially contributes to team productivity. For example, teams that are more structurally diverse with respect to business unit, geography, functional assignment, and managerial role have better access to distinct knowledge (i.e., general overviews, requirements, analytical techniques, and project reports) from other parts of an organization, which in turn leads to more recognition and positive ratings from managers (J. N. Cummings, 2004). Also, connecting with people who have different skills and experiences results in research and development teams generating more products like prototypes and papers (Reagans & Zuckerman, 2001). For both examples, having diverse connections benefits a team's collective ability to source nonredundant information and then combine it in order to achieve specific performance goals. In order to receive the benefits from connections to diverse expertise, individuals must be able to effectively search for others, which has been a long-standing topic of research interest.

Previous research has consistently demonstrated that individuals are able to effectively reach others across a social network using only local search strategies—where a person uses information about their direct contacts—while also describing the limits that a network imposes on those participating in search (Dodds, Muhamad, & Watts, 2003; Milgram, 1967; Travers & Milgram, 1969; White, 1970). The local search strategies from much of the prior research require that a person relies on the participation of direct contacts in a decentralized search process whereby a person at a farther network distance away can be reached. The effectiveness of local search strategies is partially attributed to the structure of a social network because some configurations of network connections are more efficient to search than others.

Efficiency in a network results in a person being able to access diverse people without the need to include numerous intermediaries. One type of network that is efficient to search is known as a small world network. A small world network exhibits high clustering among nodes while also having relatively short average path lengths between nodes, meaning that the tie structure is configured such that groups of nodes emerge while also having connections to different groups in the network (Watts, Dodds, & Newman, 2002; Watts & Strogatz, 1998). While a small world network can be generated from general models that only consider the probability of connecting to others, the existence of groups in a social network is commonly explained (at least partially) by exogenous factors. One such factor is organizational structure.

The structure of organizations affects the success and efficiency of search by imposing rules for interaction and influencing information flow and awareness among actors (Adamic & Adar, 2005; Friedkin, 1983; Huber, 1982). A structure supporting information flow helps members of an organization better utilize internal information and resources such that the organization as a whole benefits (Friedkin, 1978; Singh, 2005). An example of a formal structure that promotes expertise diversity is an interdisciplinary research center. The structure supports sustained collaboration among diverse participants by providing spaces for interaction between different groups of people despite disciplinary boundaries (Dahlander & McFarland, 2013; Jacobs & Frickel, 2009). Organizational structure has implications on accessing diversity because it commonly imposes functional groupings or departments that tend to be specialized in nature (Lawrence & Lorsch, 1967; Lynton, 1969).

Conducting searches in a network that are embedded within a formal organizational structure imposes constraints on finding diverse resources. Therefore, organizations regularly develop informal networks that support the flow of resources throughout an organization: knowledge, information, advice, and expertise (Brass, 1985; Brass, Galaskiewicz, Greve, & Tsai, 2004; Ibarra, 1993; Rogers & Agarwala-Rogers, 1976; Tichy, Tushman, & Fombrun, 1979; Tsai & Ghoshal, 1998). Regulating the flow of resources makes it nontrivial for teams to find the expertise diversity that helps leads to desirable performance outcomes. Expertise diversity is greatly enhanced by the presence of brokers in networks who are able to connect distinct—and otherwise separate—groups within a network (Burt, 2000, 2004). One common function of network brokers is the ability to combine multiple areas of expertise to offer diverse skills or experiences, translate solutions across domains, and help develop innovative solutions (Hargadon & Sutton, 1997). Because of the intertwined nature of networks and social structure, expertise diversity, and network search, a computational methodology helps deepen understanding by clarifying the relationships amongst the concepts.

Model Details

Model Assumptions

The first assumption of the model relates to people's ability to search to assemble a problem-solving team. The model does not include considerations for availability or workload; therefore, a key assumption is that all agents in the network are available to join a team or forward a problem any time they receive a problem. Additionally, an assumption is made that expertise can be accurately assessed and quantified for both problems and agents. The assumption results in agent expertise and problem expertise requirements being represented as a numerical vector of length *m* with each number corresponding to the amount of expertise in a given area. Each expertise area is represented as a non-negative real number between zero and one, and each number is generated from a random number generator using a truncated normal distribution $N(\mu=0.5, \sigma=1)$. Another assumption of the model is that all agents can contribute their expertise to multiple expertise areas of a problem, which means that the size of an assembled team may be less than *m* if an agent is capable of solving multiple expertise areas of a problem.

The last set of assumptions relates to problem generation and the entry of problems into the network. Every generated problem has exactly *m* expertise areas, and the maximum possible required expertise for each area is equal to the maximum expertise existing in the network. Therefore, a team capable of solving every area of every problem is guaranteed to exist. The expertise areas of problems are also assumed to be interdependent and must be addressed simultaneously by a single problem solver or team. Also, the model assumes that problems enter the network sequentially and are initially given to a random agent. At any point in time, there is only one problem for which a search is being conducted. As such, the network only attempts to assemble one team at a time. This set of assumptions does not reflect the fact that many organizations have multiple problems being solved simultaneously, nor does not consider other constraints, such as task prioritization, workload optimization, or resource allocation. However, the stated assumptions focus on network search as an independent mechanism instead of focusing on adding more realism, which allows for the current study to focus on the behaviors employed when searching a social network to assemble a problem-solving team.

Search Strategies for Team Assembly

The modeled search strategies are based on the paradigm of decentralized search and focus on actors attempting to assemble a team that is most qualified to solve a problem. Two components of the model are discussed in the current section: the rules of the two search strategies conceptualized for team assembly and the mechanisms responsible for generating the social networks in which the strategies are evaluated. The first section details the rules that agents follow during the execution of the ABM, and the second section describes the creation of the social environment that agents must navigate to succeed in assembling a team.

The concept of decentralized search is a fundamental and scalable strategy for searching networks, and it serves as the foundation of the search strategies developed to assemble diverse teams in the current study. When a source agent *s* needs to deliver a message to a target agent *t*, a decentralized search strategy relies on the participation of intermediaries to help a message traverse through a network. Typically, agent *s* is not directly connected to agent *t* and does not necessarily know the contacts of agent *t*. Therefore, according to decentralized search, agent *s* overcomes its myopia by giving the message to one of its direct contacts to serve as an intermediary, who then sends the message to agent *t* (if connected) or one of its own direct contacts (if not connected to *t*), and the process repeats itself until the message is eventually delivered or fails to find a path to agent *t* (Kleinberg, 2006; Ma et al., 2016). The current study's search strategies build on the foundational definition of decentralized search but differ in three notable ways.

The first way that the current study's search strategies differ is in the number of targets that exist for a given problem. Problems have multiple areas of expertise that must be met, but not a specified target for the problem. Problems may be solved by a single target, but there are cases for which a combination of agents is capable of solving every generated problem. The combination of agents are the eventual members of an assembled team. Building on this difference is the fact that the targets of the problem are not known a priori because the goal of search is finding any combination of agents that will meet the problem requirements. Traditional search strategies commonly only focus on routing to or searching for a single target, but this assumption is relaxed to account for the prevalence of teams that solve complex problems, which is the main goal of the current study. The last difference is that multiple agents simultaneously participate as intermediaries in search at a given step. This assumption suggests that multiple agents coordinate and collectively decide on a team of agents with expertise to match problem requirements.

Search requiring coordination is a distinct phenomenon form individual search. Agents that participate in search with other agents need to communicate with others and balance information sharing to in order for searches to be successful, but too much coordination results in suboptimal decisions that are made without much learning or exploration (Lazer & Friedman, 2007). Specifically, the amount of knowledge transfer between searchers regulates the confusion and myopia of the searchers when searching complex problem domains (Knudsen & Srikanth, 2014). These three differences are opportunities to explore how modifying decentralized search to be a search process requiring coordination illuminates an approach to assemble teams with diverse expertise.

Description

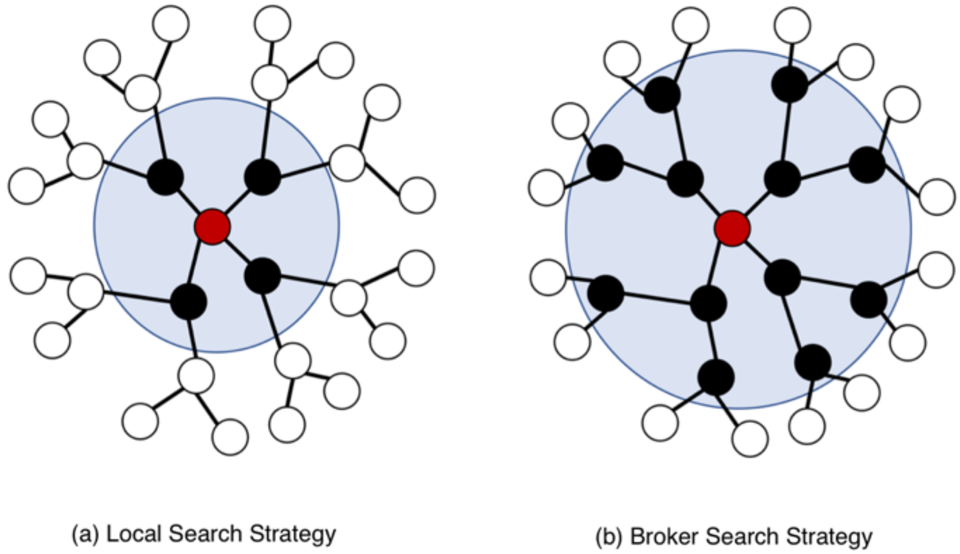


Figure 1: The radius of contacts (blue circle) that a searcher (red node) accesses during the search strategies. (a) The radius only includes the immediate contacts of a searcher. (b) The radius includes the contacts of a searcher's contacts, which offers potential for a searcher to use their contacts as brokers to other agents.

The two search strategies both rely on an agent assessing the expertise of their direct contacts when making decisions about whom to route a problem to in order to find agents to join a team capable of solving the problem. The *Local Search* strategy only allows a given agent to search among its direct contacts, whereas *Broker Search* gives an agent access to the expertise of other agents within a radius of two steps—contacts of contacts. Being able to assess expertise of agents farther away allows an agent to use a direct contact as an intermediary to reach a known intermediary with more expertise. The *Broker Search* strategy is inspired by *m*-hop task routing algorithms that consider the performance tradeoffs that exist when giving a decision-making node a larger choice set (Zhang, Horvitz, Chen, & Parkes, 2012). The two strategies behave the same, in principle, except for in cases where *Local Search* would have failed due to not having additional information beyond their immediate contacts. Figure 1 illustrates the difference between *Local Search* and *Broker Search* with respect to the information available other agents' expertise. The rules of each strategy are detailed below.

Rules

Each search strategy requires that an agent performs six steps at every time step when possessing a problem. Each problem is generated and randomly given to an agent in the network, and the rules an agent follows when searching will result in two outcomes for search: succeeding (by finding a team or individual solver) or failing to assemble a team for a problem. The details of each step of the two search strategies are explained below (see Figure 2 for a flowchart of strategy rules).

Step 1: *Assess* the expertise of current problem holders. During the search for a team, agents possessing are problem holders. Holders are agents that are actively searching for problem solvers but may become members of the team if they are qualified. The problem holder must first reflect on their own expertise and decide whether they are qualified to solve at least one expertise area of the problem. For each area of a problem, the maximum level of expertise among the holders to compared to the level of expertise required by the problem. If the maximum available expertise is greater than the problem requirement, then the expertise area may be satisfied by one of the current holders. If not, then the expertise area is designated as "unfulfilled."

Step 2: *Collaborate* with other holders. When there are multiple holders of the same problem, the group is able to coordinate during search and collaboration occurs within the group. Collaboration refers to holders aggregating their expertise during search. The holders share their expertise with the other holders for comparison with the problem requirements.

Step 3: Are the current problem holders qualified to solve all areas of the problem? Then, after collaboration, the first decision point of the model determines whether the group can successfully address the problem. The collection of holders is assessed to determine whether there are any unfulfilled expertise areas of the problem. If there are no unfulfilled areas in a problem, the current holders will agree to assemble into a team to solve the problem, and the strategy will terminate successfully. Otherwise, the strategy continues the search process.

Step 4: *Collect contacts to potentially receive the problem.** The "*" refers to the difference between *Local Search* and *Broker Search* in this step. Problem holders review their contacts. When there are multiple holders, all the contacts are combined into a single list and reviewed collectively. In the *Local Search* strategy, a list of contacts is created from all the holders' contacts. In the *Broker Search* strategy, a contact list is created from the contacts of all the holders and the contacts of those contacts. The group of holders has a list of all agents that are within a radius of two steps.

Step 5: Are the contacts an improvement over the current holders? In the previous step, problem holders create a shared list of contacts. Each expertise area that does not have a holder qualified to solve the area is designated as an "unfulfilled" area. For each "unfulfilled" area, the contact (from the list) with the highest amount of expertise is identified and compared to the most qualified problem holder in the "unfulfilled area". If no contact has higher expertise than the current holders, then a team fails to assemble. If the expertise of a contact in an unfulfilled area is higher than a current holder with the highest expertise in the area, then the contact is selected to receive the problem.

Step 6: *Forward* the problem to the selected contacts. If any current holders fulfill expertise requirements, then they remain holders for the next run of the search strategy. In the *Local Search* strategy, the problem is forwarded to any contact (within one step) that has higher expertise in an unfulfilled area. For the *Broker Search* strategy, the strategy forwards the problem in the same manner as the *Local Search* strategy unless the selected contact is a contact of a contact (a target). In this case, a contact of the target is identified as a broker and added to the new set of holders with the expectation that the target will be added to the holders in the next run of the model. Any agent that is currently a holder is removed from the set of holders when they no longer uniquely fill an expertise area of a problem.

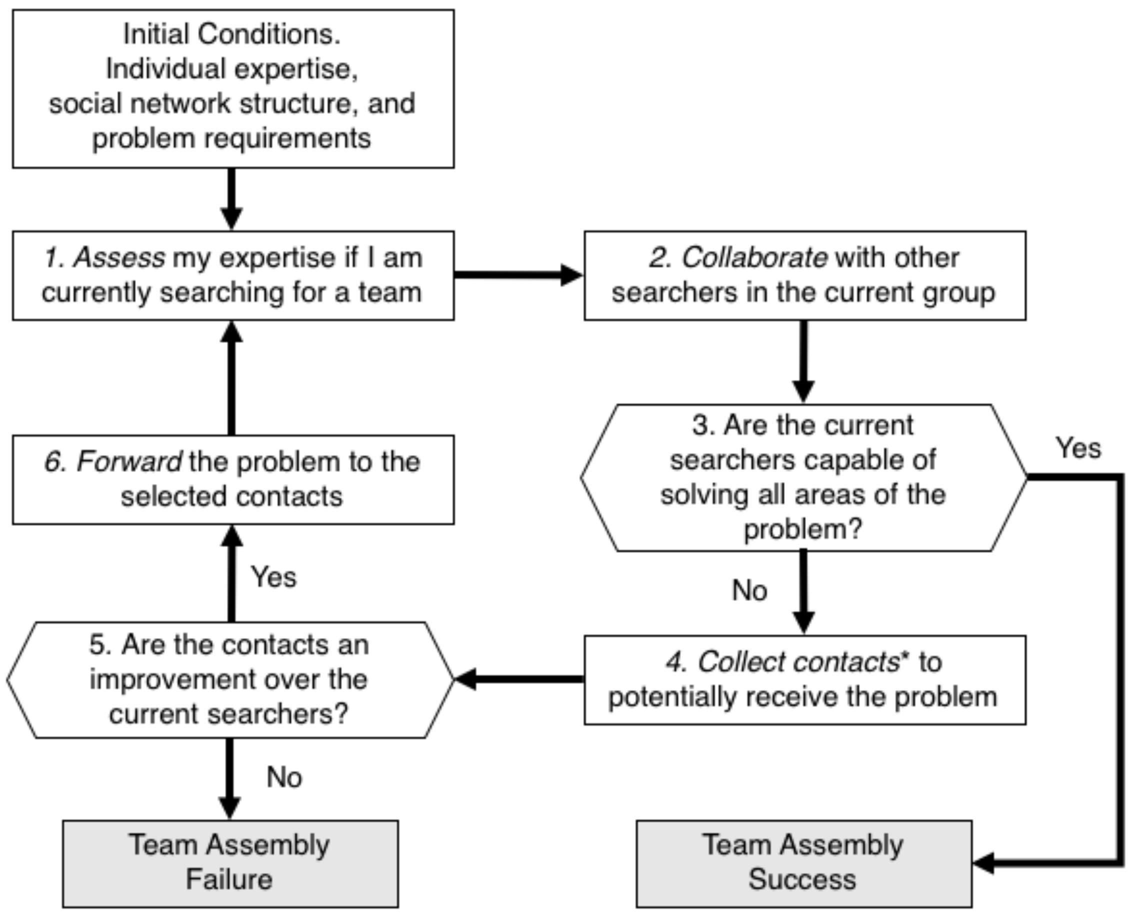


Figure 2: The *Local Search* and *Broker Search* strategies. *In Step 4, "Broker Search" uses more information than "Local Search," as indicated by the differences between the strategies

Network Generation

In the current study, directed communication networks are generated using a model where links are determined using the expertise similarity between agents in the network (Ma et al., 2016). The expertise similarity is the operationalization of homophily in the model. The presence of a link between two agents controls whether an agent can forward or send a problem to another agent in the network. The key assumption underlying the model is that agents are connected to others based on the preference for (expertise) homophily in the social network. For each agent, expertise relevant for a problem is assumed to be a numerical vector of *m* length, and the similarity between agent is calculated using the "Manhattan Distance" measure, where the absolute difference between two vectors is summed (Black, 2006). The network model assumes that there are non-exclusive groups of agents where an agent who belongs to multiple groups has more opportunity to interact with a diverse set of agents than does an agent who belongs to fewer groups. If two agents are extremely similar, they are more likely to belong to the same "small" group and are more likely to be connected to one another (e.g., the same product team in a company). On the other hand, if two agents who do not have similar expertise, then they belong to a "large" group (e.g., the same department, but different product teams). As a result, there always exists a group containing any pair of agents within the network (Kleinberg, 2002).

Modeling non-exclusive membership in groups based on expertise homophily has numerous advantages when generating a social network. Firstly, there is an intuitive mapping of expertise similarities onto group sizes. As previously stated, agents belong to either "small" or "large" groups, which may overlap among agents. Secondly, these groups are then used to probabilistically determine the creation of outgoing links. Agents are more likely to make links with others in a "small" group than to others in a "large" group. Lastly, using only the expertise similarities among agents, generated groups correspond to different levels of a social setting (e.g., same product team, same department, or same organization).

The calculated size of a group containing any two agents is the maximum number between two and the expertise difference between two agents scaled by the ratio of agents in the network (*n*) to the number of expertise areas (*m*):

$$|S(a,b)| = max\left(2, \frac{n}{m}\sum_{i=1}^{m}\left|c_{a,i} - c_{b,i}\right|\right)$$

Equation 1: Size of a group containing two agents

where $|S(a,b)|$ is the size of the group containing *agent a* and *agent b*, and $\frac{n}{m}\sum_{i=1}^{m}\left|c_{a,i} - c_{b,i}\right|$ is the expertise difference ($\sum_{i=1}^{m}\left|c_{a,i} - c_{b,i}\right|$) between the agents scaled by ratio of agents (*n*) to the number of expertise areas (*m*). This equation bounds the group size to be a minimum of two because two agents must belong to a group of at least size of two when there is negligible expertise difference between two agents (highly similar with redundant expertise), and a maximum of the entire social network when there is the largest possible expertise difference between two agents.

Each agent in the social network model has a maximum of *k* outgoing links to other agents, known as contacts hereafter. The probability of making a contact with any other agent is proportional to the calculated group size in Equation 1 with an inverse-power distribution controlling for the number of less similar contacts (Ma et al., 2016):

$$P(a \rightarrow b) \propto |S(a,b)|^{-h}$$

Equation 2: Relationship between the probability of connecting to a given agent and group size.

where $P(a \rightarrow b)$ is the probability of *agent a* creating a connection with *agent b* and $|S(a,b)|^{-h}$ is the size of the group in the inverse-power distribution of h. The parameter, h, is the preference for homophily in the network and determines how connected the network is between groups. When *h* is small, long-range contacts are created, which results in networks exhibiting the characteristics of random and small-world networks. However, only contacts within groups are made when $h \to \infty$ (see Figure 3). To determine the contacts for an expert, a distribution containing the probabilities of connecting to every other agent is constructed:

$$P(a \to b) = \frac{|S(a,b)|^{-h}}{\sum_{x \in V \setminus \{a\}} |S(a,x)|^{-h}}$$

Equation 3: Probability of connecting to a given agent

where $P(a \to b)$ is the probability of agent *a* creating a link to agent *b* and $\frac{|S(a,b)|^{-h}}{\sum_{x \in V \setminus \{a\}} |S(a,x)|^{-h}}$ is the ratio of agent *a* creating a link to agent *b* compared to agent *a* creating a link to all other agents in the network. Once this distribution is constructed, an agent independently and randomly selects one other agent to make a link to, *k* times. Following this rule, it is possible for an agent to have less than *k* outgoing links if the same contact is chosen more than once. The contact selection results in agents being more likely to connect with similar others than to agents with a greater similarity difference. Figure 3 provides an illustrative example of how *h* influences the structure of a social network.

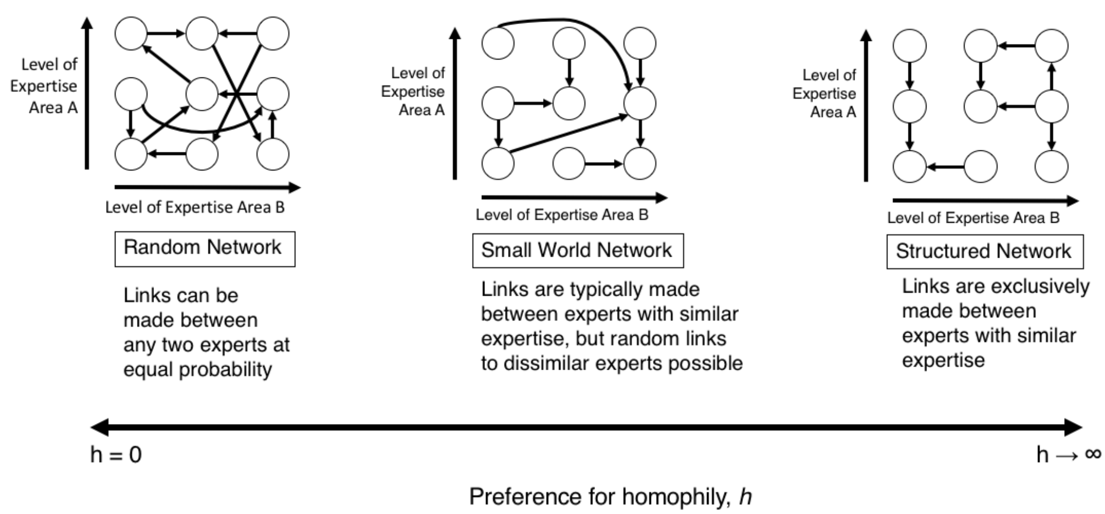


Figure 3: The network generation model and the effect changing values of the Preference for Homophily, h.

Methodological Approach

One of the current study's goals is understanding how network search influences the assembly of expertise-diverse teams. Team assembly is process that is the result of actions taken by multiple agents who coordinate their efforts. As a result, a social network cannot assemble problem-solving teams unless those within the network are performing the actions necessary for finding teammates. The setting in which teams must be assembled is a complex system of agents, social networks, and rules, and it is essential to employ a method suited for decomposing a complex system into more readily interpretable components to order to examine outcomes. For example, conceptualizing how a social network facilitates team assembly. A question considering team assembly at the network level may ask, "How does the structure of a social network influence team assembly?" However, such a question does not consider the actors who themselves are participating in the activity of team assembly. Being able to reason about team assembly by thinking about the behaviors of individuals and how those individuals, in turn, influence team assembly allows for conceptualization of rules that individuals follow when participating in network search during team assembly. Having a method that supports thinking about a complex system at a lower level helps sharpen intuition surrounding the phenomenon under investigation.

In the current study, agent-based modeling (ABM) is the chosen method to establish understanding of team assembly as a network-level outcome from individual search behaviors. By representing a complex system as a population of agents following a defined set of rules, ABM is a computational method well-suited for simulating complex systems and investigating emergent phenomenon (Macy & Willer, 2002; Schelling, 2006; Wilensky, 1999; Wilensky & Rand, 2015). The NetLogo interactive programming environment is used to implement the

ABMs conceptualized in the current study and conduct virtual experiments exploring the performance of search under various conditions (Wilensky, 1999; Wilensky & Shargel, 2002). Analyses from virtual experiments are useful because they offer data derived from a computational implementation of a complex system based on simplified and interpretable assumptions for how search is performed in a social network during team assembly.

Through the use of ABM, defining the social network structure and controlling the network generation process provides an opportunity to reason about search under different social networking conditions while having a clear understanding of how the network formed. If the current study was based in an empirical setting, the scope would be limited by the type of social network collected as well as the search activities of people in the study, which would reduce the generalizability of such research. Also, defining and evaluating search strategies that agents enact during team assembly provides a foundation for conceptualizing search strategies in empirical settings. Empirically, people's ability to search in an organization is influenced by individual differences and their positions in the social network (Singh et al., 2010), which introduces challenges when assessing a given search strategy. Since agents in an ABM simulation follow defined rules to conduct searches, it is possible to develop sharper insights about search strategies and decisions made during search.

Related Models

Prior studies of team assembly have leveraged computational models to capture and explain how collaboration patterns may have been created for given empirical settings. In Guimerà et al. (2005), using empirical data over a period of 127 years and 91,094 different products from creative and scientific industries, the model explained long-term trends by considering only three parameters. Over the history of collaboration, the model used team size, the proportion of newcomers in a team, and the tendency of incumbents to repeat previous collaborations to determine phase shifts in the structure of a collaboration networks. At one end of the spectrum, collaboration networks have a large component containing a considerable number of agents, and at the other end, there are many distinct and disconnected clusters (Guimerà et al., 2005).

Other studies have developed algorithms to assemble teams and reduce communication costs (Anagnostopoulos, Becchetti, Castillo, Gionis, & Leonardi, 2012; Lappas, Liu, & Terzi, 2009), but this work did not investigate the performance of their algorithms in networks with different levels of homophily. Instead, the algorithms were evaluated with empirical networks without an investigation of the generating mechanisms. This limitation subverts the importance of social network structure because interdependencies among agents assembling teams are one of the focal mechanisms to consider. The structure of social networks formed through worker interdependence are a factor in how teams assemble and the team or group in which a worker belongs influences the worker's productivity (Millhiser, Coen, & Solow, 2011), which suggests it is possible for highly skilled workers and their teams to have negative impacts on each other's performance. For example, when workers are not suited for a team, they may be considered a poor fit and interpersonal conflicts may arise (Jehn & Mannix, 2001; Jehn, Northcraft, & Neale, 1999; Kristof-Brown, Zimmerman, & Johnson, 2005). For the current study, an ABM is developed that accounts for social networks and specifies strategies for searching a social network to assemble teams that meet problem-solving criteria.

Computational Implementation and Experimental Design

Virtual experiments from simulations assessed the performance of search strategies through the manipulation of parameters directly related to network generation and problem complexity (see Table 1 for a description of parameters). For the virtual experiments, a total of 79,380 simulation runs were conducted, accounting for 3,969,000 searches to be evaluated. The modeling assumptions made regarding the expertise available in a network and its representation, the initial network structure, and the generation of problems in the simulation setting are discussed below.

Table 1: Description of study variables manipulated during virtual experiments

Parameter	Range	Purpose
Preference for Homophily	*h*: 0-4	Contact selection based on similarity. The parameter ranges from connecting with people randomly with no preference for homophily (h = 0) to connecting with people based on increasingly strong preferences for homophily, based on expertise profiles (h = 4).
Problem Complexity	*m:* 2-8	The number of expertise areas required by a problem.
Number of Agents	*n:* 100-500	The number of agents.
Maximum Outgoing Contacts	*k*: 2-8	Fixes the initial maximum network density.
Number of Problems	*p*: 50	Number of problems each network will assemble teams to solve.
Number of Repetitions	*t*: 10	For each condition, the number of times the condition is replicated.

Experimental Conditions

From Table 1, the "Preference for Homophily" and "Problem Complexity" parameters are key variables for evaluating the performance of the search strategies. The values of the preference for homophily are continuous numbers and range from no preference (h = 0) to a strong preference (h = 4) in 0.5 increments. Modifying the preference for homophily (with respect to expertise similarity) among contacts in the network gives insights into whether the network structure affects search. When there is no preference, agents are equally likely to connect to similar or dissimilar people; as the preference (h) increases, agents become more likely to only connect with similar others. Diversity among contacts is less common when networks are generated by agents who have high preferences for homophily.

The other key parameter is problem complexity, which is represented by the number of expertise areas. The values range from two to eight areas and directly affect the maximum possible team size for a problem. An assumption of the model is that a team needs to have expertise surpassing the required expertise of a problem (drawn randomly from a normal distribution), and it is possible for team size to grow as the problem complexity increases (i.e., a team has a maximum size of four members when a problem has four areas). Testing the number of expertise areas indicates the extent to which problem complexity affects search by determining whether more complex problems increase the difficulty in searching for team members.

There are two other variables included in the experiment that represent the social environment encompassing agents during their searches: "Number of Agents" and "Maximum Outgoing Contacts." These variables help control the network conditions under which search to assemble teams occurs; simulating strategies in different sized networks at different levels of density. Each experimental condition was replicated ten times to observe the range of outcomes for each simulation run. For all of the simulation runs, the number of problems generated is held constant at fifty problems. This constant was selected to investigate the search behaviors based on multiple problems while maintaining reasonable run times for a single simulation.

Evaluation and Results

The searches are evaluated using characteristics of assembled teams as well as search performance. Assembled teams meet the requisite expertise diversity for solving problems, but there are two ways to describe expertise in a team to measure relevant aspects of a team's expertise diversity. The first way to describe a team's characteristics is through the expertise match between a team and a problem. Matching expertise to a problem is a positive indicator that a team member will allocate attention and engage with a given problem (Haas, Criscuolo, & George, 2015). The measure is the sum of the differences between the maximum expertise of a team and the expertise required by a problem in each expertise area scaled by the number of expertise areas. A smaller difference indicates a team that is more closely matched to a problem, and therefore is a desirable characteristic for a team because organizational resources are allocated such that high-skilled experts are not addressing problems far below their skill levels. As an example, a team does not need an organization's best software developer to solve a problem that can be solved by a novice software developer. The measure is described by the following equation:

$$\frac{1}{m}\sum_{i=1}^{m}\left|c_{team\ max,i} - c_{problem\ requirement,i}\right|$$

Equation 4: Expertise match Between a Team and a Problem

The second way of measuring a team's characteristics is through the expertise coverage among team members. Because team members have to address problems with varying levels of difficulty and complexity, there is the potential for teams to have different levels of expertise diversity while still meeting problem requirements. For example, team members may have relatively similar expertise profiles (but still are able to solve a problem) or may have extremely different expertise profiles. To capture these degrees of diversity, expertise coverage is measured as the mean range of team expertise, where the sum of the differences between the maximum and minimum expertise in each area is normalized by the number of expertise areas:

$$\frac{1}{m}\sum_{i=1}^{m}\left|c_{team\ max,i} - c_{team\ min,i}\right|$$

Equation 5: Expertise Coverage of a Team

When expertise coverage is low, then only a small amount of expertise in the network is represented—similar to a team only having one type of person. However, when expertise coverage is high, then the team reflects more of the expertise available in the network; i.e., the expertise present in the network is well-represented in the team. Examples to describe a diverse team at each of the two extremes would be a team composed of members with generalized expertise (relatively similar) and a team composed of members of highly specialized expertise in different areas (extremely different). In totality, both team characteristics illustrate how expertise-diverse teams differ in the coverage of their expertise and in how well they match the problem for which they assemble to solve.

In order for teams to assemble, the search process must identify team members. Therefore, search performance is assessed using two distinct measures: the percentage of searches that succeeded and the network distance covered during a search. The percentage of searches that succeeded gives insight into the frequency that searches found agents capable of solving a problem. Search succeeds based on one of two mechanisms, finding either a team solver or an individual solver. Distinguishing between an individual solver and team solver provides higher granularity into the ways that search supports identifying problem solvers at different levels of complexity. For example, there may be levels of problem complexity where only team solvers are capable of solving a problem.

The second measure of search performance is the network distance covered during a search. The distance is defined as the number of steps that a problem travels during a search and is a proxy for the amount of time required for a search. Because more intermediaries are involved in search as distance increases, searches take longer to complete compared to shorter searches. Additional distance means that multiple agents have to employ a search strategy, follow the rules for searching, and help assemble teams. Specifically, a search that finishes one step away from the original searcher will result in a team of the original searcher's contacts, whereas a search that concludes two steps away requires at least one of the original searcher's contacts to participate in the search process (in the next model step) to find an agent not directly connected to the original searcher.

Assessing search performance is aided through the experimental design of the current study. The search strategies developed to find team members are investigated by manipulating problem complexity and the preference for homophily in the network, while also accounting for the problem difficulty based on expertise requirements. Problem difficulty is calculated as the average of all expertise requirements of a problem. From the average, problems are partitioned into four levels of difficulty "Easy," "Moderately Easy," "Moderately Hard," and "Hard." For all simulations, problem requirements were generated from a normal distribution and there are 159,485 "Easy" problems with an average difficulty of less than 0.25, 1,849,642 "Moderately Easy" problems with difficulty between 0.25 and 0.49, 1,808,934 "Moderately Hard" problems with difficulty between 0.50 and 0.74, and 150,939 "Hard" problems are greater than or equal to 0.75. Partitioning based on problem difficulty clarifies the results and helps provide insights into the how search is differentiated across experimental conditions and how expertise diversity in teams is impacted downstream.

Network Setting

Social network structure changes based on the value of the preference for homophily. Two network measures are calculated in order to describe the network conditions in which search was conducted: network density and global clustering coefficient. Network density is the overall connectedness of a network and calculated as the number of ties present in a network divided by the total number of potential ties (Wasserman & Faust, 1994). The global clustering coefficient is the number of triangles in a network divided by the total number of possible triangles (Newman, 2010). Network clustering indicates the prevalence of groups where members of a group have more ties within the group than they do outside of the group. The network density decreases, and the global clustering coefficient increases as the preference for homophily increases (see Figure 4). When there are relatively higher levels of the preference for homophily, the network generation procedure used in the current study probabilistically creates ties by more strongly considering similarity between actors. The network setting thus influences search because higher levels of the preference of homophily result in networks that are sparser and more clustered. By using these network measures, the preference for homophily is more interpretable when considering the substantive results.

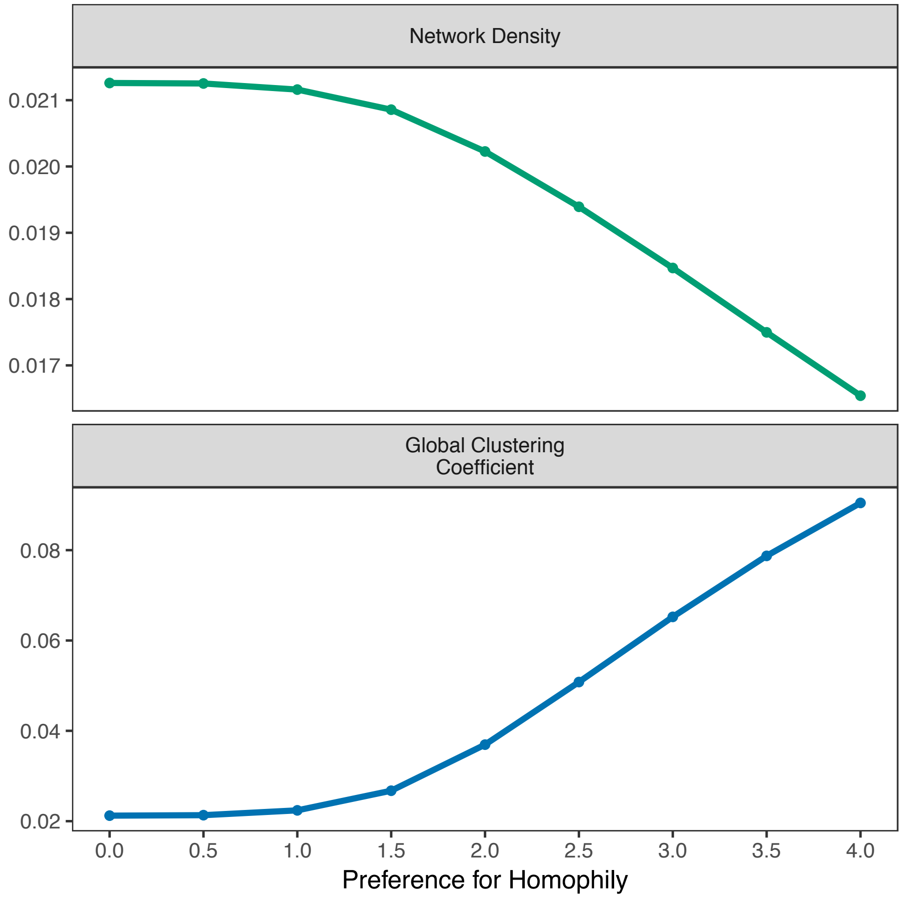


Figure 4: Network density and the global clustering coefficient are network metrics that illustrate differences among networks generated at various values of the Preference for Homophily.

Team Diversity

To meet problem requirements at varying levels of complexity, all assembled teams have at least some amount of expertise diversity. To better understand the nature of the assembled teams, two characteristics are employed: expertise match between the team and problem, and expertise coverage of the team. The average values of each measure are used to investigate team diversity across all teams under every specified condition. The expertise coverage of the team increases and the expertise match between the team and problem decreases as the problems increase in difficulty (see Figure 5). Problem difficulty has a relationship to both team characteristics because difficult problems are closer to the maximum available expertise in a social network. Therefore, for “Hard” problems, a team on average will be a closer match to a problem and have more expertise coverage. When problems are not as difficult, then high expertise coverage for a team is not necessary because teams with less coverage satisfy problem requirements. Meanwhile teams are not as well-matched to problems at lower difficulty. Overall, the observed trends show that as problems become more difficult, teams are more diverse and better suited for solving such problems as measured by expertise match.

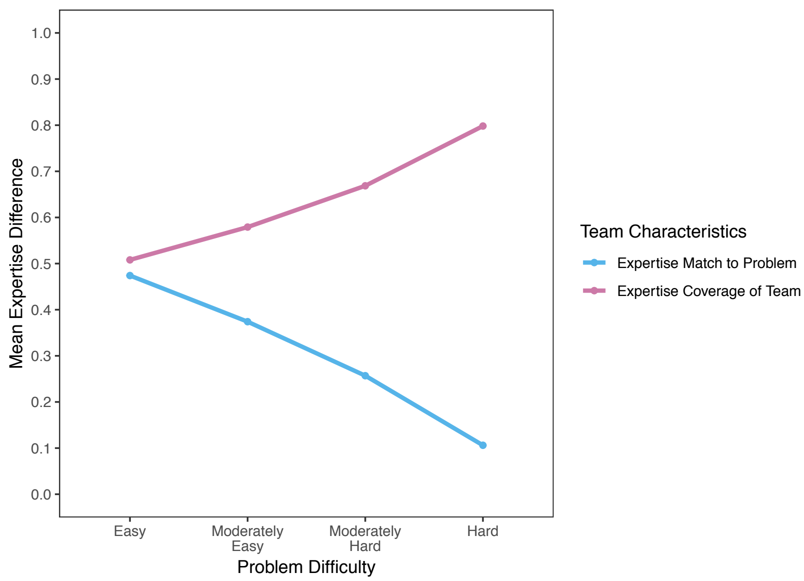


Figure 5: Team characteristics that describe a team’s expertise diversity plotted against levels of problem difficulty.

Analyzing team characteristics at different levels of problem complexity and difficulty shows that qualities of teams change based on the types of problems for which they assemble (Figure 6). While the expertise match between a team and problem decreases with problem difficulty, it increases with problem complexity. The increase indicates that more complex problems, as compared to problems of lower complexity, will have teams that do not fit the problem requirements as well. Irrespective of problem complexity, the hardest problems have teams that are better-matched.

For the expertise coverage of a team, there are notable patterns in how coverage changes with respect to both problem complexity and difficulty. At all difficulty levels, the relationship between expertise coverage and problem complexity is non-linear. For “Easy” problems, the expertise coverage has a U-shaped curve with the maximum at a complexity of two expertise areas. Teams have decreasing levels of expertise diversity as problem complexity increases up to a point where problems become highly complexity (at least six areas); then, expertise coverage begins to moderately increase. As the problem difficulty increases, the U-shaped curve contracts and eventually becomes more of a V-shape for “Hard” problems; the expertise coverage decreases to its minimum expertise at three areas of expertise before increasing at higher levels of complexity (see Figure 6). Overall, expertise coverage is relatively low at moderate levels of complexity compared to low (two expertise areas) and high complexity (more than four expertise areas). Aside from problem complexity, the preference for homophily differentially affects team characteristics based on the problem difficulty. For “Easy” problems, expertise match between a team and a problem and expertise coverage decrease as the preference for homophily increases. Social networks with more homophily result in teams that have less expertise coverage, but that are a better match for a given problem. However, as problem difficulty increases, the trend reduces for the match between a team and a problem at different values of the preference for homophily. For “Hard” problems, the match between a team and a problem does not differ greatly between low and high values of the preference for homophily. To summarize these observations, expertise coverage always decreases when the preference for homophily increases while the decline in the match between a team and a problem depends on the difficulty level of a problem (Figure 7).

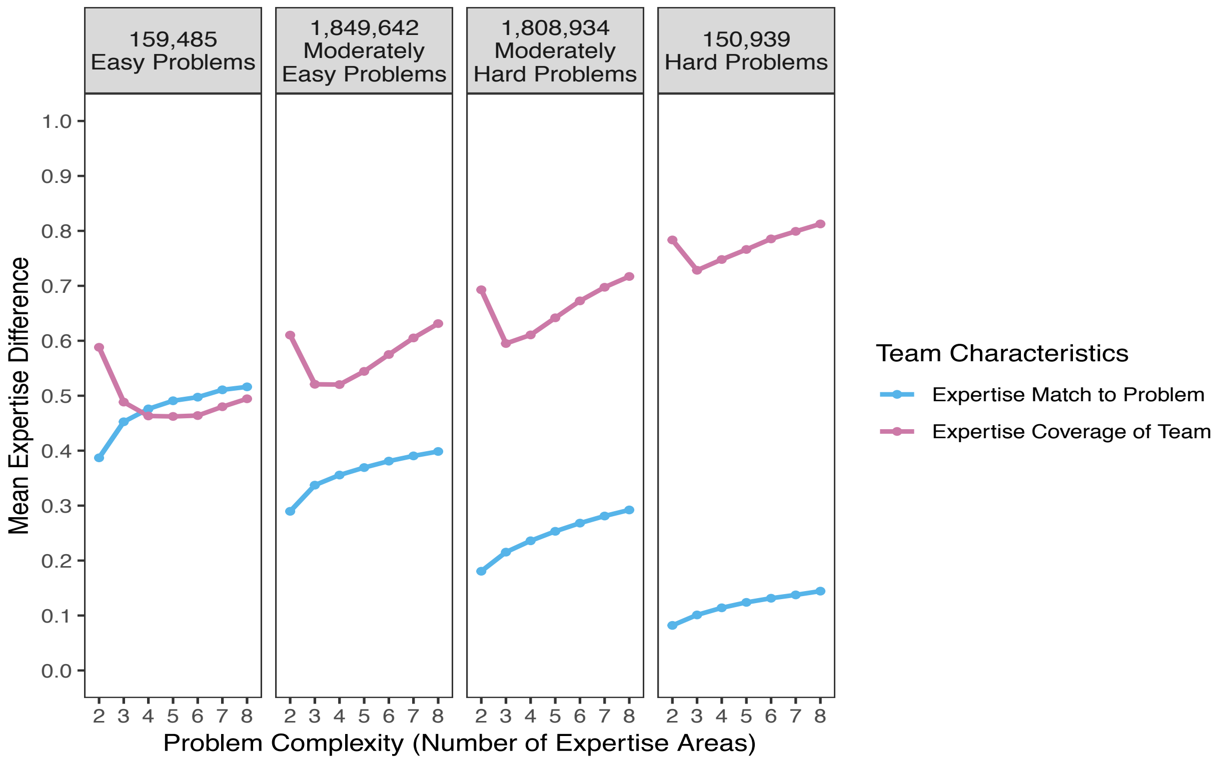


Figure 6: Team characteristics that describe a team's expertise diversity plotted against problem complexity for problems with different levels of problem difficulty.

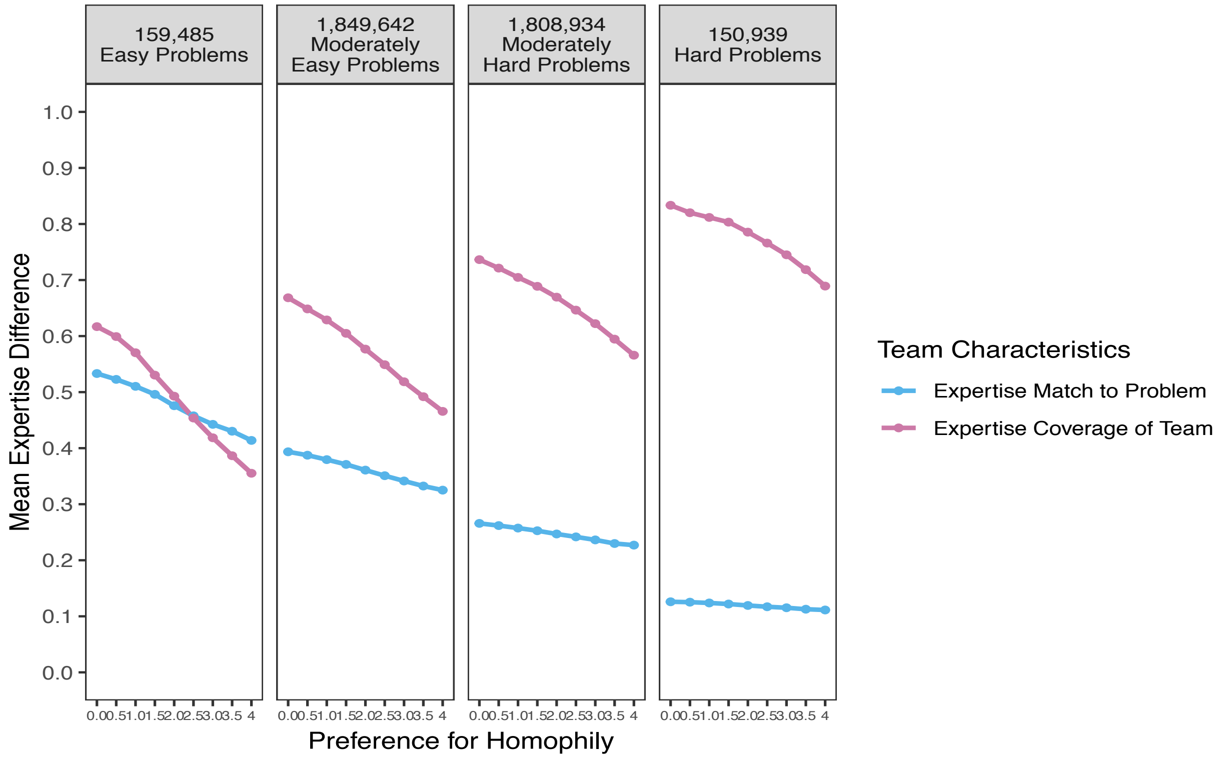


Figure 7: Team characteristics that describe a team's expertise diversity plotted against the preference for homophily for problems with different levels of problem difficulty.

The analysis of two team characteristics helps to describe the expertise diversity of teams that assemble as the result of search. Expertise coverage of a team represents the differences among team members and is influenced differently by problem difficulty, problem complexity, and the preference for homophily. On average, teams have higher expertise coverage when assembling for more difficult problems but increasing the preference for homophily in a network reduces the expertise coverage of teams. The relationship between expertise coverage and problem complexity is non-linear and changes based on problem difficulty. The match between a team and a problem decreases with problem difficulty and the preference for homophily but increases with problem complexity. It is worth noting that the effect of the preference for homophily is not as strong at the highest level of problem difficulty (i.e. "Hard" problems).

Search Success

Assessing search performance gives more insight into how team assemble. The first indicator of search performance is the percentage of searches that succeeded. Each search has two possible types of success, either by a team solver or a solo (individual) solver. The percentage is calculated by the number of searches for a given type (e.g., team solver) divided by the total number of searches. Figure 8 shows the percentage of searches that succeeded with respect to the problem complexity—operationalized by the number of expertise areas, problem difficulty, and search strategy. The percentage of team solvers increases as problem complexity increases, and the rate of increase declines at higher levels of complexity (above four expertise areas). There are two details worth noting about the effect of problem difficulty on the percentage of searches that succeeded with a team solver: there is a higher minimum and lower maximum as difficulty increases. Specifically, a higher percentage of searches result in a team solver while a lower percentage of searches are successful overall for more difficult problems (see Figure 8, top row). For solo solvers, the success percentage decreases as problem complexity increases, and problem difficulty reduces the number of solo solvers overall (see Figure 8, bottom row). The search strategies had different percentages of success dependent upon the problem difficulty. There is no appreciable difference between search strategies finding solo solvers or when finding team solvers for an “Easy” problem. At other levels of problem complexity, the *Broker Search* strategy succeeds more often than the *Local Search* strategy with the difference widening between the two strategies as problem complexity increases. *Broker Search* becomes more advantageous when problems are more difficult and complex.

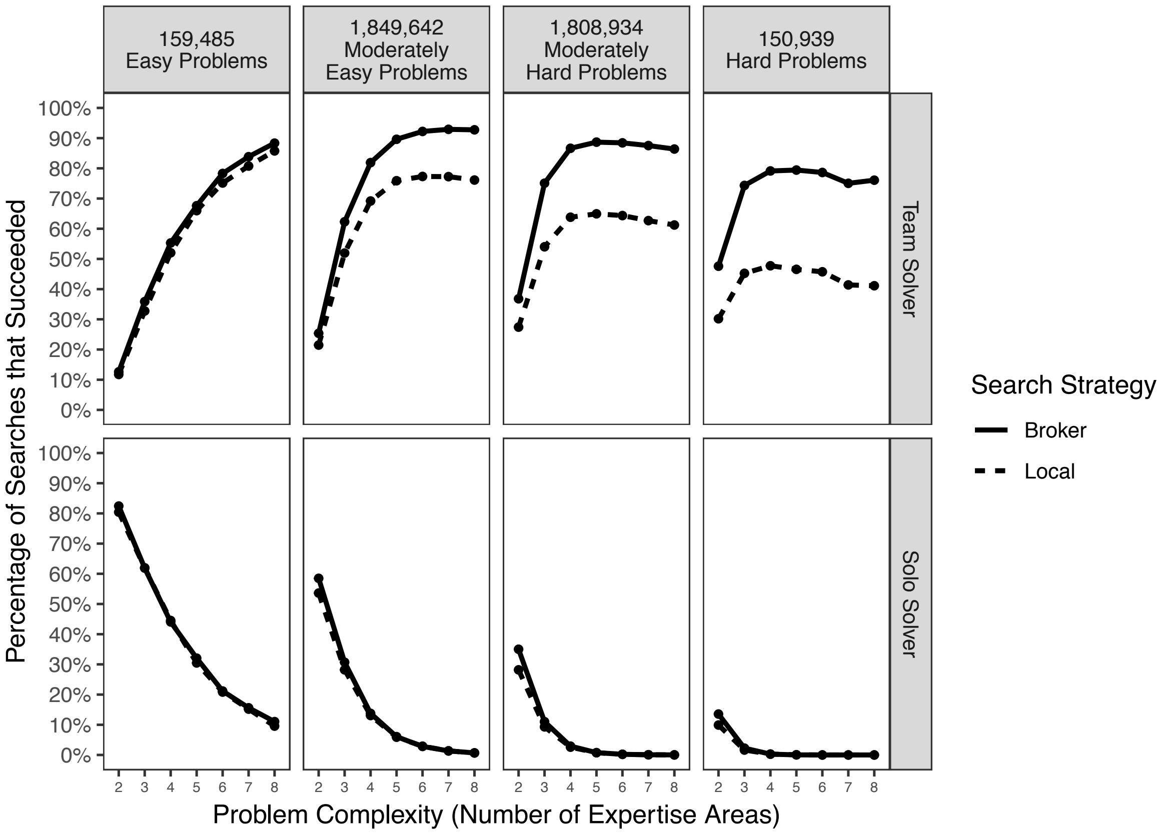


Figure 8: The percentage of searches that succeeded in finding a team solver and solo solver for each search strategy plotted against problem complexity for problems with different levels of problem difficulty.

While problem difficulty and complexity have effects on the percentage of searches that succeeded, the preference for homophily affects success as well (Figure 9). The preference for homophily's impact is apparent for team solvers of problems that were more difficult than "Easy" problems. At higher levels of problem difficulty, the percentage of searches that succeeded decreases with the preference for homophily. Both strategies decline in a similar fashion, but *Broker Search* is successful in a higher percentage of searches with the advantage increasing with problem difficulty (see Figure 9). However, for solo solvers and "Easy" problems, there is no clearly distinguishable relationship between the preference for homophily and success, nor is there an observable difference between search strategies.

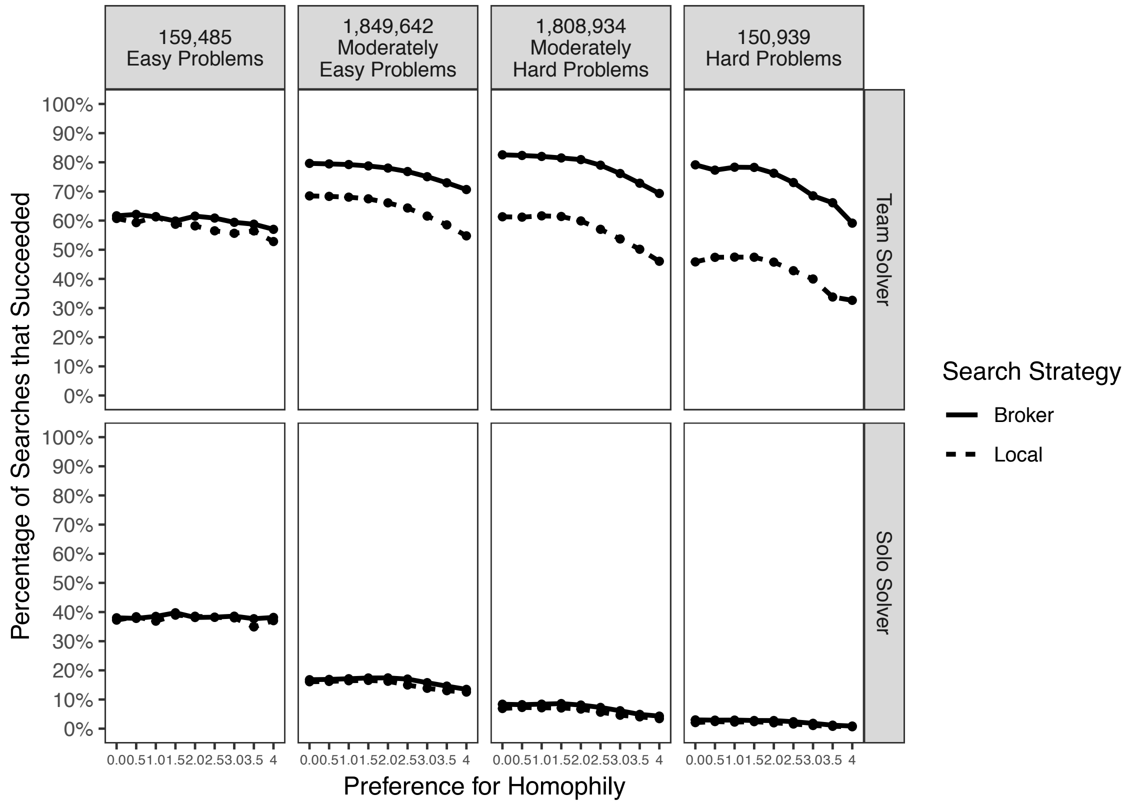


Figure 9: The percentage of searches that succeeded in finding a team solver and solo solver for each search strategy plotted against the preference for homophily for problems with different levels of problem difficulty.

To summarize observations from the percentage of searches that succeeded, team solvers exclusively become the mechanism for successful searches when problem complexity increases (solo solvers decrease to near zero). Additionally, the preference for homophily decreases the overall success for team solvers but did not notably impact solo solvers. The employed search strategy greatly impacts the success of search when problem difficulty and complexity increase. Overall, *Broker Search* has a higher success percentage than *Local Search* and teams become the only type of success as problem complexity increases.

Network Distance

The next measure of search performance is the network distance of a search. Search is defined as a decentralized process where multiple intermediaries participate in finding problem solvers. Therefore, network distance measures the mean number of steps needed to complete a search since a search requires that a problem travels some distance in a network in order to find all team members. From Figure 10, network distance has a curvilinear relationship with problem complexity. Network distance is at its maximum for problems with the lowest complexity and is at its minimum for problems of moderate difficulty.

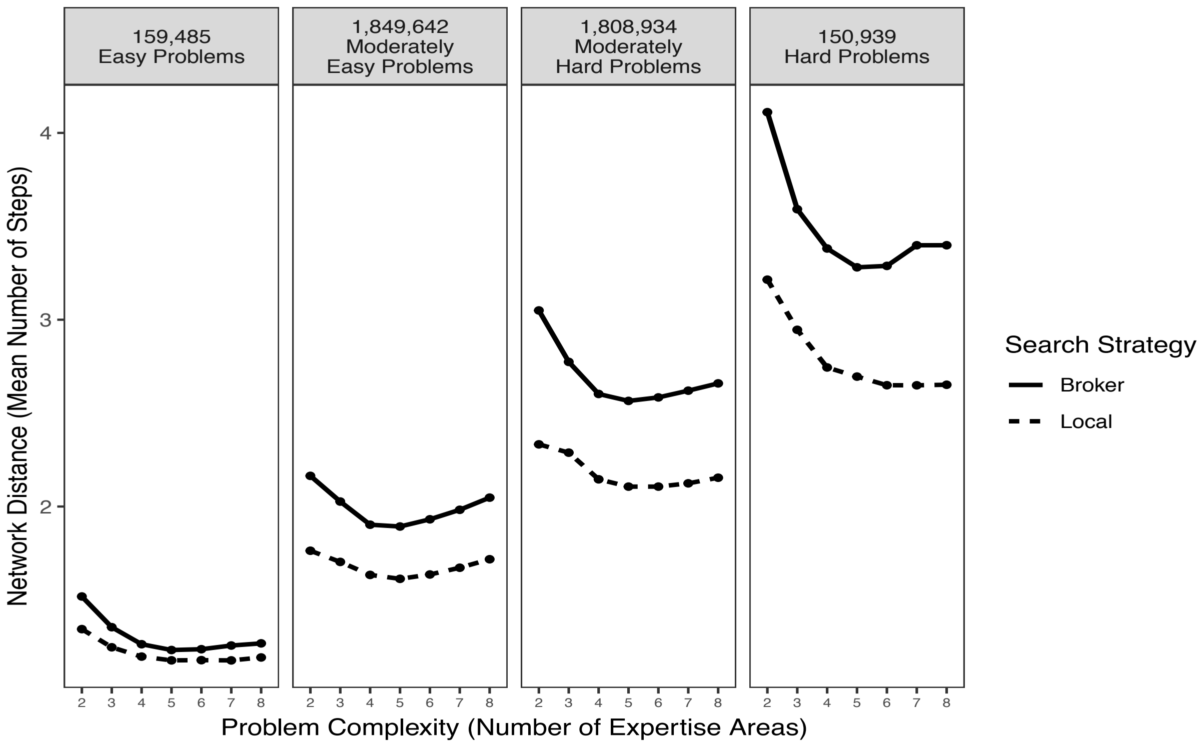


Figure 10: The network distance (mean number of steps) for each search strategy to find team members plotted against problem complexity for problems with different levels of problem difficulty.

When observing network distance with respect to the preference for homophily, the network distance increases as the preference for homophily increases (see Figure 11). Overall, for both problem complexity and the preference for homophily, the network distance increases with problem difficulty, where "Hard" problems require longer network distances to be covered in order to assemble a team. The difference between search strategies increases with problem difficulty as well with *Broker Search* having longer searches than *Local Search* on average. It is worth noting that *Broker Search* has a higher percentage of success as well, which suggests that the higher values of network distance correspond to assembling more teams.

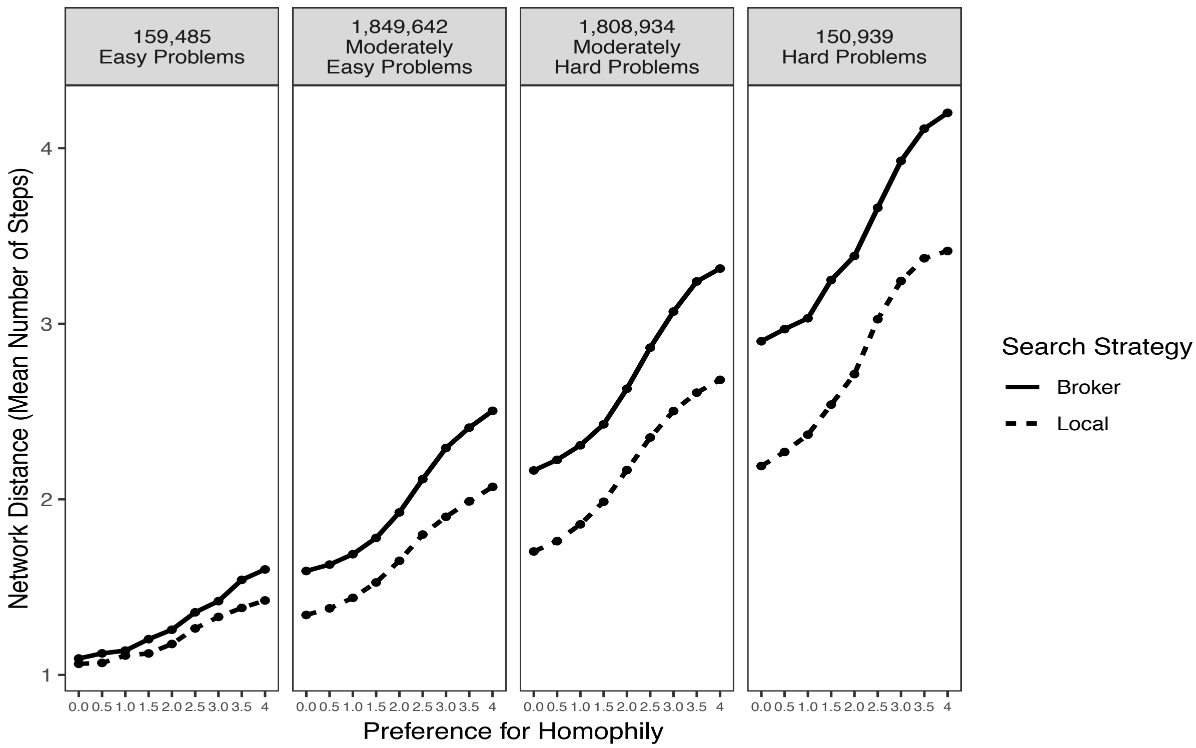


Figure 11: The network distance (mean number of steps) for each search strategy to find team members plotted against the preference for homophily for problems with different levels of problem difficulty.

Discussion

Network search has long been investigated as a means to explore how information and resources may be accessed by individuals navigating the structure of social networks (Adamic & Adar, 2005; Dodds et al., 2003; Travers & Milgram, 1969; White, 1970). However, there has also been attention given to understanding of how networks influence teams (J. N. Cummings, 2004; Reagans et al., 2004; Reagans & Zuckerman, 2001). Because network search is a vital activity of actors in social networks, investigating how search influences team assembly and team diversity contributes to building understanding of the emergence of teams. The results from evaluating a model of network search provide promising insights into team assembly and diversity as an outcome of decentralized network search.

The current study investigates network search for team members by accounting for problem difficulty, and by controlling for problem complexity and the preference for homophily to increase clarity around how these different considerations impact search and team diversity. From observed patterns of searches and team characteristics, problem difficulty relates to the viability of search for assembling expertise-diverse teams. When problem difficulty increases, teams have higher expertise coverage that better represents the social network, and teams will better match the problem for which they assemble. With regards to search, teams become more necessary to solve problems as difficulty increases, corresponding to empirical trends of the increased prevalence of teams in response to the complexity of contemporary knowledge work (Falk-Krzesinski et al., 2010; Leahey, 2016; Wuchty et al., 2007). Searching for team members also covers more network distance for more difficult problems, indicating that higher expertise requirements necessitate longer searches.

When accounting for problem complexity, non-linearity in team expertise coverage shows that diversity happens when problems are not complex as well as highly complex. For problems of low complexity, there is a sizable proportion of problems that individuals are able solve, which suggests that teams only assemble for problems that require more expertise coverage than a single individual will typically provide. However, highly complex problems demand more expertise coverage by nature of the requirements. The preference for homophily reduced expertise coverage when it increased having a stifling effect on team diversity. Expertise diversity was contingent upon a network structure that controlled whether people could connect to similar or different contacts, which has implications for team performance if individuals do not exchange a variety of information and experiences (Reagans & Zuckerman, 2001).

Evaluating two search strategies shows the importance of social network structure when assembling teams. *Broker Search* assesses actors that are within a two-step radius of contacts when deciding who participates in search or who will assemble into a team whereas *Local*

Search only assesses actors that are one-step away (direct contacts). Overall, *Broker Search* assembles more teams than *Local Search* while requiring more information processing and participants in search. However, *Broker Search* is susceptible to the same challenges as *Local Search* when employed in networks with higher preferences for homophily. Both strategies increase their network distances to assemble less diverse teams when the preference for homophily is strong. In such cases, *Broker Search* results in more effort than *Local Search* to assemble teams that are do not have as much expertise coverage compared to the effort that is expended in networks with weaker preferences for homophily.

Overall, the current study contributes to literature related to search in social networks by focusing on identifying multiple team members as the goal of search. Beginning with classical studies of the "small world problem" (Milgram, 1967; Travers & Milgram, 1969), prior research has typically been rooted in scenarios where people attempt to find a single target within the social network by relying on intermediaries who contribute to the search process. These studies have since led to subsequent research that expound upon the conditions that promote search in networks by largely focusing on network structure, which has been shown to impact search performance (Adamic & Adar, 2005; Kleinberg, 2006; Ma et al., 2016; Watts et al., 2002). The current study uncovers how traditional notions of network search apply to a scenario where a single target is not known at the start of search and when multiple people may fulfill a search. A notable contribution from the findings is that teams are the only way that problems of high complexity can be addressed; individuals no longer meet all of the expertise requirements of a problem. This finding suggests that extending network search to consider multiple targets is necessary to depict the solving of highly complex problems (with respect to the number of expertise areas needed). Therefore, under specific problem requirements, addressing problems relies entirely upon team assembly.

The contributions of the study also link to research focusing on team diversity and assembly. From the results, teams were not necessary for problems with lower expertise requirements. On the other hand, increased problem requirements resulted in higher levels of team diversity even though agents were using the same search strategies to maximize the expertise of solvers for all problems. Teams were also better matched to more difficult problems. Accordingly, these trends suggest that task demands and characteristics justify team assembly by clarifying expectations (Hackman, 1987; Harrison & Humphrey, 2010). Instead of searching for team members based on a priori goals of diversity, a more nuanced approach that evaluates what types of expertise are needed before searching for team members could help foster teams that are diverse along dimensions needed for a given problem (Hargadon & Sutton, 1997; Reagans et al., 2004). Viewing questions surrounding team diversity through the problems for which teams assemble will potentially focus attention to the problem characteristics that advantage teams over individuals.

Practitioners can derive value from the current study by concretely appraising the problems for which teams assemble, defining the strategies that people use to identify team members when assembling, and being cognizant of the ways in which social networks inhibit or enable search activities. Problem complexity and difficulty showed that assembling teams is not always necessary. If a community or organization has problems that are not considered complex or difficult for the expertise that is available, and therefore do not necessarily require innovative solutions, then leveraging individual contributors is effective and reduces coordination costs of collaboration (Dahlin, Taylor, & Fichman, 2004; Singh & Fleming, 2010). From the current study, searching for multiple team members has the most utility for problems that were in the two most difficult classes and of higher complexity. Understanding when a team's capabilities will exceed the capabilities of an individual helps to better the management of resources and expertise.

The next practical implication comes from articulating clear search rules: agents look to maximize expertise and ask their contacts to help them find others who will maximize expertise. Oftentimes, people have different approaches when searching for team members and apply different criteria for which they attempt to optimize, which increases the complexity of search. Having higher complexity present in the search process increases the opaqueness of relevant factors for selecting team members. If organizations have defined outcomes and goals for teams, then also having a defined procedure for search would be beneficial because those who rely on teams would better understand how search relates to specific team characteristics.

Lastly, value in the current research stems from the clarifying how the preference for homophily in networks affects team assembly. If there is a network where people are clustered based on specialties or expertise, then it becomes difficult to address certain types of problems. Acknowledging and addressing homophily in a network benefits those who are embedded in the network because then the network can support assembling diverse teams capable of solving complex and difficult problems. People who have diverse connections in such a network could serve as brokers, but it is also possible that the ones who need to build the teams would be peripheral in the network and not have access to needed resources and contacts (Singh et al., 2010). Taking measures to support informal networks and intellectual communities helps ensure that people have a broad, diverse set of connections (Brass et al., 2004; Jacobs & Frickel, 2009; Krackhardt & Hanson, 1993; Wenger & Snyder, 2000). In summary, the current research study helps practitioners think about the problems for which teams assemble, the ways in which people search for team members, and how social networks affect the ability to search.

Limitations and Future Directions

The limitations of the current study largely concern modeling assumptions and the applicability of the model to empirical settings. There are four assumptions embedded in the models that may constrict some of the generalizability of the current research: external validity of expertise representation, network generation, sequential problem generation, and search strategy rules. The expertise of agents and problems is represented as a numerical vector (range between 0 and 1) of a defined length, and the generalizability of such a representation may be questionable. In the model, an agent's expertise can easily be compared to and assessed against other agents and the problems in the simulations, but there is difficulty in describing how the expertise representation in the models corresponds to other representations of expertise (e.g. intelligence, credentials, or skills). A researcher would need to make careful considerations when applying the developed models to other contexts in order to adequately represent expertise in different contexts, or at least compare the current expertise representation to other representations.

Questions may also be raised regarding the network generation process. The model adapted from prior research makes assumptions about the probability of connecting to others based on similarity (Kleinberg, 2002; Ma et al., 2016). Only expertise is responsible for generating network links in the current study. The generated networks are directed, and there are other mechanisms that can explain the likelihood of people connecting to one another. An example of a social network generated from such a model would be a network in an organization where links are based exclusively on the functional area in which people reside. However, there are multiple other reasons for people to make connections and search is influenced by differences in the type of social network or by whether there is a formal hierarchy (Adamic & Adar, 2005). To alleviate this limitation, investigating search performance and team characteristics by using empirically-collected social networks would provide insights into the ways in which search identifies new team members in empirical settings. The limitations around the network generation process would greatly profit from employing an empirical social network because the developed search strategies could be compared to empirical patterns of a given setting.

The next modeling assumption relates to the sequential entry of problems into the social network. This serves as a limitation because, while reducing complexity of the model and simplifying analysis, the model loses the dynamics of the coexistence of multiple problems. Questions related to whether a problem will be ignored in favor of another problem or how agents decide which problem to search for team members cannot be investigated in the current model, but such considerations contribute to decisions that people make when allocating attention to knowledge intensive work tasks (Haas et al., 2015; Y. Kim, Jarvenpaa, & Gu, 2018; O'Leary, Mortensen, & Woolley, 2011). Lastly, the rules that govern agents' search behavior assume that all agents are attempting to maximize expertise. A more realistic set of rules would allow agents to choose between maximizing expertise and other considerations; for example, attempting to maximize the match between an agent and problem instead of maximizing on expertise. Additionally, different agents may follow alternative considerations. The current study is able to assess the match between a team and a problem as an outcome, but a model where agents attempt to optimize upon the match would be a worthwhile investigation.

Conclusion

In conclusion, the current study details the ways in which expertise diversity in teams is related to the search process responsible for identifying team members when assembling teams. Problem complexity benefited the expertise coverage of a team by demanding higher levels of diverse expertise but diminished the expertise match between a team and problem. On the other hand, the preference for homophily constrained the expertise coverage of a team but enhanced the match between a team and problem. Additionally, higher problem difficulty supports team diversity by the explicit need for high levels of diverse expertise. For search performance, results show that problem difficulty increases the importance of search strategy selection. Different search strategies have clear consequences on success in finding team members by having a broader view of a social network, which ultimately exposes a searcher to new people and more expertise in the network. The current findings contribute to extant scholarship by providing a set of considerations surrounding network search that affect the expertise diversity of teams, which brings greater clarity regarding how teams assemble for problems of varying complexity, reflecting collaboration activities in contemporary settings of knowledge intensive problem-solving.

CHAPTER 3. CHOOSING TEAMMATES IN ONLINE RECOMMENDER SYSTEMS: THE ROLES OF ONLINE RECOMMENDATIONS AND PRIOR COLLABORATION

Abstract

Inviting teammates is a foundational process in team self-assembly. In this paper, I extend Hinds, Carley, Krackhardt, and Wholey's (2000) seminal model of team member selection by incorporating a new technology platform known as a teammate recommender system (similar to an online dating website for team assembly). A total of 410 participants assembled into 63 interorganizational-interdisciplinary teams (sized 5-7 members) and left digital traces of 1,049 teammate invitations. These data were collected from two research settings, with one replicating the other. Results based on exponential random graph modeling (ERGM) of teammate invitation networks show that the tendency to send an invitation to a potential team member is a function of online recommendations, beyond the previously-established effects of prior collaboration/familiarity, skills/competence, and homophily. Importantly, an interaction effect was observed in both samples, showing prior collaborations are a boundary condition for the effect of online recommendations, such that online recommendations are less likely to be heeded when there is prior collaboration. Results specify conditions under which online recommender systems can reduce uncertainty during team formation. Overall, this study provides insight into technology-enabled team assembly, by using digital trace data analyzed with a relational perspective.

Keywords: Team formation, team assembly, social networks, exponential random graph models

Introduction

The value of social technology platforms stems from their utility in facilitating collaboration, communication, and knowledge-sharing in organizations (Kane, Alavi, Labianca, & Borgatti, 2014; Leonardi & Vaast, 2017). Online recommender systems are one type of technology that plays a role in helping people build meaningful relationships in the workplace (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. *Team assembly* refers to the relationships and activities of people as they self-select and organize into teams (Contractor, 2013; Humphrey & Aime, 2014). The 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). In recent years, the increasing prominence of social technology in organizations has augmented people's ability to select team members, and it is now commonplace for team members to initially engage with one another through such technology platforms (J. Cummings & Dennis, 2018). I contribute to research on team formation by focusing on the social interactions that occur during technology-enabled team assembly in an online recommender system. The system creates an environment where people look for teammates by reviewing a list of "matches" to their preferences, and then invite potential teammates to form project teams.

Teammate invitations signal interest from one person to another and directly result in team formation. By investigating invitations during technology-enabled team assembly, I 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, Griffith, Majchrzak, Dougherty, & Faraj, 2007). In the current study, I extend understanding of teammate selection by considering new theoretical explanations for: (a) how online recommendations influence teammate invitations, and (b) how online recommendations augment or suppress previously-established theoretical mechanisms of teammate selection.

Applying a social network perspective is key to my explanation of teammate invitations and the relevance of online recommendations. Previous research has established the importance of social networks when selecting team members (Gao, Hinds, & Zhao, 2013; Hinds, Carley, Krackhardt, & Wholey, 2000; Reagans et al., 2004). The current paper integrates considerations of individual attributes, relational attributes, social networks, and technology, to explain the process of teammate invitation. Therefore, I propose a multitheoretical, multilevel model for analyzing the emergent teammate invitation networks inherent to team self-assembly (Contractor, 2013; Contractor, Wasserman, & Faust, 2006; Monge & Contractor, 2003), and I test this model using exponential random graph modeling (ERGM).

The current study of teammate invitations gives insight into how social technology impacts team assembly, contributing to theory on team assembly in two ways. First, the paper extends understanding of team member selection by incorporating a social technology platform as a new information source. The study shows that online recommendations influence teammate invitations beyond information about potential teammate competence and homophily. The second contribution recognizes prior collaboration as a boundary condition for online recommendations, such that online recommendations no longer contribute to uncertainty reduction when there has been prior collaboration with an individual. Together, these two contributions illuminate the ways people in organizations can leverage recent technological advances to support collaboration, by better explaining how people use online recommendations during team assembly.

Theory and Hypotheses

Team assembly is the responsibility of either managers or team members themselves (Contractor, 2013; Hackman, 1987). During cases of team self-assembly, team members must assess and maintain awareness of task requirements in order to make choices about other members. Understanding the organizational environment and work design makes it possible to identify task dimensions that team members need to address (Grant, 2007; Harrison & Humphrey, 2010). Task dimensions may include task interdependence, interpersonal interactions, and the broader social context situating the work (Morgeson & Humphrey, 2008; Parker, Morgeson, & Johns, 2017). By focusing on different aspects of a task, a person selects team members using multiple information sources (Hinds et al., 2000). These information sources help reduce uncertainty during teammate invitation, according to each individual's perception of the attributes needed to maximize a team's chance of success.

Identifying relevant attributes (e.g., skills and demography) is a key consideration when inviting team members. The individual attributes then aggregate to constitute a team's composition (Klein & Kozlowski, 2000), which has traditionally been understood to influence whether a team will accomplish desired performance goals (Bell, 2007; Harrison, Price, & Bell, 1998). As an example, the skills and competence within a team determine the team's aggregate ability, configuration of skills, and member roles. Furthermore, demographic attributes such as gender, race, and tenure have implications for team performance, because diversity affects communication to external groups and access to new ideas (Ancona & Caldwell, 1992; Harrison & Humphrey, 2010; Harrison & Klein, 2007; Reagans et al., 2004; Williams & O'Reilly, 1998). Homophily in teammate invitations entails people's inviting others who share the same attributes. Homophily, in general, is the tendency for people to connect to and work with others who are similar to themselves and belong to the same social groups (Kossinets & Watts, 2009; McPherson et al., 2001; Ruef, Aldrich, & Carter, 2003; Wimmer & Lewis, 2010). Therefore, if people invite others based on homophily, then the assembled team will tend to be less diverse along certain dimensions. Demography and skills are just two examples of the many individual attributes that constitute information for people to consider when inviting teammates.

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, Xia, Gopalakrishnan, Qian, & Zhou, 2017; Jahanbakhsh, Fu, Karahalios, Marinov, & Bailey, 2017). For example, a technology platform developed by Bergey and King (2014) uses 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). Whereas this type of technology does not change whether people have attributes that are relevant or in-demand for teamwork, they do automate team member assignment by "optimally" fitting people into teams.

Recommender systems, on the other hand, help people make their own choices about teammates by providing "matches" of potential teammates who meet specified requirements and criteria (Fazel-Zarandi, Devlin, Huang, & Contractor, 2011; Malinowski, Weitzel, & Keim, 2008). 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, Iacovou, Suchak, Bergstrom, & Riedl, 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 (i.e., potential teammates in this case) (Lazer, 2015; Xiao & Benbasat, 2007). Online recommender systems offer recommendations 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, Ronen, & Wilcox, 2009; Guy, Ur, Ronen, Perer, & Jacovi, 2011). In the context of team assembly, one issue that remains is this: to what extent does the information contained in online recommendations still affect teammate invitations, when the potential target of a teammate invitation is someone whom you already know?

Attending to Online Recommendations

The act of recommending or referring another person is a common behavior in professional settings. Recommendations from others are based largely on social networks and the capital people hold within their networks (Fernandez, Castilla, & Moore, 2000; Fernandez & Weinberg, 1997; Montgomery, 1991). When considering the labor market, workers often try to find jobs by engaging their social networks, even relatively weaker connections (Granovetter, 1973). Meanwhile, employers consistently use referrals from employees to gather more information about applicants and their potential fit within the organization (Fernandez et al., 2000; Montgomery, 1991). The potential importance of recommendations for personnel decision-making has resulted in the development of recommender systems to facilitate finding social matches.

Recommender systems computationally-calculate social matches, have value for initiating social relationships, and are commonly embedded in applications that leverage rich user data (e.g., dating and social network websites) (Finkel, Eastwick, Karney, Reis, & Sprecher, 2012, 2016; Kautz, Selman, & Shah, 1997; K.-H. Lin & Lundquist, 2013; Maldeniya, Varghese, Stuart, & Romero, 2017; Pizzato et al., 2013; Pizzato, Rej, Chung, Koprinska, & Kay, 2010). Social matches are produced when recommender systems perform two functions: finding current contacts and introducing a user to strangers (Chen, Geyer, Dugan, Muller, & Guy, 2009; Guy et al., 2009, 2011). The review by Terveen & McDonald (2005) presents a general framework for recommender systems in social settings, including the following steps: modeling people, matching them with computational algorithms, introducing them to one another, and then allowing a platform for interaction. If a system can accomplish these four steps, then people are able to not only be exposed to recommended social matches, but also have a means to connect with these matches.

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, Ehrlich, & Millen, 2008). Leveraging large quantities of information to recommend new team members helps people efficiently replace team members or find new members within distributed settings (Brocco & Groh, 2009; Li et al., 2015). Because recommender systems have demonstrated value in recommending relevant people to create various types of social relationships, online recommendations will likewise contribute to teammate invitation, which is the initiation of team assembly.

H1. People are more likely to send a teammate invitation to potential teammates who have been highly recommended by the online recommender system, in comparison to potential teammates who are less highly recommended.

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., 2000). 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 are attracted to one another, have an established set of norms, and can resolve task and social conflicts effectively (Gruenfeld, Mannix, Williams, & Neale, 1996; Okhuysen, 2001; Shah & Jehn, 1993; Van Zelst, 1952). A team that possesses a shared and accurate understanding of the expertise that exists within the team will benefit from a member's ability to access relevant expertise and experience positive team performance (Faraj & Sproull, 2000; Reagans, Argote, & Brooks, 2005; Ren & Argote, 2011; Wegner, 1987, 1995, p. 199). In addition, prior collaborations allow members of a team to devote time orienting themselves to a task and the current capabilities of others, while not spending as much time establishing new social norms, which are already partly developed via past collaboration. Familiarity among team members has been empirically 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 prior collaborations helps a person establish more accurate expectations for future collaboration.

H2. People are more likely to send a teammate invitation to potential teammates who have been prior collaborators than to potential teammates who were not prior collaborators.

The Interplay Between Prior Collaborations and Recommendations

Thus far, I have hypothesized main effects of both online recommender systems and interpersonal familiarity on the teammate invitation process, extending the work of Hinds et al. (2000). I 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 and 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 process 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, I 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 you do not know and have not worked with before (e.g., at zero contact or zero acquaintance; 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.

H3. People are less likely to invite a highly recommended prior collaborator than they are a highly recommended person who is not a prior collaborator.

Hypotheses 1 through 3 are depicted in Figure 1, which summarizes the proposed effects of online recommendations and prior collaboration on teammate invitation.

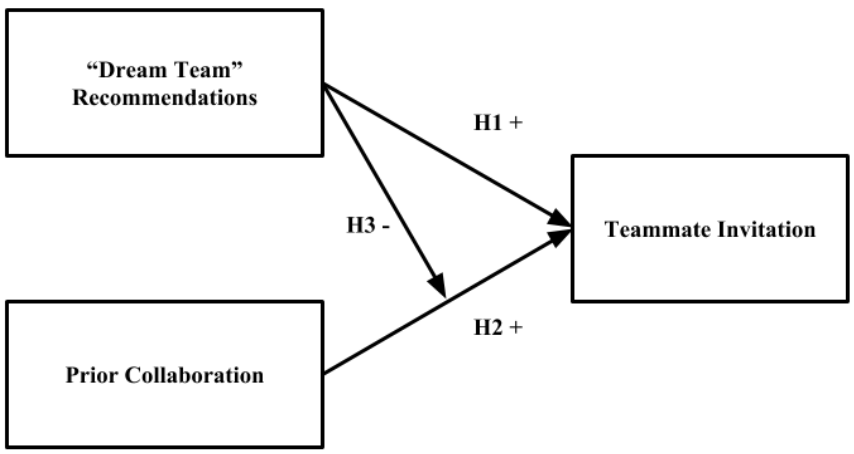


Figure 12: Model of teammate invitations

Methodology

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 one of 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). Over a period of twelve weeks, participants 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% 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% female; mean age = 21.1 years, SD = 2.57 years) in 31 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 (*My Dream Team*; http://sonic.northwestern.edu/software/c-iknow-mydreamteam/). 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 self-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 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 "Dream Team" ranking algorithm that returns an ordered list of potential teammates based on the degree to which they match the stated preferences. After receiving the online recommendations from the "Dream Team" algorithm, participants reviewed other participants' profiles and exchanged invitation messages to self-assemble 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.

"Dream Team" Recommendations. The teammate recommender system rank-ordered a list of potential teammates matched to a searcher's stated preferences. These matches are "Dream Team" Recommendations. 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. 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 rank-ordered from one to the sample size N-1 (excluding the searcher).

When a searcher performed multiple searches, only the best "Dream Team" Recommendation ranking achieved by a potential teammate was used during analysis. Therefore, each searcher has one list of potential teammates with each potential teammate's best ranking. The "Dream Team" Recommendations are then transformed into a weighted, directed social network. The nodes are the participants, a link is directed from a searcher to a potential teammate (i.e., whether a searcher saw a potential teammate listed in the recommended teammates list), and each weight is a potential teammate's "Dream Team" Recommendation ranking for the searcher (from 1 to N-1). The "Dream Team" Recommendations network was then dichotomized for analysis (a value of one was assigned to the top-ten ranked potential teammates, and a value of zero was assigned otherwise).

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, "Who have you worked with on projects?" by checking the names of prior collaborators. Responses were used to construct a binary, directed network (a value of one if the respondent selected a prior collaborator, and zero otherwise).

Controls. 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, Koskinen, & Robins, 2013). Accounting for these structural interdependencies allows for a more accurate specification of the hypothesized effects (Snijders, Pattison, Robins, & Handcock, 2006). When performing exponential random graph modeling (ERGM), the arc pattern refers to the likelihood that a link will be randomly created from one person to another (sending a teammate invitation). Another common endogenous network structure in most social interactions is reciprocity, which refers to the likelihood that a person will create a link to a person with whom there is already a link (inviting an inviter). Activity hubs and popularity hubs are people who have more outgoing or incoming links than are expected by chance (active inviters, popular invitees). The calculation of the hub structure statistics produces positive estimates when people 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 (common invitation). Triadic closure occurs when sending an invitation to a person who already shares a common partner with the sender (closure in invitations). Each of these endogenous network structures is potentially theoretically interesting in the context of team self-assembly, but the current study uses them as controls to avoid biased estimates when testing the hypothesized effects (Lusher et al., 2013).

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," "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. The competencies of the sender and receiver of each invitation were considered in analyses.

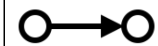
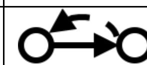
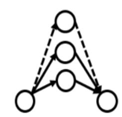
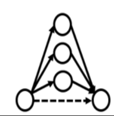
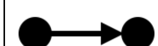
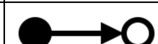
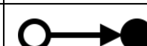
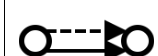
I also assessed two types of homophily: gender homophily and having the same university affiliation. Participant gender was self-reported using the item, "What is your gender? (male, female, other)", and responses were used to create dyadic gender homophily variables for women who invite other women (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, Kalish, & Lusher, 2007; Robins, Snijders, Wang, Handcock, & Pattison, 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 (i.e., H1, H2, and H3). 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; J. Y. Kim, Howard, Cox Pahnke, & Boeker, 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, Lusher, Pattison, & Robins, 2013; Rank, Robins, & Pattison, 2009), and product team communication based on technical design interdependencies (Sosa, Gargiulo, & Rowles, 2015). In the current study, measures at the individual, dyadic, and network levels of analysis including endogenous network structure are used, explained, and described in Tables 1, 3, and 4. Table 1 is derived from tables found in Kim et al. (2016) and Lusher et al. (2013).

ERGM is useful when the dependent variable is a social network; and the technique is analogous to a logistic regression where each parameter estimate is a log-odds. 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. 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 associated 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, Hunter, Butts, Goodreau, & Morris, 2014; Hunter, Handcock, Butts, Goodreau, & Morris, 2008).

Table 2: Summary of effects used in ERGM analysis

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 spread	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 spread	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 Two-paths	The likelihood that individuals invited by a person will, in turn, converge on who they invite (many people inviting the same person)	Common Inviters	
Generalized transitive closure	The likelihood that an individual sends an invite to a third party who is invited by other recipients of invitations	Closure of Invitations	
Actor relation 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 covariate (sender)	An invitation being sent when the sender has high competence	Competence (continuous)	
Nodal covariate (recipient)	An invitation being received when the recipient has high competence	Competence (continuous)	
Covariate network effects			
Exogenous relationships (entrainment)	An invitation being sent when the sender views the recipient with a “Dream Team” Recommendation, or when the sender has had a Prior Collaboration with the recipient	“Dream Team” Recommendation Prior Collaboration	

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 Hypotheses 1 through 3. As shown in Table 2, the individual-level measures (gender, university affiliation, and competence) are not statistically 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 correlations among all three network-level variables are positive and statistically significant. Importantly, 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).

Table 3: Individual-Level Variables: Descriptive Statistics and Correlations

				Pearson Correlations		
		Mean	SD	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 4: Network-Level Variables: Descriptive Statistics and QAP Correlations

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

Note. * $p < 0.05$; Quadratic assignment procedure (QAP) correlations between two social networks measured on the same set of people reveals the associations between relationships (Krackhardt, 1987).

Next, ERGM analyses are used to test the three hypotheses regarding teammate invitations while controlling for the endogenous network effects, individual effects, and dyadic effects (see Table 4). 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 provides inferences regarding the emergence of the teammate invitation network.

Most effects are significant and replicate across both samples. Sending a teammate invitation is negative and significant ($p < 0.001$) meaning it is not likely for people to send a teammate invitation to a random person, which is reflected by the observed sparsity of the teammate invitation networks. Inviting an inviter was positive in both samples, but only significant in Sample 1 ($p < 0.01$). The positive effect appears to capture reciprocity in teammate invitations when members of a dyad both invite one another. The presence of popular recipients is indicated by a negative and significant popularity effect ($p < 0.001$). The interpretation of a negative estimate in this model signals an inequitable distribution of popularity, meaning that popular recipients are more likely to receive teammate invitations, consistent with the principle of preferential attachment (Barabasi & Albert, 1999; Hunter, 2007). On the other hand, the presence of active inviters was not 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 has 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 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 the results. While it could be expected that competence of a recipient would positively predict teammate invitations, the 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 in Sample 1 are 1.55 times ($OR_{S1} = 1.55$) more likely to send an invitation and 1.82 times ($OR_{S2} = 1.82$) more likely in Sample 2. 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 1.22 times (Sample 1) and 1.32 times (Sample 2) more likely to invite another woman to a team. 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 Hypotheses 1 - 3. Model 2 tests Hypotheses 1 and 2. Hypothesis 1 stated that online recommendations positively predict teammate invitations. Using the "Dream Team" 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). Hypothesis 2 stated that prior collaborations positively predict teammate invitations. The results in both samples support this hypothesis. 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 establish the relationship between prior collaborations and teammate invitations--as well as the relationship between online recommendations and teammate invitations.

Next, I test Hypothesis 3, which states that prior collaborations dampen the positive effect of online recommendations on teammate invitation. Model 3 (Table 4) includes the interaction term between “Dream Team” 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 3 in both samples.

The goodness of fit assessment clarifies the consistency between the observed network and simulated networks from an ERGM (Hunter et al., 2008; Robins, Pattison, & Wang, 2009). For Models 2 and 3 (which are the basis of the hypothesis tests), plots for the goodness of fit (see Figure 14 and Figure 15) demonstrate reasonable fits for all statistics. In each sample, there were between one to 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.

Table 5: ERGM Estimates predicting Teammate Invitation Network (Hypotheses 1 – 3)

	Log Odds Estimates (*SE*)					
	Model 1		Model 2		Model 3	
	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						
"Dream Team" 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						
"Dream Team" 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. *** p < 0.001, ** p < 0.01, * p < 0.05						

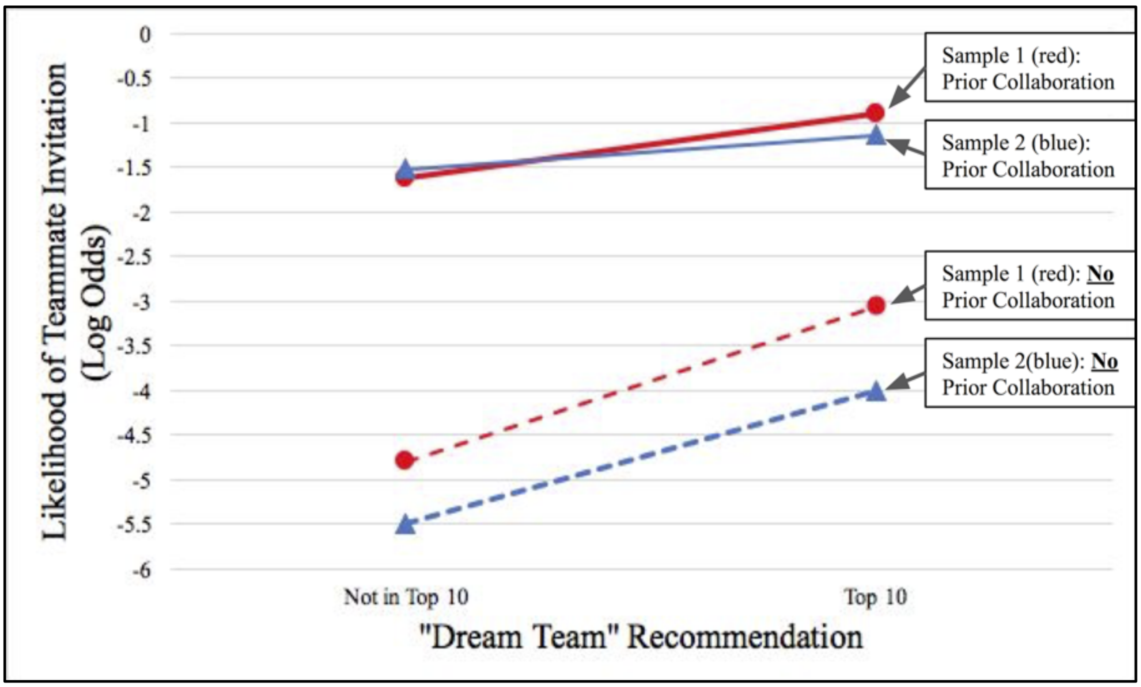


Figure 13: "Dream Team" Recommendations X Prior Collaboration predicting Likelihood of Teammate Invitation (H3: Table 5, Model 3)

Sample 1 **Sample 2**

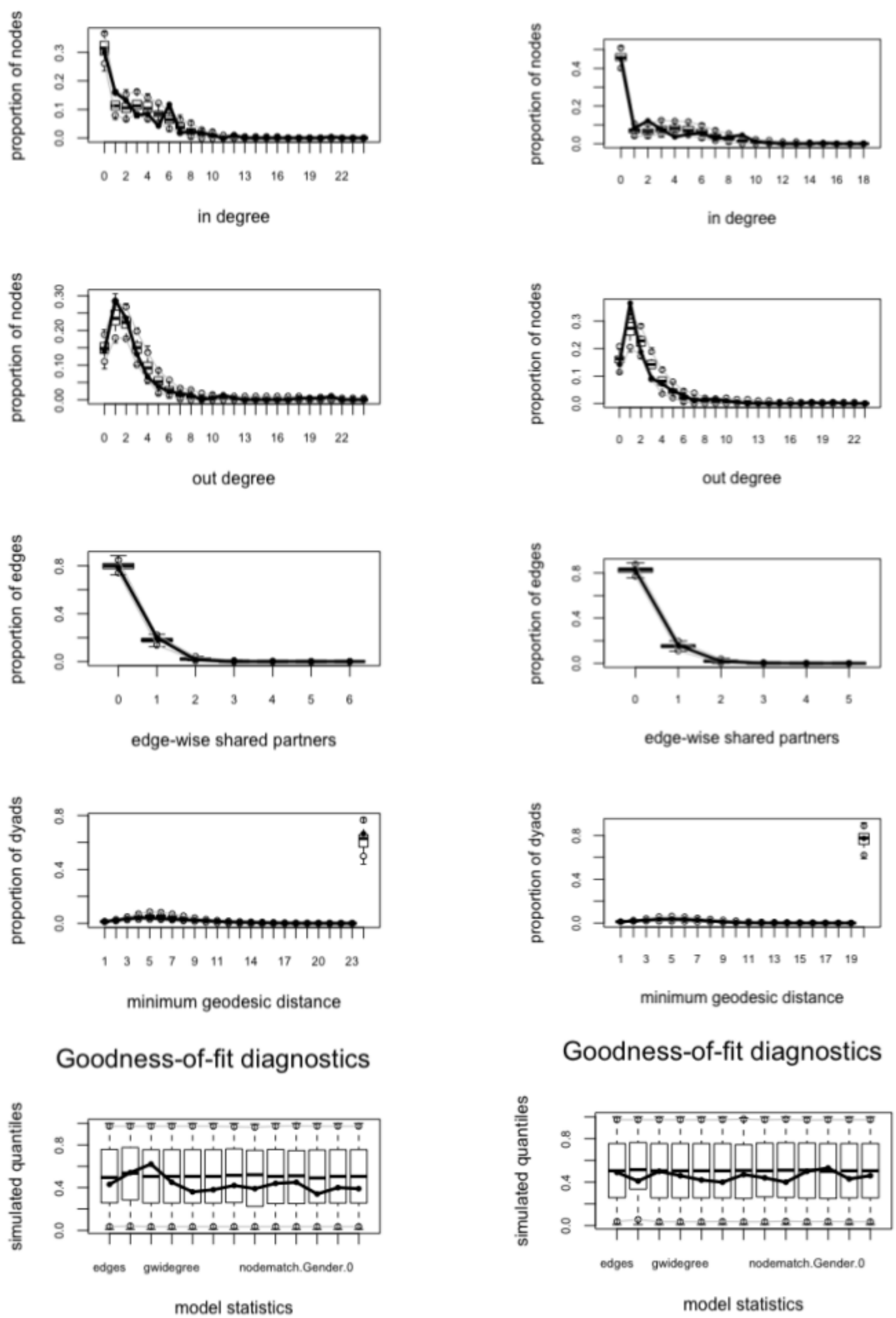


Figure 14: Goodness of Fit plots of model statistics for Model 2.

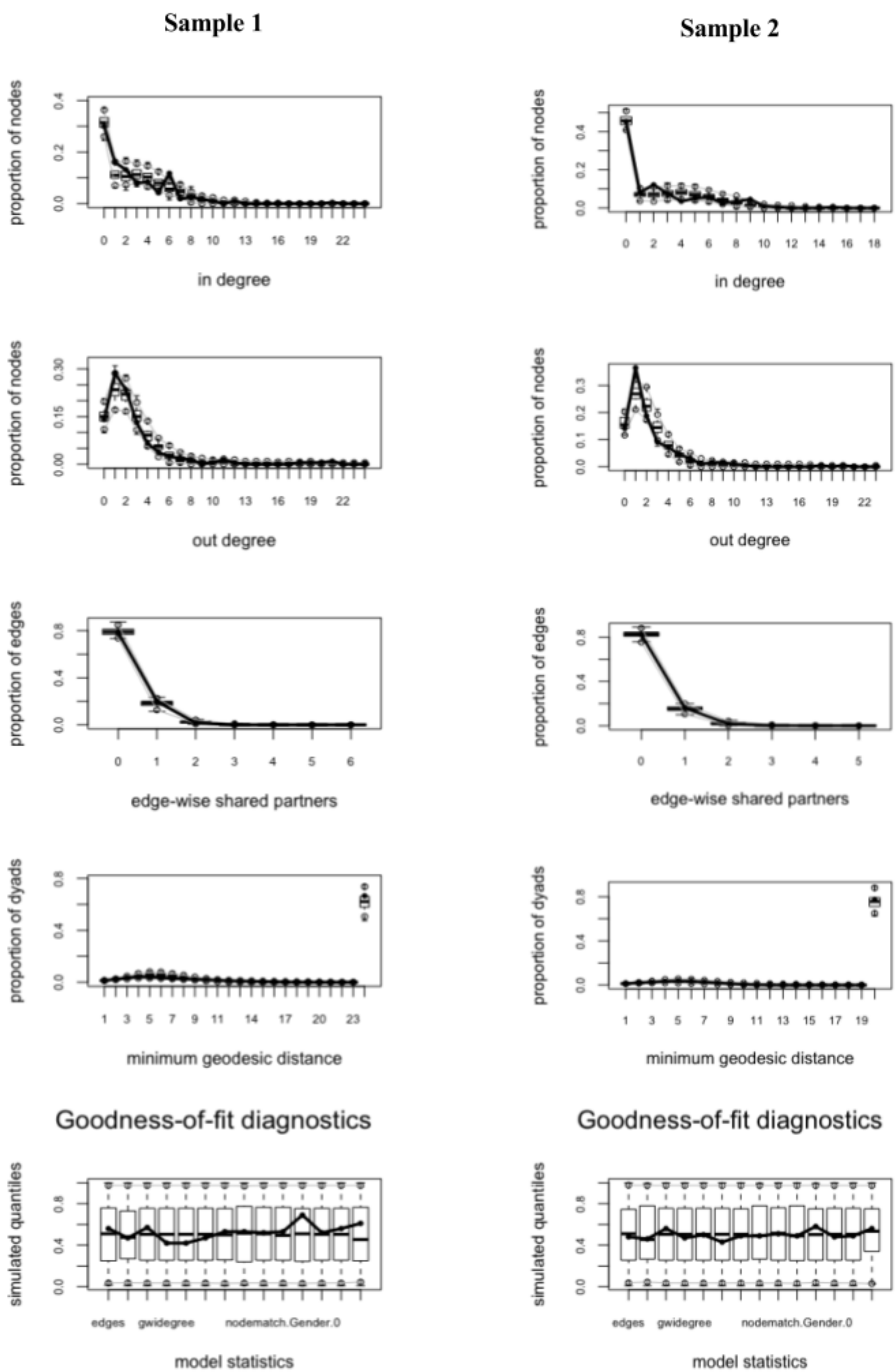


Figure 15: Goodness of Fit plots of model statistics for Model 3.

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 teammate invitations. 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 is 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, 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 mechanism familiarity, because similarity breeds more frequent communication and cohesion (Harrison et al., 1998; van Knippenberg, De Dreu, & Homan, 2004; Williams & O'Reilly, 1998).

Familiarity possesses information value in collaborative settings, because prior collaboration can be thought of as an uncertainty reduction mechanism (Crozier, 2009; Hinds et al., 2000; J. D. Thompson, 1967) during teammate invitation. One proposed origin of familiarity is that people become attracted to others as they have more interaction (Bornstein, 1989, p. 1; Reis, Maniaci, Caprariello, Eastwick, & Finkel, 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, Aven, & Kush, 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

There are two streams of future research that follow directly from the current research: (a) investigation into the influence of teammate invitations on team processes, team performance outcomes, and team diversity composition, and (b) investigation into technology features that govern and support digital interactions that take place within a technology platform during team self-assembly. There is a long tradition of team composition research linking individual attributes to team processes and outcomes (Bell, 2007; Kozlowski & Ilgen, 2006; Mathieu et al., 2017, 2008), but 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 in teams with other highly skilled people) (Gómez-Zará et al., 2019) or other individual attributes.

The other stream of research involves the technology platform for team self-assembly. Online recommendations within an organization are prevalent for numerous applications (e.g., networking, expertise finding, and knowledge sharing), and there are multiple design considerations that determine both the use and effectiveness of recommendations (Chen et al. 2009, 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 of how platforms influence team collaboration downstream. For example, technology platforms commonly serve as the first place that teams interact and where members begin to form impressions of one another (J. Cummings & Dennis, 2018). Having studies focused on the understanding the information signals provided through user profiles and teammate preferences helps clarify technology's role as a mediator in team assembly and team norm formation. This also open 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.

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 self-assembly. Second, the statistical network modeling approach (ERGM) used in the study does not account for the dynamic nature of teammate invitation behaviors over time. Temporal dynamics influence people's invitations because each invitation potentially affects future choices to invite teammates. This limitation does not nullify the value of ERGM, because understanding the overall network structure of teammate invitations remains essential; but there is more research needed to investigate the temporal dynamics of invitations that may contribute to team self-assembly.

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 and geographically dispersed, and of having complete team rosters accessible. Also the use of two samples provides the great advantage of allowing for a direct replication of effects. It is unclear how many organizations have implemented and utilized similar technology platforms capable of supporting team self-assembly in the ways studied in the current research. Whereas there are a number of enterprise technology platforms used for expert and expertise finding within corporations (Lin et al. 2009), little data are available about the extent to which such platforms are used to support team self-assembly.

Conclusion

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

CHAPTER 4. UNDERSTANDING THE COEVOLUTION OF LEADERSHIP AND COMMUNICATION NETWORKS IN TEAMS ASSEMBLED WITH TECHNOLOGY

Abstract

Leadership and communication are essential relationships for teams to establish during collaboration. In this study, I investigate the coevolution of leadership and communication networks while incorporating digital trace data from an online technology platform to understand the role of team self-assembly behaviors on collaboration. Using stochastic actor-oriented modeling (SOAM or SIENA) to detail the coevolution of leadership and communication in teams, results show that each network influences the evolution of the other over the course of a collaboration, and that invitations sent in the online platform exert both a positive influence on the evolution of communication networks and a negative influence on leadership reliance on those invited. Therefore, results provide greater detail into how teams establish their own social structures and relationships by integrating interactions that contribute to team assembly. Also, teammate recommendations collected from the online platform do not have an effect on the coevolution of the team networks, which suggests that collaboration dynamics, such as the emergence or evolution of relationships, are best explained by the team environment and direct social interactions instead of information signals people consume before collaborating. Other findings show that endogenous network effects are more important factors for explaining network evolution relative to the hypothesized factors. Overall, this study provides insights into the boundaries of deploying technology-enabled team assembly as an explanatory mechanism for the coevolution of emergent team relationships.

Introduction

Before collaboration begins, technology contributes to teams in ways that support teamwork. In general, technology helps alleviate many coordination challenges that arise in the modern work environment where people are located remotely, collaborate through software, and communicate through multiple channels (Birnholtz & Ibara, 2012; D'Angelo & Begel, 2017; Gutwin, Penner, & Schneider, 2004; Kraut, Attewell, & Kiesler, 1997). Technology likewise plays a role in contributing to social interaction when individuals form teams. As an example, team members now commonly form impressions of one another by reviewing digital profiles and activity traces (e.g., posts and comments) in online platforms (J. Cummings & Dennis, 2018). Additionally, online platforms are now becoming places where individuals aggregate information about others and make choices to assemble teams (Gómez-Zará et al., 2019; Jahanbakhsh et al., 2017). Given the central role technology plays in how teams are formed, the current study investigates how the usage of a technology platform for team formation influences the coevolution of within-team networks.

Technology platforms facilitate information-seeking because users learn about others through the presentation of data in a given platform. Individuals seek information to help them select prospective teammates by focusing on information signals that help to reduce uncertainty around future interpersonal interactions (Berger & Calabrese, 1975; Bradac, 2001; Hinds et al., 2000; Knobloch, 2015). Often, individuals review online profiles and content to acquire knowledge regarding the expertise and skills of others, as well as the social relationships that exist within an organization or community (Contractor & Monge, 2002). Such activities are enhanced by technology because people expand their perceptions of the surrounding social environment by engaging with user-generated content that often represents the knowledge and interests of others (Leonardi, 2015, 2018). The social interactions between future teammates that occur within online platforms also have the potential to influence the evolution of relationships within a team that forms at a later time, which is the focus of the current study. Of particular interest are the ways in which team assembly interactions in technology affect team communication and leadership.

For decades, the concept of leadership has been recognized as an essential behavior present within organizations and work groups (Lord et al., 2017; Yukl, 1989, 2010). However, leadership—and the development of leadership—is also understood to be a broad-reaching concept that encompasses countless behaviors, traits, and situations (Eagly & Karau, 1991; Foti & Hauenstein, 2007; Lord et al., 2017; Stogdill, 1948). Specifically, leadership research over previous decades has covered topics ranging from behavioral styles, demographic and personality traits, and relationships among team members (for a review, see Lord, Day, Zaccaro, Avolio, & Eagly, 2017). Leadership emerges through enacted behaviors and the establishment of relationships among group members and may even be distributed across multiple members in a group (Carnabuci, Emery, & Brinberg, 2018; Contractor, DeChurch, Carson, Carter, & Keegan, 2012; Emery, 2012; Luther, Fiesler, & Bruckman, 2013). More recently, extant literature has started to emphasize the temporal dynamics of leadership, noting that leadership is rarely stable (McClean, Barnes, Courtright, & Johnson, 2019). In the current study, I investigate how the informal leadership structure within a team emerges and changes over time.

The emergence of leadership is coupled to communication because communication is a behavior that is performed when leaders engage with those who follow them. In general, teams must effectively communicate in order to achieve adequate performance since information-sharing helps ensure that the collaboration is meeting expectations and team members understand the status of the task (Cataldo & Ehrlich, 2012). For virtual teams—where members interact through technology—the quality and speed of communication both contribute to the emergence of leadership nominations when interacting through technology (Charlier, Stewart, Greco, & Reeves, 2016). In the current study, capturing digital traces from user behaviors—teammate search and invitation—from a technology platform during team assembly helps to further understand the emergence of leadership with respect to communication in a team by observing the interactions that lead directly to team formation. Therefore, I investigate the following research question: How do leadership and communication within teams coevolve throughout a collaboration, and how do team assembly interactions affect the coevolution of team relationships?

The current study uses social network analysis as the primary tool for investigation, which offers promise in helping disentangle the connections that exist between leadership and communication. While leaders need to communicate in order to be effective, there are questions about whether the structure of communication directly corresponds to the structure of leadership. The study will help clarify the connections between communication (a behavior) and leadership (a status nomination). The rest of the study is organized as follows. First, hypotheses are developed from relevant literature and prior research. Then, I describe the empirical setting of the current study. Next, the analytical approach employing social network analysis and stochastic actor-oriented modeling is detailed. Then, the results from analysis are shared and findings are elaborated. Finally, the paper closes with a discussion of the study contributions.

Hypothesis Development

Given that future teammates are first exposed to one another during team assembly, there is potential for the relationships and activities conducted when organizing the group to influence the later collaboration that occurs. Leadership is one of the more notable aspects of organizing since the influence of team leaders on other members has substantial impacts on the effectiveness of a team with respect to tasks and the relationships that emerge while collaborating (Hiller, DeChurch, Murase, & Doty, 2011; Kozlowski & Ilgen, 2006; Mathieu et al., 2008). Importantly, leadership characteristics within a team determine team performance and govern the social norms and interactions among team members (Mehra, Dixon, Brass, & Robertson, 2006; Sparrowe & Liden, 2005; Varella, Javidan, & Waldman, 2012). The vast literature on leadership accounts for multiple aspects of the relationship, including the personality traits and enacted behaviors of leaders, the work context of the group, and the structure of the relationships (e.g., hierarchical or flat) that describe leadership in a specific situation (House, 1996; Lord, Day, Zaccaro, Avolio, & Eagly, 2017; Yukl, 2010).

The Lord et al., 2017 review paper classifies the trajectory of leadership scholarship into different paradigms and "waves" that encapsulate considerations for leadership and detail the maturation of research on leadership, ranging from individual attributes to relationships as well as including shared leadership arrangements and multilevel perspectives of leadership. From the most recent wave of leadership research, Leader-Member Exchange (LMX) theory focuses on the relational aspect of leadership and accounts for leader and follower perceptions of leadership. LMX is based upon Vertical Dyad Linkage (VDL) (Dansereau, Graen, & Haga, 1975) and extended to contain the relationships that exist within larger collectives (e.g., teams and work groups), which progressed conceptualization of leadership from individual and dyads to more of a social network consideration (Graen & Uhl-Bien, 1995). In recent years, the network structure of leadership has been an active topic for investigation. Leadership is represented by social networks at multiple levels of organization: the individual (ego) network, the organizational network, and the interorganizational network. Effective leaders must interact and engage in different behaviors across these three networks. For example, effective leaders in the intraorganizational network participate in boundary spanning to acquire new information for their own organization whereas effective leaders in the organizational network cultivate relationships to enhance their popularity in the organization (Balkundi & Kilduff, 2006). With respect to teams, leadership structure exists among a relatively small set of actors and is a relationship that emerges based on the needs of a team.

Over the course of a collaboration, the leadership within a team may shift between individuals and the structure of leadership relations may change because individual perceptions of leadership determine how the structure of leadership evolves. Based on how team members recognize leadership, teams may form hierarchical or shared leadership structures in order to create a structure that is congruent with the leadership schema of its members (DeRue & Ashford, 2010; DeRue, Nahrgang, & Ashford, 2015). In other words, leadership in a given team reflects the expectations that members have regarding leadership. As an example, informal leadership structures in teams evolve by group members shifting their attributions of leadership to make their perception of the leadership network more consistent with a linear ordering schema to cognitively represent information about leadership (Carnabuci et al., 2018). For leadership to evolve and change, team members are constantly processing information through interacting with one another during a work task. By processing new information, teams with clear hierarchies can share leadership by delegating responsibilities based on dynamic contingencies, such as changes to the work environment and reflections on relationships and personal attitudes (Klein, Ziegert, Knight, & Xiao, 2006). To facilitate such shifting and change of leadership activities, a necessary process within a team is communication.

Communication is a social process that facilitates collaboration and how individuals work together. In most teams, the ability of members to effectively communicate and manage information flow is beneficial for teams addressing complex projects (Cataldo & Ehrlich, 2012; Cataldo & Herbsleb, 2008). Communication between leaders and other team members is especially important because leaders must be able to serve as information providers and sources in an effective manner while providing guidance to direct project work (Charlier et al., 2016; Ehrlich & Cataldo, 2014; Susskind, Odom-Reed, & Viccari, 2011). Additionally, communication and leadership are intertwined with one another based on the different behaviors that leaders enact and their positioning in a team's social network (Balkundi & Harrison, 2006; Balkundi, Kilduff, & Harrison, 2011; Mehra et al., 2006).

From the prior literature, leadership is often the perception—by either followers and leaders—of an authoritative relationship, and communication is one behavior—among many—that leaders employ within teams to establish their relationships with followers. Given that effective leadership relies on sharing information and communicating goals and expectations (Yukl, 1989), there is likely a positive association between leadership and communication. As such, the first hypothesis investigates the relationship between leadership and communication in teams.

H1a. Team members who frequently communication with a teammate are more likely to rely on the teammate for leadership over time.

H1b. Team members who rely on a teammate for leadership are more likely to communicate frequently with the teammate over time.

Establishing effective communication practices and leadership relationships in teams now commonly requires the implementation of technology. Many teams that rely on technology as a communication medium tend to use technology in response to task demands prioritizing effective knowledge sharing regardless of physical location (Cataldo & Herbsleb, 2008; Jarvenpaa & Leidner, 1999; Nomura et al., 2008; Olson & Olson, 2000). However, when attempting to find teammates, individuals now commonly need to use technology to learn more about the expertise and social relationships present within an organization (Leonardi, 2015). Social recommender systems are a technology that is helpful for finding social matches when individuals are looking to build relationships with others (Guy, 2015; Terveen & McDonald, 2005). For teams, recommender systems help determine which individuals to add to teams as replacements and can even create new team member combinations while optimizing for performance outcomes (Alkan et al., 2018; Li et al., 2015). Recommended teammates have been given exposure through their visibility within a technology platform, and such exposure has a role in building relationships within a team because people are more likely to interact with those they have at least some familiarity with due to “the mere exposure effect” to people who have desirable expertise and social connections (Chen et al., 2009; Guy et al., 2009, 2011; Reis et al., 2011; Zajonc, 1968). Such exposure potentially accentuates the value that individuals place upon skillsets and knowledge by drawing attention to certain expertise areas.

Aside from recommendations, the social interaction that takes place within technology platforms helps teams form. Within recommender systems, there is often functionality to facilitate interpersonal interaction and messaging (Terveen & McDonald, 2005). During team assembly, the messages exchanged when people are negotiating membership and inviting one another to collaborate provides a perspective into how collaborations are initiated. The invitations serve the purpose of helping organize teams and also give an indication of the features that will be present within the teams that form. Specifically, team invitations show which attributes of people are desirable and the distribution of such attributes in teams (Gómez-Zará et al., 2019). Because invitations are the entry phase to collaboration, they present an opportunity to begin to communicate with future teammates and establish leadership relationships. The act of inviting someone to a team is an act that requires that an individual exercises agency in selecting team members, which signifies active participation in the team assembly process; it is communication with potential future teammates through intentional messaging. Also, with respect to leadership, being an inviter of others does not necessarily result in a person relying on the invited to become leaders in the subsequent collaboration. Therefore, a positive relationship between sending invitations and then communicating within a team is expected, whereas a negative relationship is expected between sending invitations and then relying on the invited for leadership. Formally stated as the following hypotheses:

H2a. A team member who sends an invitation to a teammate is less likely to rely on the teammate for leadership (team members do not invite their leaders).

H2b. A team member who sends an invitation to a teammate is more likely to communicate frequently with the teammate.

Methodology

Data and Sample

Participants were students from one of two universities that enrolled in the same dual-university course. Teams worked together during a semester to complete an interdisciplinary project on environmental sustainability. Social psychology courses at one university were linked to the environmental ecology courses at another university. Over a period of eight weeks, participants were required to collaborate in geographically distributed (dual-university) teams to complete a term project. The data sample includes 213 participants (mean age = 20.8 years; SD = 2.79) in 32 interdisciplinary, dual-university teams (mean team size = 6.65; SD = 0.48).

Procedure

Teams collaborated for eight weeks creating the deliverables for the project. After the first four weeks of collaboration, participants were surveyed at three different time points (approximately two weeks apart) to report team and relational experiences as they progressed on the project. The longitudinal data affords the opportunity of observing the evolution of team relationships and processes across time. Within-team social networks were collected for all teams as were responses about team process. It must be noted that the purpose of this study is the investigate how team relationships like leadership and communication are influenced by behaviors that occur during technology-enabled team assembly.

Before collaborating, participants assembled their own teams using a teammate recommender system (*My Dream Team*; http://sonic.northwestern.edu/software/c-iknow-mydreamteam/). The software enabled participants to form teams of at least six and at most seven members over a five-day period. If there were any individuals who were not a member of a team or if any teams were below the minimum team size at the end of the five-day period, then participants were merged into teams so that all teams had the required number of members. Participants answered survey questions about demographics, pre-existing relationships, competence, and other characteristics through an online survey administered as part of registration in the platform.

To facilitate data collection, all participants were added to the platform as a closed group of people by an administrator. In addition to completing the online survey, participants could optionally create a short biographical profile to share additional personal information with other participants. The survey responses and profile information were used when participants performed searches for specific attributes (characteristics, skills, or relationships), received recommendations for stated preferences, and reviewed one another's profiles. After exploring potential teammates, participants exchanged invitation messages to assemble teams.

Measures

Dependent Variables

Describing the evolution of team communication and leadership networks is the analytical goal of the study. To capture both dependent variables, network roster surveys were administered at the team level and participants responded by selecting the names of teammates from a roster that only included members of a given team. The team communication network was recorded with the following question: "Who do you communicate with frequently? (choose all that apply)" The leadership network was recorded with the following question: "Who do you rely on for leadership? (choose all that apply)" Responses were used to construct binary matrices (a value of one if the respondent selected a teammate, and zero otherwise) for each team. The individual team matrices were then combined into a larger matrix including responses from all teams in the sample. Essentially, each team's relationships lie along the diagonal of the matrix. From the complete matrix, a directed network is generated where all teams only have ties among their own members.

Independent Variables

The first independent variable is the recommendation ranking that participants received about other participants from the teammate recommender system. The recommender system rank-ordered a list of potential teammate matches to a searcher's stated preferences. The recommendations were calculated as a cumulative score based on potential teammate's 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. 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 rank-ordered from one to the sample size N-1 (excluding the searcher).

When a searcher performed multiple searches, only the best recommendation ranking achieved by a potential teammate was used during analysis. Therefore, each searcher has one list of potential teammates with each potential teammate's best ranking. The complete list of recommendations is then transformed into a weighted, directed social network. The nodes are the participants, a link is directed from a searcher to a potential teammate (i.e., whether a searcher saw a potential teammate listed in the recommended teammates list), and each weight is a potential teammate's recommendation ranking for the searcher (from 1 to N-1). The recommendations network was then dichotomized for analysis (a value of one was assigned to the top-ten ranked potential teammates, and a value of zero was assigned otherwise). After dichotomizing the network, it was filtered to only include ties between team members to restrict focus exclusively to team member recommendations.

The second independent variable is the network of invitation messages to potential teammates. Messages were exchanged between participants over five days and collected using digital trace data generated by the teammate recommender system. The trace data is a complete transcript 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. As with recommendations, the invitation network was then filtered to only include the invitations exchanged amongst members of the same team.

Controls

There are different types of control variables included for analysis: endogenous network effects, exogenous networks, individual attributes, and shared dyadic attributes. Endogenous network effects are included to account for network structure that may account for and contribute to network evolution (Snijders, 2001; Snijders, van de Bunt, & Steglich, 2010). Six different effects included in models: report of a relationship (outdegree), reciprocity, transitive triplets, popularity (indegree), and activity (outdegree). The report of a relationship is analogous to the outdegree of an actor and must always be included since ties constitute networks because the reports result in a network forming. Reciprocity shows when two actors have a relationship with one another and is commonly included when modeling social networks. Transitive triplets represent network closure by the number of triangles that form in a network, representing hierarchy. A simple example of transitivity in a team is “a leader of my leader is also my leader,” indicating that networks are likely to result in groups of people who agree on relationships. Popularity is a measure of how many times an actor is reported by others in the team, and activity is a measure of how many times an actor reports other team members in the team. For reference, detailed descriptions and formulae for the endogenous network effects are found in the RSIENA manual (Ripley, Snijders, Boda, Vörös, & Preciado, 2018).

From the use of the technology platform, three individual-level control variables are created to complement the independent variables at the network level: number of invitations sent, number of invitations received, and number of searches. From the complete invitation log data, the number of invitations that each participant sent and received is calculated to give measures of activity and attention in the invitation network. The number of searches for each participant is calculated from the log of search queries used to generate recommendations. Taken together, the three control variables describe how individuals used technology in the current study.

Another type of control is an exogenous network. Prior collaboration and enjoyable working relationship are networks that were collected during participant registration. As part of a network roster survey, participants responded to the relationship questions, "Who have you worked with on projects?" and "With whom on this list do you enjoy working?" by checking the names of participants from a roster including names of all other people in the course across both universities. Responses were used to construct a binary, directed network (a value of one if the respondent selected a person, and zero otherwise).

There are multiple other controls as well. Leadership experience is an individual attribute and was measured from eight statements about prior leadership experiences on 5-point Likert scales. Participants were asked to, "Think back to the leadership roles you have held in your school. How accurate are the following statements about you?" (ratings from "1 = Inaccurate" to "5 = Very Accurate"). They reflected on the following eight experiences: "Directed others in group activities in high school or college," "Participated in student and/or school politics," "Influenced other people in high school or college," "Held leadership positions in high school or college," "Picked people for teams," "Describe yourself as a leader in high school or college," "Felt your classmates respected you," "Active in political clubs and student council in high school or college" (Cronbach's $\alpha = 0.83$).

The next control at the individual level is participant competence, 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," "Publishing, print media, and/or design" (Cronbach's $\alpha = 0.64$). These project skills items were generated by consensus of the course instructors to capture the skills needed for success on the project. Personality was assessed using self-ratings on the Five-Factor model (Goldberg et al., 2006). A subset of four items was used for each factor from the International Personality Item Pool (https://ipip.ori.org/newBigFive5broadKey.htm): surgency or extraversion (Cronbach's $\alpha = 0.77$), agreeableness (Cronbach's $\alpha = 0.71$), conscientiousness (Cronbach's $\alpha = 0.70$), negative emotional stability (Cronbach's $\alpha = 0.57$), and intellect or imagination (Cronbach's $\alpha = 0.72$).

The next set of control variables are gender and university affiliation, and both are individual attributes as well as used to construct shared dyadic attributes to indicate similarity; gender homophily and having the same university affiliation. Participant gender was self-reported using the item, "What is your gender? (male, female, other)", and gender homophily is a shared dyadic attribute for individuals who share the same gender. University affiliation is a binary indicator of the university at which a participant was enrolled during the study. Having the same university affiliation is a shared dyadic attribute for participants who attend the same university.

Analytical Approach

Stochastic actor-oriented models (SOAM) or simulation investigation for empirical network analysis (SIENA) models are agent-based simulations where actors are responsible for creating, maintaining, and dissolving network ties between time periods representing the evolution of a network; each tie choice of an actor is probabilistically determined between observations based on a series of assumptions describing longitudinal relationships (Ripley et al., 2018; Snijders et al., 2010). One assumption is that a relationship endures as a continuous process over time but is only observed at a minimum of two points in time. Specifically, the model assumes that ties in the network can change between observations. Another assumption that the evolution of a network is a Markov chain, approximating the stochastic nature of tie changes in a network. The third assumption is that actors have some amount of agency over their ties. The agency stems from an actor making choices based on the parameters of a model, which may include individual attributes and endogenous network structure. The last assumption is that ties only change one at a time; this is a simplifying assumption that prevents large proportions of a network changing at a single timestep. Instead, large changes are considered one tie at a time and built incrementally over the course of a simulation. In a SIENA model, a rate function parameter accounts for the number of opportunities each actor has to change ties between network observations.

The current study is interested in the coevolution of multiple networks. Estimating coevolution is more complicated than the general description of SIENA models given above, but coevolution is a common use case for SOAM when the research question focuses on the changes between different networks or between a network and a behavior (attitude). By modeling the coevolution of multiple networks, questions may be raised regarding the influences that coexisting networks have on one another's dynamics (Snijders, 2017; Snijders, Lomi, & Torló, 2013). For example, the coevolution of perceived team cohesion and network ties within a team—including friendship, advice, and difficulty—offer insights into how people react and behave in response to interactions in teams (Schulte, Cohen, & Klein, 2012). Directly applicable to this study is the use of SIENA to explain the emergence of leadership networks (Carnabuci et al., 2018; Emery, 2012).

Because network ties among team members are being analyzed, the SIENA estimation procedure needs to account for the restriction in possible network ties. Structural zeros were employed to constrain the modeling by not allowing ties to exist between members of different teams. In SIENA, structural zeros are manually defined using a coded value that indicates a tie between two actors is impossible. The structural zeros are necessary because the administered survey questions on within-team relationships specifically asked about relationships among teammates and the options of the network roster only included other team members. Therefore, structural zeros help more accurately model the within-team networks since participants were not providing information about all other people in the data sample.

An additional consideration of the SIENA models is the applicability of the approach given the observed tie changes between time periods as well as the convergence of the estimation procedure. The manual for the RSIENA package in the open software R recommends supplemental analysis to help ensure appropriate modeling (Ripley et al., 2018). One analysis involves the use of Jaccard similarity indices for each observed network to determine whether the changes between time periods would lead to SIENA inadequately modeling the network dynamics between periods. Jaccard similarity between networks is calculated by the proportion of ties present in both time periods and ties that changed (either created or dissolved). Low Jaccard values indicate networks that have changed substantially between observations and will potentially lead to unstable estimates, and the recommended value for Jaccard similarity index is 0.3 (Snijders et al., 2010). All Jaccard values in the study were above this threshold (see Table 8). The convergence of the estimation requires evaluating the t-ratios for convergence provided from the simulation algorithm. In RSIENA, a convergent model will have t-ratios less than or equal to 0.10 for each parameter, and the complete model will have an overall maximum convergence of approximately 0.25 (Ripley et al., 2018). The convergence values of models in the current study are comparable to the suggested thresholds for performance.

Another note must be made about interpreting parameter estimates from SOAM. The estimation procedure uses variables relating to endogenous network structure, individual attributes, dyadic attributes, and exogenous networks. These different types of variables have different scales and potential values, leading to unstandardized parameter estimates. When interpreting the estimates provided from a SIENA model, only significance and directionality are readily interpretable. To address this shortcoming of estimation, a procedure to generate the relative importance of each parameter is employed. Relative importance of parameter estimates normalizes the effect sizes of each parameter for every observed network, such that all values are between zero and one and sum to one (Indlekofer & Brandes, 2013). The relative importance used in conjunction with the parameter estimates clarifies meaningful effects included in a model. Additionally, the relative importance of parameters contributes to a measure of the degree of certainty for a SIENA model. The degree of certainty contributes an understanding of how much variance in each observed network is explained by the model (Snijders, 2004).

Results

Descriptive results (Table 6) show correlations among individual-level variables. Variables collected from the technology platform encapsulate interactions users conducted when assembling teams. The number of invites sent to teammates when self-assembling teams is positively correlated with competence, having leadership experience, being a female, openness, extraversion, and agreeableness. There is, however, a negative correlation with the number of invites received from teammates, suggesting that team members who send invites to teammates do not typically receive invites from their teammates. Receiving invites from teammates is positively correlated with the number of searches performed. Meanwhile, searches are negatively correlated with leadership experience and extraversion. The pattern of correlations will be helpful for interpreting the estimates from the main SIENA models that test hypotheses.

Descriptive statistics at the network level (Table 7) display the overall activity present in the relationships of interest for the current study. There are two types of networks included in the study: within-team networks and pre-team networks. The within-team networks are communication and leadership collected at three different time points. For both communication and leadership, the number of network ties increases from T1 to T3. Based on the average team size (between 6 and 7 members), members reported no more than half of the team for both networks as shown by the density measure; density was measured based on the total number of possible ties within a team. Communication density was at least 0.49 in all time periods, showing that individuals reported communicating with about half of their team members whereas leadership density ranged between 0.318 and 0.390, meaning that individuals only relied on about a third of their teammates for leadership.

Table 6: Individual-Level Variables: Descriptive Statistics and Correlations

				Pearson Correlations										
		Mean	**SD**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**
	Individual-Level Variables													
1.	Invites Sent	2.71	3.45											
2.	Invites Received	2.71	3.01	-0.145*										
3.	Number of Searches	4.38	4.53	-0.077	0.351*									
4.	Competence	3.59	0.70	0.294*	0.028	-0.026								
5.	Leadership Experience	3.63	0.73	0.281*	-0.119	-0.136*	0.313*							
6.	Intellect or Imagination	3.95	0.63	0.263*	-0.001	-0.102	0.205*	0.299*						
7.	Conscientiousness	3.82	0.69	0.118	0.075	0.057	0.073	0.098	0.030					
8.	Extraversion	3.24	0.82	0.245*	-0.073	-0.168*	0.265*	0.411*	0.243*	0.088				
9.	Agreeableness	3.95	0.62	0.249*	0.084	0.02	0.132	0.202*	0.427*	0.323*	0.231*			
10.	Negative Emotional Stability	2.40	0.66	-0.040	0.047	0.012	-0.102	-0.085	-0.076	-0.242*	-0.142*	-0.144*		
11.	Gender (m=0, f=1)	0.47	0.50	0.172*	-0.070	0.037	0.091	0.140*	-0.009	0.138*	0.015	0.312*	0.105	
12.	University affiliation (0 or 1)	0.45	0.50	0.046	0.015	-0.031	-0.119	-0.099	-0.120	0.070	-0.070	-0.171*	0.029	-0.06

Note. * $p < 0.05$

Table 7: Network-Level Variables: Descriptive Statistics and QAP Correlations

	Number of Ties	Average Out-Degree	Density[a]	QAP Correlations[b]								
				1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
1. Communication T1	596	2.81	0.492									
2. Communication T2	611	2.90	0.504	0.742								
3. Communication T3	632	2.99	0.521	0.737	0.786							
4. Leadership T1	385	1.82	0.318	0.639	0.533	0.553						
5. Leadership T2	427	2.03	0.352	0.595	0.670	0.620	0.632					
6. Leadership T3	473	2.24	0.390	0.599	0.642	0.685	0.609	0.726				
Pre-Team Networks												
7. Invitation Network	182	1.71	0.150	0.426	0.378	0.372	0.301	0.281	0.287			
8. Teammate Recommendation (1 = Top 10, 0 = not Top 10)	92	0.86	0.076	0.304	0.270	0.266	0.203	0.192	0.226	0.323		
9. Prior Collaboration	65	0.61	0.054	0.322	0.287	0.313	0.186	0.200	0.241	0.320	0.244	
10. Enjoyable Working Relationship	144	1.35	0.119	0.465	0.416	0.448	0.276	0.295	0.327	0.406	0.267	0.629

Note.
a. Density is calculated based on the number of possible ties within a team, totaling 1212 possible within-team (sized 6 and 7) ties;
b. All QAP correlations are significant at $p < 0.05$.

The pre-team networks give indications of how much interaction and exposure teammates had with one another before collaborating. All of the pre-team networks were sparser than the within-team networks. The recommendation and prior collaboration networks had the lowest densities of less than one teammate on average, meaning teammates were not commonly exposed to other teammates through recommendations or prior collaboration. On the other hand, invitations and having an enjoyable working relationship were both denser networks, indicating that both were the more common relationships created before assembling into teams.

The correlations between networks were measured using quadratic assignment procedure (QAP) correlations (Krackhardt, 1987). All networks were positively correlated with each other. The within-team networks had the strongest correlations; communication and leadership had more positive correlations with each other compared to correlations with the pre-team networks. Invitation and "enjoyable working relationship" networks were the pre-team networks most highly correlated with the within-team networks. Correlations involving the teammate recommendation network were the smallest correlations in magnitude, with the exception of the correlation with the leadership network at T1. Overall, the correlations suggest the strongest relationships among networks exist between the within-team networks.

Given the dynamic and temporal nature of the current study, tie changes between observations of within-team networks hold information relevant to understanding network dynamics. Table 8 specifies the ways that communication and leadership networks change over the course of collaboration. Focusing first on communication, between the first and second observations (Period 1), the network changed substantially with 160 new ties being reported while 145 previous ties were no longer reported. The change suggests that as teams collaborated, members maintained most of their communication partners, but changed a notable proportion of them as well. Between the second and third observations (Period 2), fewer ties were created or dropped. Therefore, the communication network changed more in Period 1 than it did in Period 2. Shifting attention to leadership, 42 more ties were created than dropped in Period 1 and 46 more ties were created in Period 2. However, 70 more ties were maintained in Period 2 as compared to Period 1. Taken together, the changes show that team members are recognizing new leaders over time, but leadership also stabilizes around previously-reported leaders. The leadership network at T2 is more similar to leadership at T3 than it is to leadership at T1, as demonstrated by the Jaccard Index.

Table 8: Within-Team Network Ties Created, Maintained, and Dropped During Time Periods

Within-Team Networks	Period 1 (T1-T2)	Period 2 (T2-T3)
Communication		
Initial Ties	596	611
Maintained	451	491
Created	160	141
Dropped	145	120
Jaccard Index	0.597	0.653
Leadership		
Initial Ties	385	427
Maintained	257	327
Created	170	146
Dropped	128	100
Jaccard Index	0.460	0.570

The SIENA models reported in Table 9 contain the main results for hypothesis testing. Within-team leadership and communication were simultaneously estimated as outcomes from a single model. Models were estimated using the default procedure in RSIENA, the method of moments. Interpreting SIENA models requires determining the significance of parameter estimates using t-statistics calculated by dividing an estimate by its standard error and then comparing the calculated value to a normal distribution centered around zero; a t-statistic greater than an absolute value of two indicates statistical significance at 0.05 (Ripley et al., 2018, p. 72). Another aspect of interpreting a SIENA model is assessing the parameter estimate for the rate function. It is important to note that parameter estimates for the rate function do not require significance testing since the estimate corresponds to observed changes between network observations. Overall, and for both within-team networks, actors had more opportunities to change ties between the T1 and T2 observations (Period 1) than between T2 and T3 (Period 2). For both relationships, the rate functions decreased between periods; actors had at least three chances to change ties during Period 1 and between two and three chances during Period 2.

Three separate SIENA models are presented. Model 1 tests all three hypotheses while only controlling for endogenous network effects and individual attributes corresponding to behavioral traces from usage of the technology platform. Meanwhile, Model 2 tests the three hypotheses by controlling for endogenous network effects, individual attributes distinct from those in Model 1, shared dyadic attributes, and exogenous network effects. Lastly, Model 3 tests the hypotheses in a full model including all controls in the study. Model 1 achieved the best convergence where the overall maximum convergence met the recommended 0.25 ratio and all t-ratios for parameter convergence were less than 0.1 in absolute value. Models 2 and 3 only achieved a maximum convergence of 0.30, which is considered “reasonable” according to the RSIENA manual (Ripley et al., 2018, p. 62). However, Model 3 has two t-ratios for parameter convergence that exceed the recommended 0.1 in absolute value. The less than ideal convergence statistics do not necessarily dismiss the value of reported results, but they are limitations on the quality of model estimations. The goodness of fit for all models assessed the differences between the observed networks and simulated networks using the indegree and outdegree distributions. All of the simulated indegree distributions were not significantly different from the observed leadership and communication networks, but all of the outdegree distributions were significantly different. The models all reflect the incoming reports of within-team relationships, but do not adequately account for the outgoing reports of within-team relationships (see Figure 17 to Figure 20).

Across all three models, there are positive effects of a communication tie on leadership ($p < 0.001$) and a leadership tie on communication ($p < 0.001$); there is support for H1a and H1b, which test both directions of the positive association between leadership and communication. There was support for the invitation network negatively affecting leadership reliance from an invitation sender (H2a). While the effect was negative in all three models, it was only significant in Model 3 ($p < 0.05$). The interpretation of the effect is that sending an invitation to a teammate makes a person less likely to rely on that same teammate for leadership, meaning that people do not invite teammates that they expect to lead them. Sending an invitation to a teammate had a positive effect on communicating frequently with said teammate ($p < 0.01$) in Model 1, supporting H2b. However, the effect decreased as more controls were added in Models 2 and 3. Invitations only had a significant and positive effect when accounting for endogenous network effects and individual attributes that were captured through digital trace data.

The control parameters included in the models help describe and provide more understanding of the coevolution of leadership and communication. The endogenous network effects describe the structure of both networks. Negative effects for the outdegree term, "report of a relationship," indicate that actors do not report many ties at random, which is reflected because the leadership and communication networks were sparse and did not have a majority of team members selected (average outdegree in Table 7). There were team members who nominated more leaders than others (activity), and some team members were relied on for leadership more than others (popularity), but there was not much hierarchy in teams (transitive triplets). Taken together, these effects show that the leadership structure was centralized based on the popularity and activity parameters, but teams were not necessarily hierarchical. Reporting frequent communication had different patterns of endogenous network effects. Teammates agreed with one another about whom they communicated with frequently (reciprocity) and triangles formed within teams (transitive triplets), but there were not popular team members in the communication network.

Having the same university affiliation had positive effects on both communication and leadership, showing that team members relied on those who were geographically collocated in the team over members at the other university. In the leadership networks, the individual-level effect for university affiliation of an alter was negative. Participants from one of the universities were not commonly reported as sources of leadership. On the other hand, university affiliation of an ego had a positive effect on communication. No effects were observed for teammate recommendation on either communication or leadership network. Also, having an enjoyable working relationship with a team member had a positive effect on communication, but not leadership. In total, all of the controls better clarify the mechanisms responsible for the coevolution of within-team communication and leadership networks.

Table 9: SIENA Results of Leadership and Communication Coevolution Within Teams

	Model 1 Estimate (SE)		Model 2 Estimate (SE)		Model 3 Estimate (SE)	
Parameter	**Leadership**	**Comm.**	**Leadership**	**Comm.**	**Leadership**	**Comm.**
Intercept						
Report of a relationship (Outdegree)	-3.41*** (0.38)	-0.06 (0.28)	-3.52*** (0.42)	-1.05** (0.34)	-3.47*** (0.45)	-1.02** (0.35)
<u>Control Variables</u>						
Endogenous Network Effects						
Reciprocity	-0.07 (0.11)	0.76*** (0.10)	-0.14 (0.12)	0.40*** (0.10)	-0.11 (0.12)	0.43*** (0.12)
Transitive Triplets	-0.63** (0.23)	0.97*** (0.16)	-0.63* (0.27)	0.80*** (0.17)	-0.57* (0.27)	0.81*** (0.17)
Popularity (Indegree)	0.56*** (0.09)	-0.41*** (0.08)	0.58*** (0.10)	-0.28** (0.09)	0.56*** (0.10)	-0.29** (0.09)
Activity (Outdegree)	0.29*** (0.05)	-0.07 (0.04)	0.30*** (0.06)	0.02 (0.04)	0.30*** (0.06)	0.02 (0.04)
Individual Attributes						
Invites sent (alter)	-0.01 (0.01)	0.00 (0.01)			0.00 (0.02)	-0.01 (0.02)
Invites sent (ego)	-0.02 (0.02)	-0.01 (0.01)			-0.02 (0.02)	-0.01 (0.02)
Invites received (alter)	0.02 (0.02)	-0.03 (0.02)			0.02 (0.02)	0.00 (0.02)
Invites received (ego)	0.01 (0.02)	0.00 (0.02)			0.01 (0.02)	0.00 (0.01)
Number of searches (alter)	0.01 (0.01)	0.01 (0.01)			0.01 (0.01)	0.02 (0.01)
Number of searches (ego)	-0.02 (0.01)	-0.02* (0.01)			-0.02 (0.01)	-0.02 (0.01)
Leadership Experience (alter)			-0.04 (0.08)	-0.06 (0.07)	-0.04 (0.07)	-0.04 (0.08)
Leadership Experience (ego)			0.01 (0.08)	-0.05 (0.07)	0.02 (0.08)	-0.05 (0.07)

Competence (alter)			0.07 (0.08)	-0.06 (0.07)	0.06 (0.08)	-0.06 (0.08)
Competence (ego)			-0.01 (0.08)	0.07 (0.07)	0.02 (0.08)	0.09 (0.07)
Intellect or Imagination (alter)			-0.09 (0.09)	0.13 (0.10)	-0.08 (0.09)	0.15 (0.09)
Intellect or Imagination (ego)			0.12 (0.09)	-0.05 (0.09)	0.12 (0.09)	-0.06 (0.08)
Conscientiousness (alter)			0.09 (0.08)	-0.09 (0.08)	0.09 (0.08)	-0.09 (0.08)
Conscientiousness (ego)			0.10 (0.08)	-0.01 (0.07)	0.1 (0.08)	-0.01 (0.07)
Surgency or Extraversion (alter)			-0.11 (0.07)	0.04 (0.07)	-0.11 (0.07)	0.04 (0.07)
Surgency or Extraversion (ego)			0.04 (0.07)	-0.02 (0.06)	0.03 (0.07)	-0.02 (0.06)
Agreeableness (alter)			0.07 (0.10)	0.01 (0.10)	0.05 (0.10)	-0.00 (0.10)
Agreeableness (ego)			-0.18 (0.10)	0.21* (0.10)	-0.15 (0.10)	0.23* (0.09)
Negative Emotional Stability (alter)			0.11 (0.08)	-0.09 (0.08)	0.11 (0.08)	-0.09 (0.08)
Negative Emotional Stability (ego)			0.05 (0.08)	0.04 (0.07)	0.04 (0.08)	0.05 (0.07)
Gender (alter)			-0.22 (0.12)	0.30** (0.11)	-0.20 (0.12)	0.32** (0.11)
Gender (ego)			0.01 (0.11)	-0.08 (0.09)	0.02 (0.11)	-0.08 (0.10)
University Affiliation (alter)			-0.25* (0.11)	0.09 (0.10)	-0.25* (0.11)	0.10 (0.11)
University Affiliation (ego)			0.13 (0.10)	0.22* (0.09)	0.14 (0.11)	0.23* (0.09)
Shared Dyadic Attributes						
Gender Homophily			-0.13 (0.10)	-0.05 (0.10)	-0.12 (0.10)	-0.05 (0.10)
Same University Affiliation			0.33* (0.14)	0.98*** (0.12)	0.32* (0.13)	0.98*** (0.12)
Exogenous Network Effect						
Teammate Recommendation	0.22 (0.20)	0.24 (0.20)	0.09 (0.20)	0.10 (0.19)	0.17 (0.20)	0.16 (0.22)
Prior Collaboration			0.32 (0.27)	0.25 (0.41)	0.30 (0.28)	0.18 (0.46)
Enjoyable Working Relationship			0.14 (0.21)	1.05*** (0.30)	0.20 (0.22)	1.12*** (0.30)

<u>**Hypothesized Variables**</u>						
Exogenous Network Effects						
Communication: H1a	1.14*** (0.18)		1.06*** (0.23)		1.03*** (0.22)	
Leadership: H1b		0.73*** (0.20)		0.85*** (0.21)		0.81*** (0.20)
Invitation Sent: H2	-0.17 (0.14)	0.46** (0.15)	-0.26 (0.15)	0.09 (0.15)	-0.34* (0.16)	0.03 (0.16)
Rate function						
Rate period 1 (T1-T2)	3.19 (0.30)	3.08 (0.27)	3.08 (0.29)	3.80 (0.50)	3.10 (0.29)	3.80 (0.41)
Rate period 2 (T2-T3)	2.25 (0.20)	2.45 (0.24)	2.26 (0.22)	2.83 (0.27)	2.29 (0.20)	2.83 (0.29)
Maximum Convergence Ratio	0.25		0.30		0.30	
All Convergence t-ratios <	0.09		0.09		0.13	

Note. All significance levels are two tailed; *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.

To supplement the significance testing of parameters, Table 10 shows the relative importance (RI) of parameter estimates at each time point for Model 1, which had the best convergence. To summarize the utility of RI, the degree of certainty is an additional measure reported that describes how well a model captures variation in tie changes that represent actor decisions. For the leadership network, the four most important parameters account for RI of approximately 0.88 in T1: reporting a relationship (0.31), popularity (0.28), activity (0.15), and communication (0.14). Simply reporting a relationship was a strong signal of relying on a teammate for leadership, which suggests that people did not randomly nominate teammates as leaders. Next, the high relative importance of popularity shows that a team member who is relied upon for leadership is relied upon by multiple teammates. Activity indicates that a single person relying on multiple teammates for leadership is also relatively more important than other model parameters. Lastly, communicating frequently with a teammate is important for determining whether a teammate will be relied upon for leadership. Other parameters of note relate to the technology platform. The RI of the invitation network, the number of searches by a reporter (ego), and number of invitations received (alter) all had relative importance values of approximately 0.01. The degree of certainty for tie changes decreased from T1 to T3, indicating that the model is better at T1 (0.149) and T2 (0.142) compared to T3 (0.117).

The relative importance for the communication network is likewise informative. The four most important parameters account for approximately 0.84 of RI in T1 and are all endogenous network effects: popularity (0.31), transitive triplets (0.25), reciprocity (0.14), and activity (0.14). Taken together, the RI shows that communication network encompassed team members who were popular, communicated within sub-groups, agreed on their reports of communication partners, and active in communicating with others. With respect to the hypothesized effects, explaining communication with the leadership network was three times more important than the invitation network (0.09 compared to 0.03). The number of invites that an alter received and the number of searches conducted (by ego and alter) were the only other parameters with effects greater than 0.01. The degree of certainty for the communication network model increased from 0.117 at T1 and 0.123 at T3, which shows that the model best captured the network at T3 compared to other time points. The RI of parameters for the less convergent Models 2 and 3 are reported in Tables Table 11 and Table 12, and may be interpreted in a similar fashion. It is worth noting that the degrees of certainty for Models 2 and 3 are higher than those for Model 1, but Model 1 was the most stable estimation.

Table 10: Relative importance of SIENA Parameters in Model 1.

	Relative Importance					
	Leadership Network			**Communication Network**		
Parameter	**T1**	**T2**	**T3**	**T1**	**T2**	**T3**
Intercept						
Report of a relationship (Outdegree)	0.308	0.304	0.292	0.016	0.016	0.015
<u>Control Variables</u>						
Endogenous Network Effects						
Reciprocity	0.006	0.006	0.007	0.142	0.139	0.142
Transitive Triplets	0.061	0.068	0.075	0.249	0.252	0.252
Popularity (Indegree)	0.282	0.281	0.285	0.305	0.303	0.301
Activity (Outdegree)	0.146	0.148	0.152	0.142	0.139	0.142
Individual Attributes						
Invites sent (alter)	0.005	0.005	0.005	0.004	0.003	0.003
Invites sent (ego)	0.006	0.006	0.006	0.006	0.006	0.006
Invites received (alter)	0.010	0.010	0.011	0.024	0.022	0.021
Invites received (ego)	0.003	0.003	0.002	0.002	0.002	0.002
Number of searches (alter)	0.006	0.006	0.006	0.014	0.014	0.013
Number of searches (ego)	0.011	0.011	0.011	0.019	0.019	0.019
Exogenous Network Effects						

Teammate Recommendation	0.006	0.005	0.004	0.007	0.006	0.007
Hypothesized Variables						
Exogenous Network Effects						
Communication: H1a	0.142	0.138	0.136			
Leadership: H1b				0.090	0.089	0.092
Invitation Sent: H2	0.009	0.009	0.009	0.029	0.031	0.031
Degree of Certainty	0.149	0.142	0.117	0.117	0.115	0.123

Table 11: Relative importance of SIENA Parameters in Model 2.

	Relative Importance					
	Leadership Network			Communication Network		
Parameter	**T1**	**T2**	**T3**	**T1**	**T2**	**T3**
Intercept						
Report of a relationship (Outdegree)	0.258	0.255	0.244	0.188	0.186	0.189
Control Variables						
Endogenous Network Effects						
Reciprocity	0.010	0.010	0.011	0.049	0.049	0.051
Transitive Triplets	0.051	0.058	0.062	0.161	0.168	0.169
Popularity (Indegree)	0.236	0.234	0.239	0.164	0.164	0.168
Activity (Outdegree)	0.123	0.126	0.130	0.022	0.023	0.023
Individual Attributes						
Leadership Experience (alter)	0.004	0.004	0.004	0.008	0.007	0.007
Leadership Experience (ego)	0.001	0.001	0.001	0.005	0.005	0.005
Competence (alter)	0.007	0.008	0.008	0.007	0.007	0.007
Competence (ego)	0.001	0.001	0.001	0.008	0.008	0.008
Intellect or Imagination (alter)	0.008	0.008	0.008	0.016	0.015	0.015
Intellect or Imagination (ego)	0.009	0.009	0.009	0.005	0.005	0.005
Conscientiousness (alter)	0.009	0.009	0.009	0.012	0.012	0.012
Conscientiousness (ego)	0.009	0.009	0.009	0.001	0.001	0.001
Surgency or Extraversion (alter)	0.013	0.013	0.013	0.006	0.006	0.006
Surgency or Extraversion (ego)	0.004	0.004	0.004	0.003	0.003	0.003
Agreeableness (alter)	0.005	0.006	0.006	0.001	0.001	0.001
Agreeableness (ego)	0.013	0.013	0.013	0.020	0.020	0.019
Negative Emotional Stability (alter)	0.011	0.011	0.011	0.011	0.011	0.011
Negative Emotional Stability (ego)	0.004	0.004	0.004	0.005	0.005	0.005
Gender (alter)	0.017	0.017	0.017	0.031	0.031	0.031
Gender (ego)	0.001	0.001	0.001	0.008	0.008	0.008

University Affiliation (alter)	0.019	0.019	0.018	0.010	0.009	0.009
University Affiliation (ego)	0.010	0.010	0.009	0.022	0.022	0.021
Shared Dyadic Attributes						
Gender Homophily	0.013	0.013	0.013	0.006	0.006	0.006
Same University Affiliation	0.032	0.032	0.032	0.122	0.118	0.113
Exogenous Network Effects						
Teammate Recommendation	0.002	0.002	0.002	0.002	0.002	0.002
Prior Collaboration	0.006	0.005	0.005	0.002	0.003	0.002
Enjoyable Working Relationship	0.005	0.005	0.004	0.025	0.027	0.023
<u>Hypothesized Variables</u>						
Exogenous Network Effects						
Communication: H1a	0.111	0.107	0.106			
Leadership: H1b				0.078	0.074	0.078
Invitation Sent: H2	0.011	0.011	0.011	0.004	0.004	0.004
Degree of Certainty	0.161	0.155	0.136	0.159	0.165	0.164

Table 12: Relative importance of SIENA Parameters in Model 3.

	Relative Importance					
	Leadership Network			**Communication Network**		
Parameter	**T1**	**T2**	**T3**	**T1**	**T2**	**T3**
Intercept						
Report of a relationship (Outdegree)	0.253	0.250	0.241	0.176	0.174	0.177
<u>Control Variables</u>						
Endogenous Network Effects						
Reciprocity	0.007	0.008	0.008	0.049	0.050	0.051
Transitive Triplets	0.046	0.052	0.056	0.156	0.164	0.164
Popularity (Indegree)	0.227	0.226	0.231	0.162	0.161	0.166
Activity (Outdegree)	0.120	0.123	0.127	0.022	0.023	0.023
Individual Attributes						
Invites sent (alter)	0.000	0.000	0.000	0.004	0.004	0.004
Invites sent (ego)	0.006	0.006	0.006	0.003	0.003	0.003
Invites received (alter)	0.009	0.009	0.009	0.001	0.001	0.001
Invites received (ego)	0.004	0.004	0.004	0.001	0.001	0.001
Number of searches (alter)	0.003	0.003	0.003	0.014	0.014	0.013
Number of searches (ego)	0.009	0.009	0.009	0.012	0.012	0.011
Leadership Experience (alter)	0.004	0.004	0.004	0.006	0.006	0.005

Leadership Experience (ego)	0.002	0.002	0.002	0.006	0.006	0.006
Competence (alter)	0.005	0.006	0.006	0.008	0.008	0.007
Competence (ego)	0.001	0.001	0.001	0.010	0.010	0.010
Intellect or Imagination (alter)	0.007	0.007	0.007	0.006	0.006	0.005
Intellect or Imagination (ego)	0.010	0.009	0.009	0.006	0.006	0.006
Conscientiousness (alter)	0.008	0.008	0.009	0.017	0.017	0.017
Conscientiousness (ego)	0.009	0.008	0.008	0.006	0.006	0.006
Surgency or Extraversion (alter)	0.012	0.013	0.012	0.011	0.011	0.010
Surgency or Extraversion (ego)	0.003	0.003	0.003	0.001	0.001	0.001
Agreeableness (alter)	0.004	0.005	0.005	0.006	0.006	0.006
Agreeableness (ego)	0.011	0.011	0.011	0.003	0.003	0.002
Negative Emotional Stability (alter)	0.010	0.010	0.010	0.000	0.000	0.000
Negative Emotional Stability (ego)	0.004	0.004	0.004	0.021	0.021	0.020
Gender (alter)	0.015	0.015	0.016	0.011	0.011	0.011
Gender (ego)	0.002	0.002	0.002	0.005	0.005	0.005
University Affiliation (alter)	0.018	0.018	0.018	0.032	0.031	0.031
University Affiliation (ego)	0.011	0.011	0.010	0.008	0.008	0.008
Shared Dyadic Attributes						
Gender Homophily	0.012	0.012	0.012	0.006	0.006	0.006
Same University Affiliation	0.031	0.031	0.031	0.116	0.112	0.107
Exogenous Network Effects						
Teammate Recommendation	0.004	0.003	0.003	0.003	0.003	0.003
Prior Collaboration	0.005	0.005	0.005	0.002	0.002	0.001
Enjoyable Working Relationship	0.007	0.006	0.006	0.026	0.028	0.023
Hypothesized Variables						
Exogenous Network Effects						
Communication: H1a	0.107	0.102	0.101			
Leadership: H1b				0.071	0.067	0.071
Invitation Sent: H2	0.014	0.014	0.014	0.001	0.001	0.001
Degree of Certainty	0.158	0.152	0.135	0.161	0.170	0.169

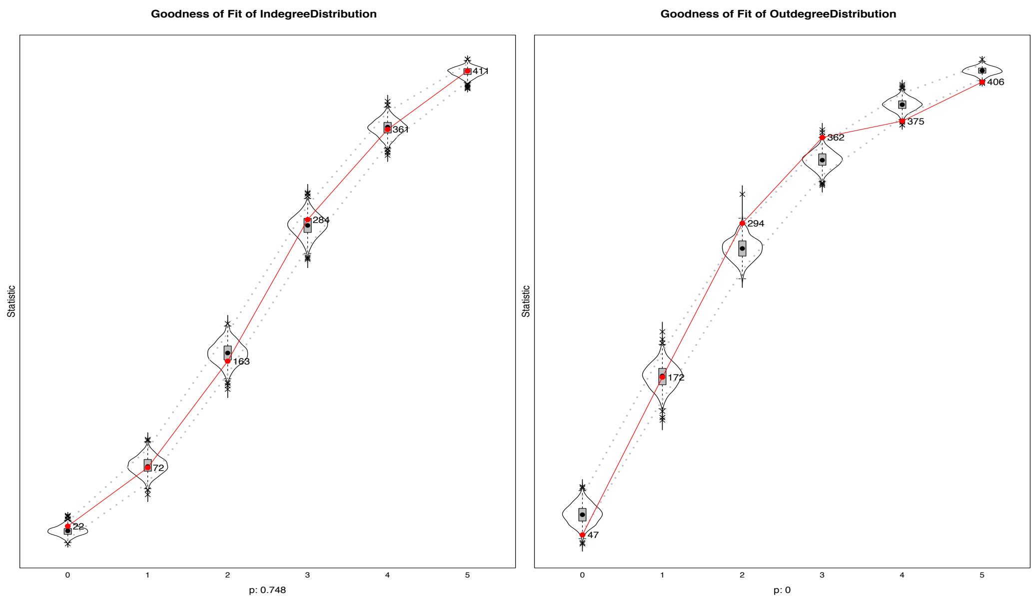


Figure 16: Model 1 Goodness of Fit for Communication indegree and outdegree distributions.

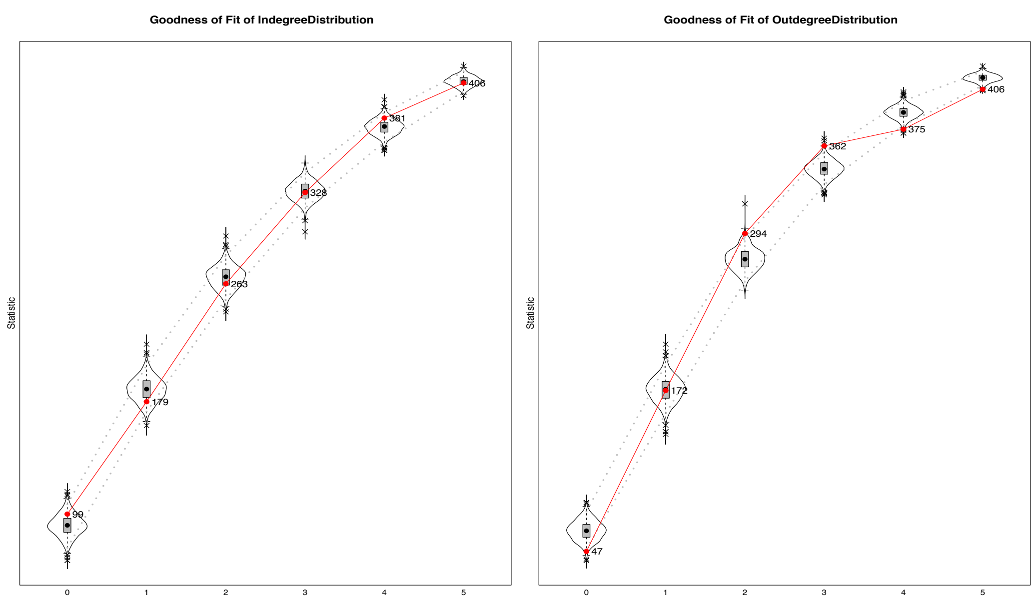


Figure 17: Model 1 Goodness of Fit for Leadership indegree and outdegree distributions.

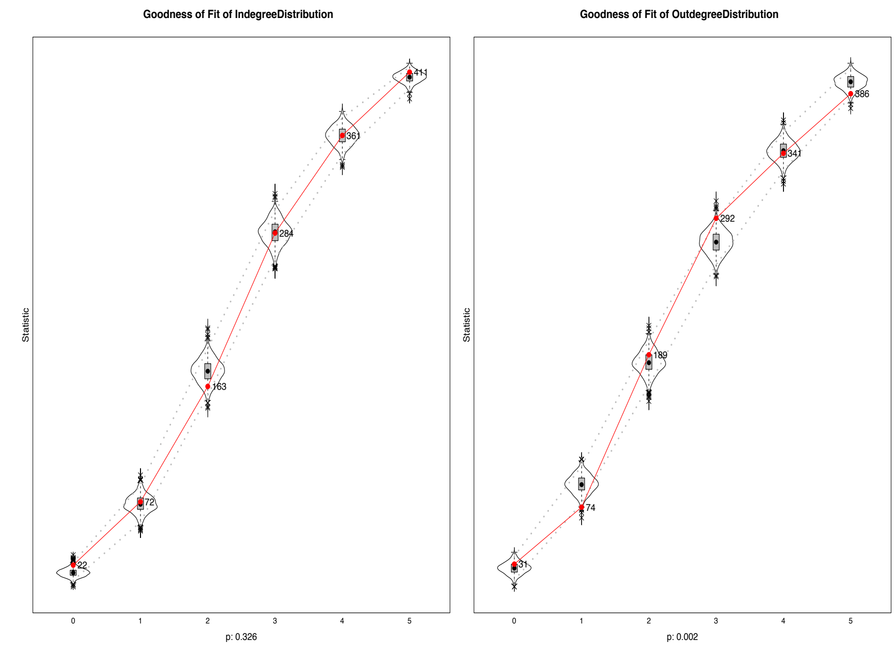


Figure 18: Model 2 Goodness of Fit for Communication indegree and outdegree distributions.

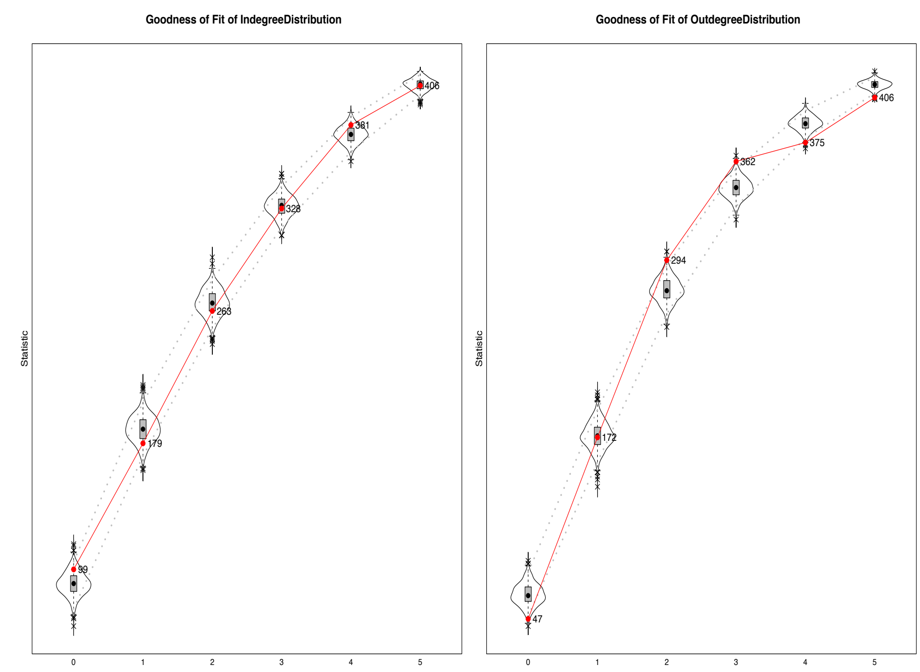


Figure 19: Model 2 Goodness of Fit for Leadership indegree and outdegree distributions.

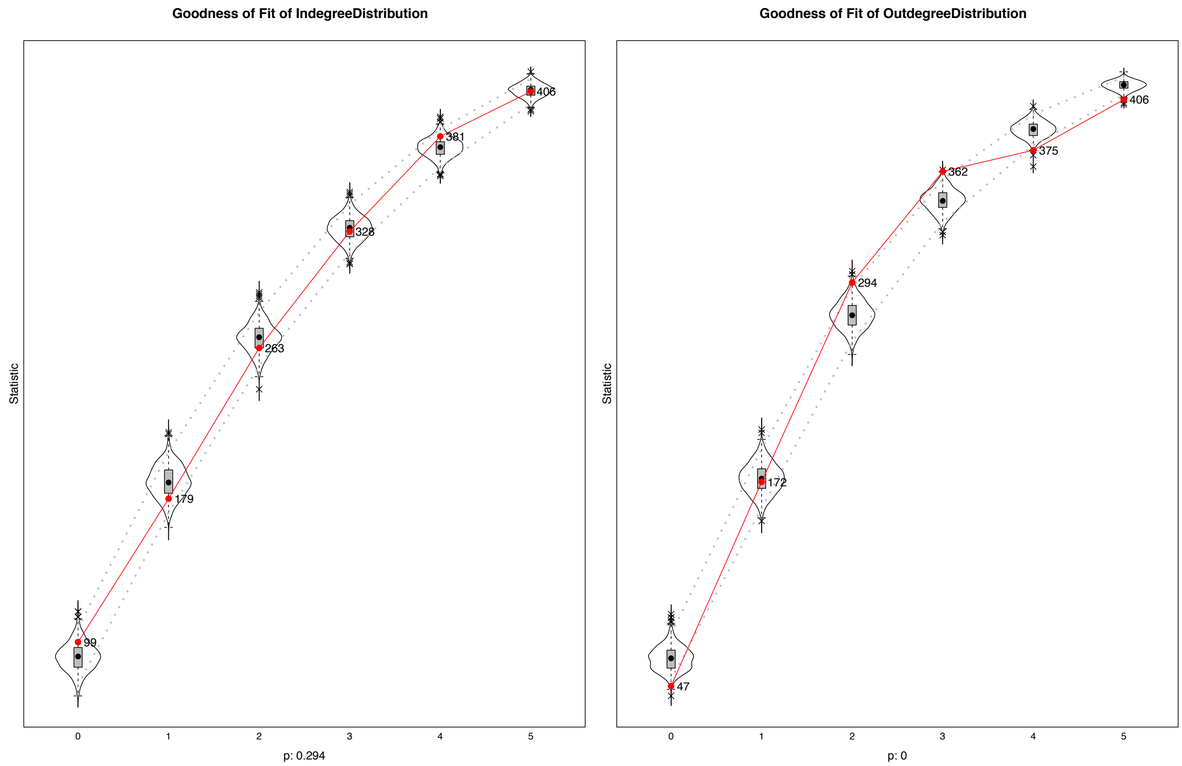


Figure 21: Model 3 Goodness of Fit for Leadership indegree and outdegree distributions.

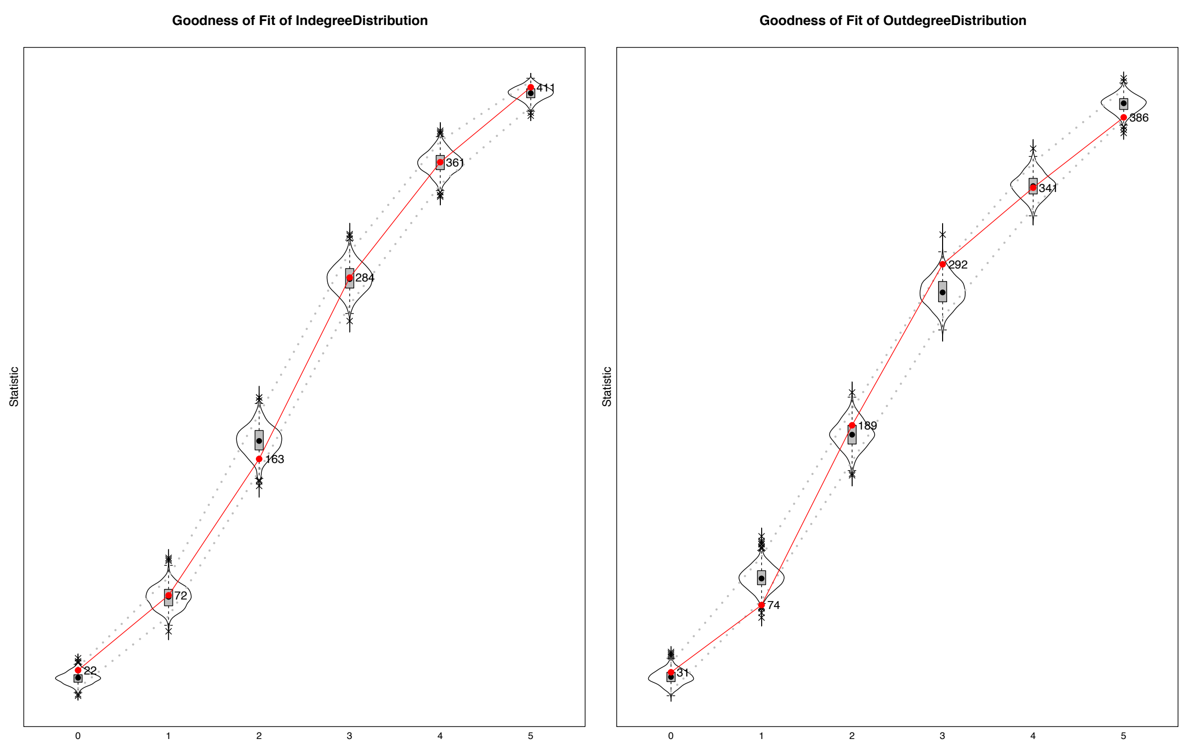


Figure 20: Model 3 Goodness of Fit for Communication indegree and outdegree distributions.

Replication of Analysis

This section details the replication of the main analysis using the data described as Sample 2 in Chapter 3. The sample includes 197 participants (54% female; mean age = 21.1 years, SD = 2.57 years) in 31 teams (mean team size = 6.35; SD = 1.25). Participants followed the same procedure as previously described in the current chapter. There were no significant differences between samples with respect to team size, gender representation, or age. The individual-level attributes (e.g. personality and leadership) are also comparable to the main sample. Participants sent and received under two invitations on average while conducting one more search on average than the main sample. The descriptive statistics for the second observation of the Sample 2 networks show a distinct difference from the main sample of the study: the number of ties decreased for all networks in the second observation.

From the SIENA modeling, results from the replication further illustrate the relationship that exists between leadership and communication. Leadership and communication both have positive effects on each other (see Table 16), replicating support for H1, and communication has a larger relative importance on leadership than leadership has on communication across all three models (see Table 17Table 18Table 19). However, the invitation networks did not show relationships to communication and leadership (H2 not supported). The lack of effects points to the limits of team self-assembly in explaining the emergence and evolution of relationships in teams. A team has the ability to develop the necessary social structures based on multiple aspects, as evidenced by prior collaboration and university affiliation having positive effects on communication. In totality, the replication shows that leadership and communication in peer collaborations have a strong relationship, while teammate invitations do not have a robust effect.

Table 13: Sample 2 Individual-Level Variables: Descriptive Statistics and Correlations

				Pearson Correlations										
		Mean	**SD**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**
	Individual-Level Variables													
1.	Invites Sent	2.40	2.78											
2.	Invites Received	2.40	3.07	-0.146*										
3.	Number of Searches	5.48	6.94	0.016	0.339*									
4.	Competence	3.51	0.77	0.401	-0.078	0.128								
5.	Leadership Experience	3.53	0.77	0.289*	-0.017	-0.019	0.376*							
6.	Intellect or Imagination	3.88	0.60	0.285*	-0.059	-0.041	0.160*	0.222*						
7.	Conscientiousness	3.79	0.72	0.101	-0.002	0.062	0.137	0.168*	0.073					
8.	Extraversion	3.13	0.92	0.223*	-0.129	-0.097	0.156*	0.494*	0.182*	0.074				
9.	Agreeableness	3.84	0.69	0.320*	-0.035	-0.038	0.185*	0.333*	0.289*	0.196*	0.283			
10.	Negative Emotional Stability	2.39	0.65	-0.077	0.042	0.053	0.021	-0.011	-0.232*	-0.111	-0.029	-0.113		
11.	Gender (m=0, f=1)	0.54	0.50	0.136	0.003	0.009	0.109	0.028	0.017	0.261*	0.054	0.312*	0.126	
12.	University affiliation (0 or 1)	0.44	0.50	0.066	0.093	0.089	-0.111	-0.103	-0.010	0.167*	0.012	0.085	-0.084	0.097

Note. * $p < 0.05$

Table 14: Sample 2 Network-Level Variables: Descriptive Statistics and QAP Correlations

				QAP Correlations[b]								
Within-Team Networks	**Number of Ties**	**Average Out-Degree**	**Density[a]**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
1. Communication T1	432	2.19	0.392									
2. Communication T2	425	2.16	0.386	0.777								
3. Communication T3	496	2.52	0.450	0.762	0.823							
4. Leadership T1	326	1.65	0.296	0.588	0.514	0.517						
5. Leadership T2	315	1.60	0.286	0.604	0.636	0.624	0.674					
6. Leadership T3	366	1.86	0.332	0.559	0.602	0.668	0.625	0.740				
Pre-Team Networks												
7. Invitation Network	173	0.88	0.157	0.387	0.361	0.357	0.341	0.322	0.306			
8. Teammate Recommendation (1 = Top 10, 0 = not Top 10)	68	0.35	0.062	0.225	0.197	0.187	0.192	0.209	0.155	0.330		
9. Prior Collaboration	120	0.61	0.109	0.481	0.480	0.469	0.264	0.290	0.292	0.372	0.131	
10. Enjoyable Working Relationship	119	0.60	0.108	0.469	0.469	0.450	0.281	0.322	0.322	0.381	0.176	0.719

Note. a. Density is calculated based on the number of possible ties within a team, totaling 1102 possible within-team (sized 6 and 7) ties;
b. All QAP correlations are significant at $p < 0.05$.

Table 15: Within-Team Network Ties Created, Maintained, and Dropped During Sample 2 Time Periods

Within-Team Networks	Period 1 (T1-T2)	Period 2 (T2-T3)
Communication		
Initial Ties	432	425
Maintained	334	379
Created	91	117
Dropped	98	46
Jaccard Index	0.639	0.699
Leadership		
Initial Ties	326	315
Maintained	217	252
Created	98	114
Dropped	109	63
Jaccard Index	0.512	0.587

Table 16: SIENA Results of Leadership and Communication Coevolution Within Teams in Sample 2

	Model 1 Estimate (SE)		Model 2 Estimate (SE)		Model 3 Estimate (SE)	
Parameter	**Leadership**	**Comm.**	**Leadership**	**Comm.**	**Leadership**	**Comm.**
Intercept						
Report of a relationship (Outdegree)	-3.48*** (0.48)	0.26 (0.27)	-3.61*** (0.51)	-2.74*** (0.55)	-3.59*** (0.51)	-2.74*** (0.53)
<u>Control Variables</u>						
Endogenous Network Effects						
Reciprocity	-0.20 (0.15)	1.42*** (0.15)	-0.23 (0.17)	0.74*** (0.17)	-0.22 (0.17)	0.74*** (0.18)
Transitive Triplets	-0.42 (0.32)	1.53*** (0.17)	-0.34 (0.33)	0.75*** (0.20)	-0.32 (0.32)	0.75*** (0.21)
Popularity (Indegree)	0.54*** (0.11)	-0.68*** (0.09)	0.55*** (0.12)	-0.25* (0.10)	0.53*** (0.12)	-0.25* (0.12)
Activity (Outdegree)	0.23*** (0.07)	-0.14*** (0.04)	0.21** (0.07)	0.18** (0.07)	0.21*** (0.06)	0.18** (0.06)
Individual Attributes						
Invites sent (alter)	-0.02 (0.02)	-0.02 (0.03)				
Invites sent (ego)	-0.04 (0.02)	-0.02 (0.03)				
Invites received (alter)	0.02 (0.02)	-0.02 (0.02)				
Invites received (ego)	0.00 (0.02)	0.02 (0.02)				
Number of searches (alter)	0 (0.01)	0 (0.01)				
Number of searches (ego)	-0.01 (0.01)	0.00 (0.01)				
Leadership Experience (alter)			-0.04 (0.11)	-0.05 (0.11)	-0.05 (0.11)	-0.04 (0.12)
Leadership Experience (ego)			0.14 (0.11)	-0.03 (0.10)	0.14 (0.11)	-0.03 (0.11)
Competence (alter)			-0.08 (0.10)	-0.07 (0.10)	-0.10 (0.11)	-0.07 (0.11)
Competence (ego)			-0.04 (0.10)	0.08 (0.10)	-0.03 (0.10)	0.1 (0.10)
Intellect or Imagination (alter)			0.02 (0.11)	0.09 (0.12)	0.02 (0.12)	0.1 (0.12)
Intellect or Imagination (ego)			-0.20 (0.13)	-0.09 (0.11)	-0.18 (0.12)	-0.09 (0.11)

Conscientiousness (alter)			0.19* (0.09)	0 (0.10)	0.19 (0.10)	-0.01 (0.10)
Conscientiousness (ego)			-0.19 (0.10)	-0.16 (0.09)	-0.18 (0.11)	-0.16 (0.09)
Surgency or Extraversion (alter)			-0.07 (0.08)	0.04 (0.08)	-0.05 (0.08)	0.04 (0.08)
Surgency or Extraversion (ego)			0.11 (0.08)	0.1 (0.07)	0.11 (0.09)	0.11 (0.07)
Agreeableness (alter)			-0.19 (0.11)	-0.19 (0.11)	-0.19 (0.11)	-0.19 (0.11)
Agreeableness (ego)			-0.25* (0.11)	-0.06 (0.10)	-0.25* (0.11)	-0.05 (0.10)
Negative Emotional Stability (alter)			-0.12 (0.10)	0.08 (0.11)	-0.14 (0.11)	0.07 (0.11)
Negative Emotional Stability (ego)			0.04 (0.11)	0.05 (0.09)	0.04 (0.11)	0.05 (0.09)
Gender (alter)			-0.06 (0.14)	0.24 (0.15)	-0.05 (0.15)	0.25 (0.16)
Gender (ego)			0.06 (0.15)	-0.13 (0.13)	0.04 (0.15)	-0.14 (0.13)
University Affiliation (alter)			-0.25 (0.14)	0.19 (0.15)	-0.29* (0.15)	0.2 (0.15)
University Affiliation (ego)			0.07 (0.14)	0.53*** (0.14)	0.07 (0.14)	0.53*** (0.13)
Shared Dyadic Attributes						
Gender Homophily			0.05 (0.14)	0.07 (0.13)	0.07 (0.15)	0.07 (0.13)
Same University Affiliation			0.36 (0.29)	2.14*** (0.30)	0.37 (0.29)	2.14*** (0.28)
Exogenous Network Effects						
Teammate Recommendation	-0.03 (0.26)	0.02 (0.29)	-0.22 (0.27)	-0.06 (0.31)	-0.19 (0.28)	-0.03 (0.30)
Prior Collaboration			-0.40 (0.27)	1.09** (0.39)	-0.40 (0.27)	1.08** (0.41)
Enjoyable Working Relationship			0.43 (0.27)	-0.13 (0.35)	0.44 (0.28)	-0.13 (0.37)
Hypothesized Variables						
Exogenous Network Effects						
Communication: H1a	1.87*** (0.23)		1.71*** (0.42)		1.71*** (0.44)	
Leadership: H1b		1.15*** (0.24)		1.22*** (0.25)		1.21*** (0.24)
Invitation Sent: H2	-0.02 (0.18)	0.3 (0.19)	0.04 (0.20)	-0.17 (0.21)	-0.07 (0.20)	-0.10 (0.23)
Rate function						
Rate period 1 (T1-T2)	2.15 (0.21)	2.33 (0.26)	2.08 (0.19)	2.99 (0.37)	2.08 (0.19)	2.99 (0.40)
Rate period 2 (T2-T3)	1.79 (0.19)	2.02 (0.22)	1.82 (0.19)	2.64 (0.38)	1.83 (0.19)	2.63 (0.34)

Maximum Convergence Ratio	0.20	0.30	0.34
All Convergence t-ratios <	0.07	0.12	0.12

Note. All significance levels are two tailed; *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.

Table 17: Relative importance of SIENA Parameters in Model 1 for Sample 2.

	Relative Importance					
	Leadership Network			Communication Network		
Parameter	**T1**	**T2**	**T3**	**T1**	**T2**	**T3**
Intercept						
Report of a relationship (Outdegree)	0.353	0.362	0.362	0.055	0.052	0.049
Control Variables						
Endogenous Network Effects						
Reciprocity	0.015	0.016	0.018	0.183	0.186	0.169
Transitive Triplets	0.040	0.031	0.040	0.194	0.192	0.220
Popularity (Indegree)	0.245	0.237	0.242	0.304	0.312	0.308
Activity (Outdegree)	0.110	0.104	0.117	0.120	0.120	0.128
Individual Attributes						
Invites sent (alter)	0.007	0.007	0.007	0.008	0.008	0.007
Invites sent (ego)	0.012	0.012	0.012	0.007	0.007	0.007
Invites received (alter)	0.010	0.011	0.010	0.013	0.012	0.011
Invites received (ego)	0.001	0.001	0.001	0.009	0.008	0.008
Number of searches (alter)	0.003	0.003	0.003	0.001	0.001	0.001
Number of searches (ego)	0.005	0.004	0.005	0.004	0.004	0.004
Exogenous Network Effects						
Teammate Recommendation	0.001	0.001	0.001	0.000	0.000	0.000
Hypothesized Variables						
Exogenous Network Effects						
Communication: H1a	0.198	0.211	0.183			
Leadership: H1b				0.089	0.085	0.078
Invitation Sent: H2	0.001	0.001	0.001	0.013	0.012	0.011
Degree of Certainty	0.210	0.200	0.210	0.246	0.263	0.258

Table 18: Relative importance of SIENA Parameters in Model 2 for Sample 2.

	Relative Importance					
	Leadership Network			Communication Network		
Parameter	**T1**	**T2**	**T3**	**T1**	**T2**	**T3**
Intercept						
Report of a relationship (Outdegree)	0.290	0.291	0.295	0.250	0.260	0.256
<u>Control Variables</u>						
Endogenous Network Effects						
Reciprocity	0.014	0.014	0.016	0.057	0.057	0.056
Transitive Triplets	0.026	0.021	0.027	0.073	0.070	0.090
Popularity (Indegree)	0.196	0.189	0.194	0.086	0.089	0.096
Activity (Outdegree)	0.081	0.078	0.089	0.087	0.082	0.092
Individual Attributes						
Leadership Experience (alter)	0.004	0.004	0.004	0.004	0.004	0.004
Leadership Experience (ego)	0.013	0.013	0.013	0.002	0.002	0.002
Competence (alter)	0.007	0.007	0.007	0.006	0.006	0.005
Competence (ego)	0.004	0.004	0.004	0.007	0.006	0.006
Intellect or Imagination (alter)	0.002	0.002	0.002	0.007	0.007	0.006
Intellect or Imagination (ego)	0.014	0.014	0.014	0.006	0.006	0.006
Conscientiousness (alter)	0.019	0.020	0.018	0.000	0.000	0.000
Conscientiousness (ego)	0.016	0.016	0.016	0.012	0.012	0.012
Surgency or Extraversion (alter)	0.009	0.009	0.009	0.005	0.005	0.005
Surgency or Extraversion (ego)	0.012	0.012	0.012	0.010	0.010	0.010
Agreeableness (alter)	0.017	0.017	0.017	0.015	0.015	0.015
Agreeableness (ego)	0.020	0.019	0.020	0.004	0.004	0.004
Negative Emotional Stability (alter)	0.011	0.011	0.010	0.006	0.006	0.005
Negative Emotional Stability (ego)	0.003	0.003	0.003	0.003	0.003	0.003
Gender (alter)	0.004	0.005	0.004	0.016	0.015	0.014
Gender (ego)	0.004	0.004	0.004	0.009	0.009	0.008
University Affiliation (alter)	0.017	0.018	0.017	0.012	0.012	0.011
University Affiliation (ego)	0.005	0.005	0.005	0.034	0.033	0.032
Shared Dyadic Attributes						
Gender Homophily	0.006	0.006	0.006	0.006	0.006	0.005
Same University Affiliation	0.035	0.037	0.034	0.196	0.197	0.177
Exogenous Network Effect						
Teammate Recommendation	0.003	0.004	0.003	0.001	0.001	0.001
Prior Collaboration	0.011	0.012	0.011	0.020	0.019	0.015
Enjoyable Working Relationship	0.012	0.013	0.012	0.002	0.002	0.002

Hypothesized Variables						
Exogenous Network Effects						
Communication: H1a	0.145	0.152	0.134			
Leadership: H1b				0.062	0.061	0.059
Invitation Sent: H2	0.002	0.002	0.002	0.004	0.004	0.004
Degree of Certainty	0.230	0.212	0.232	0.290	0.288	0.297

Table 19: Relative importance of SIENA Parameters in Model 3 for Sample 2.

	Relative Importance					
	Leadership Network			Communication Network		
Parameter	**T1**	**T2**	**T3**	**T1**	**T2**	**T3**
Intercept						
Report of a relationship (Outdegree)	0.283	0.283	0.287	0.245	0.255	0.252
Control Variables						
Endogenous Network Effects						
Reciprocity	0.013	0.013	0.014	0.055	0.056	0.054
Transitive Triplets	0.024	0.019	0.025	0.072	0.069	0.089
Popularity (Indegree)	0.187	0.181	0.185	0.084	0.086	0.094
Activity (Outdegree)	0.079	0.076	0.087	0.084	0.080	0.089
Individual Attributes						
Invites sent (alter)	0.002	0.002	0.002	0.003	0.003	0.003
Invites sent (ego)	0.003	0.003	0.003	0.002	0.002	0.002
Invites received (alter)	0.009	0.009	0.008	0.007	0.007	0.006
Invites received (ego)	0.002	0.002	0.002	0.003	0.003	0.003
Number of searches (alter)	0.008	0.009	0.008	0.003	0.003	0.003
Number of searches (ego)	0.002	0.002	0.002	0.002	0.002	0.002
Leadership Experience (alter)	0.005	0.005	0.005	0.003	0.003	0.003
Leadership Experience (ego)	0.013	0.013	0.013	0.002	0.002	0.002
Competence (alter)	0.009	0.010	0.009	0.006	0.005	0.005
Competence (ego)	0.002	0.002	0.002	0.007	0.007	0.007
Intellect or Imagination (alter)	0.001	0.001	0.001	0.007	0.007	0.006
Intellect or Imagination (ego)	0.013	0.013	0.013	0.006	0.006	0.006
Conscientiousness (alter)	0.019	0.019	0.018	0.001	0.001	0.001
Conscientiousness (ego)	0.015	0.015	0.015	0.012	0.012	0.012
Surgency or Extraversion (alter)	0.007	0.007	0.006	0.004	0.004	0.004
Surgency or Extraversion (ego)	0.013	0.013	0.013	0.010	0.010	0.010
Agreeableness (alter)	0.017	0.017	0.016	0.015	0.014	0.014
Agreeableness (ego)	0.020	0.019	0.019	0.004	0.004	0.004
Negative Emotional Stability (alter)	0.012	0.012	0.011	0.005	0.005	0.005

Negative Emotional Stability (ego)	0.003	0.003	0.003	0.004	0.003	0.003
Gender (alter)	0.004	0.004	0.004	0.016	0.016	0.015
Gender (ego)	0.003	0.003	0.003	0.009	0.009	0.009
University Affiliation (alter)	0.020	0.021	0.020	0.012	0.012	0.012
University Affiliation (ego)	0.005	0.005	0.005	0.033	0.032	0.032
Shared Dyadic Attributes						
Gender Homophily	0.007	0.007	0.007	0.006	0.006	0.005
Same University Affiliation	0.034	0.036	0.034	0.193	0.194	0.174
Exogenous Network Effects						
Teammate Recommendation	0.003	0.003	0.003	0.000	0.000	0.000
Prior Collaboration	0.011	0.012	0.011	0.020	0.019	0.015
Enjoyable Working Relationship	0.012	0.013	0.012	0.002	0.002	0.002
<u>Hypothesized Variables</u>						
Exogenous Network Effects						
Communication: H1a	0.143	0.148	0.131			
Leadership: H1b				0.061	0.059	0.057
Invitation Sent: H2	0.003	0.003	0.003	0.003	0.003	0.002
Degree of Certainty	0.232	0.213	0.233	0.290	0.289	0.298

Discussion

The results from this study provide insights into the coevolution of leadership and communication networks by including considerations for networks in which team members interact before collaborating. Technology has now created spaces for individuals to integrate personal information, form impressions about potential teammates, and communicate when forming teams (J. Cummings & Dennis, 2018; Gómez-Zará et al., 2019; Jahanbakhsh et al., 2017). These interactions offer opportunities for teammates to establish relationships before collaborating. In the current study, leadership and communication relationships in teams are investigated dynamically as coevolving networks.

From the results, the invitations that were exchanged online when self-assembling teams showed effects on both relations. When only accounting for behaviors in technology, the invitation network positively contributed to communication within teams. However, the effect was diminished when controlling for social relationships before collaborating and individual attributes, such as university affiliation and gender. The results also showed that invitations negatively impacted leadership in a team. While inviters are not necessarily team leaders, they exercise agency during team self-assembly and do not rely on invited teammates for leadership. From the main results, it is important to note that endogenous network effects are more important than other types of effects in explaining the coevolution of leadership and communication.

The main theoretical contribution of the study lies in establishing limits for the explanatory role of technology-based interactions during team self-assembly. The digital trace data provides nuance in understanding how teams self-assemble with respect to who were invited amongst teammates, recommendations individuals viewed, and the level of activity of individuals in the technology. However, the most important factors for explaining coevolution of within-team relationships were the relationships themselves and the endogenous network effects that describe the emergent network tie patterns. Communication and leadership both influence one another, and the invitation network generated during team self-assembly also contributes, but it appears that relationships within a team are more important factors (according to the SIENA relative importance measure) in understanding collaboration.

The practical implications from the current research are centered around categorizing and understanding the types of interactions in technology that contribute to relationships in teams. In most technology platforms, there are multiple kinds of interactions that individuals enact, such as viewing recommendations and exchanging messages. Some types of interactions may be more informative than others with respect to describing subsequent collaboration practices. From the current study, interpersonal interactions have more influence than simply acquiring information about potential teammates. Leveraging such differences will help better bridge team self-assembly to team collaboration.

Future Directions

The current study lends itself to future research that will extend the key findings. Future research could incorporate analysis of digital trace data to capture within-team communication with higher granularity over the course of a collaboration. The data used in the current study is helpful for understanding who communicated with each other in a team but accessing the conversations that happen within a team will greatly complement the collected networks. Investigating the topics and information that individuals communicated with one another helps build insight into the work tasks being conducted and will provide a better measure of communication frequency and activity. Essentially, continuously capture communication interactions and message content expands the types of research questions to be explored in the current line of inquiry.

Another core area for extension is an investigation of formal team leadership and informal leadership networks. The teams investigated in this study did not have formally assigned leaders and investigating whether a formal role assignment corresponds with reported patterns of leadership is valuable for better understanding the leadership relationship that was captured in the current study. Leaders were reported at different points of a collaboration, requiring that team members reflect and make judgements about which teammates (if any) they relied on for leadership, but the current study does not clarify whether leaders were openly acknowledged as leaders by other teammates. The reports do not necessarily reflect the tasks that nominated leaders performed to be considered as leaders, which could also be meaningful to consider. Future research has the opportunity to clarify how leadership emerges in teams, the tasks that are associated with leadership, and how emergent leadership compares to formal leadership roles. Lastly, future directions could include a more comprehensive study of the coevolution of team networks. Currently, only reported leadership and communication partners are studied, but there is theoretical interest in investigating how such relationships are impacted by negative team interactions, such as team conflict or social loafing. Including negative interactions or relationships that occur in teams better illuminates how teams collaborate and how negativity coevolves with other team dynamics.

Conclusion

In conclusion, the current study contributes to research on teams by explaining the coevolution of leadership and communication networks while accounting for the effects of digital interaction networks that emerge during the use of an online platform. Results demonstrated that team networks affect one another during coevolution. On the other hand, there are limits on how much digital interaction networks contribute to either relationship within a team. When studying the team network dynamics, data collected during collaboration was more informative than digital trace data. The current findings establish boundaries for the utility of digital trace data from online platforms when investigating team relationships during collaboration. By giving insight into how within-team networks coevolve over the course of collaboration, the current study deepens understanding of team collaboration in the contemporary work environment.

CHAPTER 5. DISCUSSION

This dissertation investigated team self-assembly through two behaviors, teammate search and invitation, and uncovers insights into how team self-assembly emerges as well as its effects on relevant components of collaboration, such as team diversity and relationships among team members. Teams commonly use technology to support collaboration, and technology impacts the ways that individuals select teammates and assemble into teams. In general, technology platforms and software algorithms in professional settings have transformed the ways that individuals engage with their work and socially interact with others (Colbert et al., 2016; Ellison, Gibbs, & Weber, 2015; Kane et al., 2014). In response, individuals commonly engage with technology to acquire knowledge from their environment about collaborators and others who possess relevant expertise and knowledge (J. Cummings & Dennis, 2018; Leonardi, 2015, 2018; Walther, 2015). The infrastructure provided by technology platforms helps facilitate self-assembly because individuals have access to interfaces that provide information and aid communication when individuals look for teammates and initiate collaborations.

Individuals who select their own teammates and assemble teams leverage functionality commonly found in technology platforms in at least two ways. Because exchanging messages and viewing content from others is typically part of engagement in online platforms, the first way that people leverage technology for team assembly stems from technology's role as a space for interpersonal interaction and communication. The ability to maintain a large list of contacts and having a common platform in which to engage with them—through public postings and private messaging—supports socialization, communication, and relationship maintenance (boyd & Ellison, 2007; Burke & Kraut, 2016; Ellison & Boyd, 2013; Leonardi & Vaast, 2017; Walther, 1996). Team assembly benefits from technology that supports such social interactions because communication and people-finding are two mechanisms that contribute to the pursuit of collaborators. When searching for experts in a global organization, a technology platform with information about expertise and organizational hierarchy helps a user identify potential contributors to a project or team (C. Y. Lin et al., 2009; Shami, Ehrlich, Gay, & Hancock, 2009; Shami et al., 2008). Another useful feature of technology is its ability to route requests or questions to relevant people based on an understanding of the broader social network and individual knowledge (and interests) (Horowitz & Kamvar, 2010). However, providing the space for people to communicate during team self-assembly is not the only helpful feature of technology.

The other way individuals use technology when assembling teams is by consuming recommendations of content and people by making use of technology's ability to aggregate, transform, and present complex information (Chen et al., 2009; Guy et al., 2009, 2011; Pizzato et al., 2013, 2010; Resnick & Varian, 1997; Terveen & McDonald, 2005). For example, technology leveraged in this dissertation transformed attributes of potential teammates into recommendation rankings by matching preferences of searchers, which resulted in a population of teammate candidates being ordered based on desirable attributes. With the recommendation rankings, technology supported searchers in making choices regarding whom to invite by representing other individuals and reducing the complexity of information presented to a user.

In addition to providing a space for social interaction and transforming complex information into recommendations, the technology platform also served as a repository of digital trace data describing users' patterns of invitations. Digital trace data are an essential aspect of the research conducted as part of this dissertation because invitations have typically been an unobserved behavior. Studying invitations as a social network is a relatively new endeavor that is afforded because of access to behavioral log data gained from technology, which is "digital exhaust" generated as users interact within a given platform (Contractor, 2013; Eagle, Pentland, & Lazer, 2009; Kane et al., 2014; Lazer et al., 2009). By accessing digital trace data, the investigations of Chapters 3 and 4 address questions of how individuals assemble into teams and the impacts from team self-assembly on team collaboration.

The first study in Chapter 2 notably does not directly address technology as a medium for search when assembling teams nor does it rely on digital trace data. However, the two developed search strategies for assembling teams represent distinctions that are realized when a searcher has access to information that extends an actor's perceptions of a social network and the other actors therein. The differences between the two strategies were pronounced when problems were difficult and complex, and intellectual diversity and interdisciplinarity is often a requirement for such problems, making teams an attractive option (Hargadon & Sutton, 1997; Jacobs & Frickel, 2009; Leahey, 2016). Team diversity along certain dimensions suggests that group members access perspectives and information from different parts of a social network (J. N. Cummings, 2004; Reagans et al., 2004). The predilection of teams assembling for more complex and difficult problems corresponds to observed empirical patterns of the increasing prevalence of scientific teams (Falk-Krzesinski et al., 2010; Guimerà et al., 2005; Wuchty et al., 2007). Assembling a diverse team benefits from employing a search strategy that has the capability of tapping into different parts of a social network and acquiring more information.

Like other research studies focusing on network search, actors had to actively navigate a social network in Chapter 2. When people navigate social networks, they are constrained by their understanding of where knowledge resides in the network as well as by their contacts in the network (Contractor & Monge, 2002). However, the structure of a network may be at least somewhat apparent given organizational hierarchies or commonalities in group memberships and expertise levels (Adamic & Adar, 2005; Kossinets & Watts, 2009). To help individuals navigate and engage in social networks, technology platforms are often used. The presence of technology platforms that increase visibility into interpersonal interactions enable the observation of connections that exist throughout a social network. Enhancing visibility of interaction allows individuals to develop more accurate perceptions of expertise as well as increase shared cognition about the expertise of others in an organization (Leonardi, 2015, 2018). Increasing accuracy and awareness about others is one of the main functions of expertise finding systems (Horowitz & Kamvar, 2010; C. Y. Lin et al., 2009), which help individuals search when they would otherwise be unable to find those who meet their needs. Effectively searching for individuals with whom to collaborate and making the decision regarding whom to invite requires numerous considerations and the studies in the dissertation help to clarify both activities that contribute to team self-assembly.

Implications

The implications from this set of research studies have wide-ranging implications for different fields and practitioners. Because collaboration has been shifting towards a more open model where membership is fluid and boundaries between teams are less distinguished (Edmondson, 2012; O'Leary et al., 2011), questions of team self-assembly are more relevant now than in previous decades. Technology has helped to shepherd a more open environment for collaboration by expanding the coordination capabilities of groups in online communities. For example, open source software development projects and Wikipedia rely heavily on dedicated users who coordinate and collaborate digitally to create complex products and artifacts (Dabbish, Stuart, Tsay, & Herbsleb, 2012; Hahn, Moon, & Zhang, 2008; Kittur, Lee, & Kraut, 2009). Additionally, technology is the infrastructure supporting virtual teams and geographically distributed work groups (Gibson & Gibbs, 2006; Gilson, Maynard, Jones Young, Vartiainen, & Hakonen, 2015; Jarvenpaa & Leidner, 1999). Therefore, the impacts from studying team self-assembly in technology apply to pertinent questions for scholarship relating to online collaboration.

The research developed through this dissertation is also relevant for social networks literature because Chapter 2 is a direct extension of well-developed ideas surrounding network search. Many prior research studies of decentralized network search focus on finding a single target from search (Adamic & Adar, 2005; Dodds et al., 2003; Milgram, 1967; Travers & Milgram, 1969). Therefore, the current research in the dissertation is different from prior research because it focuses on designing decentralized search strategies to find multiple team members that complement one another.

Another implication from Chapter 2 applies to teams and groups research. The relationship between expertise diversity of teams and problem complexity is U-shaped with minimum expertise diversity occurring at levels of moderate problem complexity. The pattern materializes for two reasons; (1) expertise diversity must increase as more expertise areas are required by a problem (complexity increases) and (2) because individuals are capable of solving a sizable proportion of problems at low levels of complexity, teams only assemble for problems of low complexity when there are requirements for highly specialized expertise in different expertise areas of a problem. Stated simply, diverse teams only need to be as diverse as the problem requires, and problems with moderate complexity tend to require the lowest amount of expertise diversity in teams.

Chapters 3 and 4 contribute to the larger body of literature on social networks because they involve the analysis of a rarely studied relationship (invitations) and investigate its impacts on other relationships. An invitation represents the entry phase of collaboration because an invitation is the act of initiating a relationship with a potential teammate. The structure of invitations emerges as individuals reduce uncertainty surrounding their desirable teammates. Exploring the invitation relationship is essential for understanding the creation of relationships among team members and the uncertainty reduction that occurs during team assembly. Such investigations connect to prior research focusing on uncertainty reduction theory and initial stages of relationships (Berger & Calabrese, 1975; Knobloch, 2015; Solomon, 2015), which have more general implications for understanding human relationships and communication. Also, this research has implications for understanding team member preferences during self-assembly and how such preferences for collaboration lead to inequality among teams with respect to skills relevant for projects (Gómez-Zará et al., 2019).

There are also other implications for teams and groups research because the dissertation contributes to prior research on team formation, focusing on the emergent interactions of team assembly. Much literature has identified antecedents to collaboration and linked them to team processes, dynamics, and outcomes (Bell, 2007; Humphrey & Aime, 2014; Ilgen, Hollenbeck, Johnson, & Jundt, 2005; Kozlowski & Klein, 2000; Mathieu et al., 2017), and the value in this dissertation lies in the investigations into emergent behaviors that are a part of the team self-assembly through social network analysis and agent-based modeling.

There are three main practical implications presented in this dissertation that are valuable for practitioners to consider. The first implication—from Chapter 2—is rooted in balancing the costs and benefits of selecting a search strategy with a broad view of a social network instead of a more localized search strategy. A search strategy with a broad view of the network will use more information and require more effort when searching because there are more options available to review. Therefore, uncovering the circumstances where a local search performs comparably to a broader search strategy helps increase the overall efficiency of search since individuals will not exert more effort than needed when looking for teammates. Findings show that there is no difference between strategies in terms of team expertise diversity, and there is no benefit in using a search strategy with a broad view of the network, except for difficult problems. For less difficult problems, performance between strategies was similar, and problems that required fewer expertise areas (less complexity) had a higher proportion of individual solvers, meaning that teams were not needed to solve such problems. Taken together, findings illustrate the importance of understanding the types of problems to be addressed, which determines whether a team is necessary and whether a more powerful search strategy will yield unique benefits.

From findings in Chapter 3, the next implication exemplifies the need to recognize and manage the tension between individuals and technology. Technology has saturated much of the modern world and offers much value for facilitating social interactions. However, the information provided from technology through recommendations and rankings coexists with individual experiences and perspectives. To make use of external information from technology recommendations, individuals must reflect on personal perspectives to negotiate to what extent they will balance their own beliefs with those offered from technology—and often from an algorithm based on logic that may not be readily apparent. When reviewing information about potential teammates during team assembly, findings show that individuals rely on their prior collaborations with others more than recommendations, which offers insight into the boundaries that people place on the usefulness of recommendations from technology. Acknowledging that people attend to multiple information sources when making decisions about teammates helps to clarify expectations for how humans use technology when assembling teams.

The last implication comes from Chapter 4 and establishes bounds on the explanatory power of team self-assembly interactions on the coevolution of team relationships. The observed network of invitations exchanged in a technology platform positively contributed to the evolution of communication and had a negative effect on leadership. However, recommendations from technology and other user interactions in technology did not contribute to explanations of either team leadership or communication. The limits show that team members will form relationships that evolve over the course of a collaboration regardless of the interactions that lead to the team assembling. Prior relationships have repeatedly been shown to impact subsequent collaboration (including in this dissertation), but technology has a weaker impact overall. While technology is a useful tool for facilitating team self-assembly by providing information about prospective collaborators and space for social interaction, findings suggest that teams will develop social structure and establish norms during the course of collaboration and interactions within technology do not necessarily influence how team dynamics and relationships evolve over time.

Future Directions

Different areas for future research arise directly from the research developed in this dissertation. One area is a line of experimental research to isolate and test mechanisms explaining decision-making during team self-assembly. In the dissertation, search during self-assembly was investigated through agent-based modeling. The model leveraged strategies derived from decentralized network search to illustrate different types of information individuals use when searching for teammates. To extend this research, and increase the broader applicability of the model, I plan on conducting social network experiments to observe how individual decision-making heuristics and behaviors are impacted by social network structure.

Social network experiments afford the ability to observe how an individual's behaviors are impacted by their social connections. An example experiment would place a participant into a social network and give them the task of finding teammates to help them solve a problem by using experimentally-controlled information about their contacts, similar to a vignette study. For each problem, there will be people in the network who are better qualified than others to solve the problem, but the structure of the social network will influence which people are ultimately selected. The design of the social network experiment is similar to research designs that focus on information diffusion and behavioral influences, but is a noteworthy extension on such research because it focuses on how a social network impacts a person's ability to find others to solve a problem, which is a common task in many collaborative settings. Increasing understanding around how network structure influences individual search behaviors will have broader implications for research related to collaboration. Insights potentially can help organizations counteract the issues that arise from fractured or disconnected networks to promote more knowledge sharing across disciplines.

From Chapters 3 and 4, the composition of preferences during search was not directly analyzed; recommendations (an output of search) were investigated since they are a representation of the match between search preferences and attributes available in potential teammates. I currently participate in related research that uncovers insights into commonly-selected search preferences. The findings suggest that individuals have unique preferences for their teammates, but also that such preferences lead to biases in teammate selection, which result in a segregated set of teams that are unbalanced along attributes relevant for collaboration (Gómez-Zará et al., 2019). Future investigations related to such topics include studies exploring whether preferences are flexible and shift as teams assemble, whether technology platforms serve as agents of segregation or help mitigate biased teammate selection, and whether preference statements are indicative of other personality traits.

Relatedly, future research focusing on interaction design for team self-assembly has ripe opportunities for exploration. Recommendations and invitations are key interactions under investigation, but there are other technology interactions that are worth exploring. For example, discussion forums and wall postings are publicly visible areas of interactions where individuals engage with others. What is the value of these interactions for explaining team self-assembly? It is possible that the value of using technology for team assembly is promoting a greater awareness of the pool of potential teammates in addition to serving as a space where people interact to assemble teams. Another area for exploration is the use of technology to assess the quality of a collection of teammates before finalizing a team. A platform that provides recommendations also has the ability to provide a team-level score for the overall match amongst team members. Investigating whether team performance has a relationship to such a score helps team self-assembly better explain questions related to team performance.

Conclusion

The research in this dissertation spans across different behaviors and uncovers relational mechanisms that contribute to team self-assembly. By investigating network search as an approach for finding teammates, the findings illustrate new explanations of how team diversity arises during the course of team assembly and how different conditions contribute to expertise diversity. From the investigation of invitation networks, the tension that individuals negotiate when integrating information from technology is highlighted while exhibiting the boundaries that exist in the explanatory power of recommendations from technology. Technology as a tool for facilitating team self-assembly has the ability to provide information and space for interaction, but it does not necessarily overwhelm the agency of those who are making choices about teammates. The effects of actions taken during team self-assembly are also limited in explaining the coevolution of team relationships. Given that collaboration is more prevalent and open, understanding how individuals select team members and the impacts of such choices on teams has wide-ranging impacts for scholarship and practice.

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APPENDICES

APPENDIX A

This appendix describes the agent-based models used in CHAPTER 2, the study investigating the teammate search practice. There are numerous assumptions and variables that were implemented in the models for teammate search, and more supplementary information is included here to increase the transparency of the models used to generate results. All models and simulations were conducted in the NetLogo software platform (Wilensky, 1999; Wilensky & Shargel, 2002).

Details and Pseudocode for Agent-Based Models

NetLogo Extensions

- nw (https://ccl.northwestern.edu/netlogo/docs/nw.html): A set of NetLogo functions for managing network data and performing a series of network analysis calculations.
- table (https://ccl.northwestern.edu/netlogo/docs/table.html) A set of NetLogo functions for managing data represented in a tabular manner.

Variables

The variables needed to conduct the simulations are included inTable 20.

Table 20: Table of Agent-Based Modeling Parameters.

Type	Variable Name	Descriptive Name	Purpose
Variable Parameters (also in Table 1)	num-expertise	Problem Complexity (m)	The number of expertise areas required by a problem.
	num-people	Number of Agents (n)	The number of agents.
	connect-rate	Preference for Homophily (h)	Contact selection based on similarity. The parameter ranges from connecting with people randomly with no preference for homophily (h = 0) to connecting with people based on increasingly strong preferences for homophily, based on

			expertise profiles (h = 4).
	num-contact	Maximum Outgoing Contacts	Fixes the initial maximum network density.
	num-queries	Number of Problems	Number of problems each network will assemble teams to solve.
Global	ratio	Ratio of Actors to Expertise Areas	The ratio of actors to the amount of expertise. Represents the overall diversity in network
	max-diff	Maximum difference	Maximum for the expertise difference between actors
	current-query	Current Problem Identification Number	The ID for the active problem
	union-contacts	Search Group Contacts	The union of contacts in group of searchers
	unfilled-areas	Unfulfilled Expertise Areas of Problem	The gaps in the search group's expertise for the current problem
	first-step	Contacts within a radius of 1	A list of direct contacts for a search group
	second-step	Contacts within a radius of 2	A list of contacts of direct contacts for a search group
	init-holder	First Searcher	First holder of current query
Actor	expertise	Actor Expertise	The expertise vector of m length
	expertise-diff	List of Expertise Differences	The list of similarity groupings that exist between agents.
	link-probabilities	Probability of Creating a Tie	A list of probabilities of creating a tie to every other actor
	prob-distribution	Probability Distribution of Linking to Each Actor	A distribution where all agents occupy some percentage of connecting

Problem	required-expertise	Problem Requirements	This is the expertise requirement of a problem to be solved
	holders	Search Group	The current search group
	complete?	Success Flag	Whether it succeeded or failed
	team	The Problem-solving Team	The final set of problem holders who are capable of solving the problem.
	num-hops	Network Distance	The number of steps needed to find solvers for the problem

Pseudocode

The functions necessary for performing the simulations are provided below and organized as follows. There are two main procedures: setup and go. Within each of these main procedures are sub-procedures that contain the logic necessary for searching a network to assemble teams. The pseudocode is modified from the original NetLogo programming language to enhance readability. Functions that perform actions are bolded. Brief descriptions for each line of code are given in most cases. Pseudocode is typeset in `Consolas`, and explanations are in Times New Roman.

1. Helper Functions: There are two functions that are implemented to help perform tasks that are needed to build the model. One function "under-required-positions" finds the positions of all minimum values in a list. It was retrieved from a NetLogo discussion forum (http://netlogo-users.18673.x6.nabble.com/Positions-of-all-the-min-values-in-a-list-td4866767.html). The second function is "random-normal-in-bounds," which generates a truncated normal distribution by resampling (http://stackoverflow.com/questions/20230685/netlogo-how-to-make-sure-a-variable-stays-in-a-defined-range).

```
to-report under-required-positions [my-list]
     report THE POSITIONS OF NEGATIVE VALUES IN A LIST
end

to-report random-normal-in-bounds [mid dev mmin mmax]: mid is the
middle value of distribution, dev is the standard deviation, mmin is the minimum allowed
value, and mmax is the maximum allowed value.
     let result random-normal mid dev
     if (result < mmin) or (result > mmax):
          report random-normal-in-bounds mid dev mmin mmax:
          resample if outside of bounds
     report result: return value
end
```

2. Setup: The setup procedure is necessary at the start of any simulation run. This is where data is cleared from memory and a new set of actors and problems are generated. Also, a social network is created during this procedure.

```
to setup
   clear-all: Clear data from simulation run
   random-seed behaviorspace-run-number: Make the run reproducible
   nw:set-context people links: Identify the nodes and links of network
   create-people num-people
         set expertise with num-expertise and fill with random expertise
         values
   assess-network: Determines the similarity between agents and link probabilities
   reset-ticks: Reset the simulation clock
end
```

A. assess-network: Determines the similarity between actors and sets the encompassing group sizes

```
to assess-network
      calculate-similarity: The similarity between actors
      calculate-groups: The group sizes that encapsulate actors, based on similarity
end
```

B. calculate-similarity: Calculates the absolute value of the expertise difference that exists among each pair of actors, and each actor creates a list of other actors with their expertise difference as well.

```
to calculate-similarity
      set max-diff 0: Maximum difference that exists between any two actors
      ask people
            set expertise-diff to EMPTY LIST
            foreach ID of other people: [expert] ->
                  set expertise-diff by appending the ID of expert
                  along with the total expertise difference between
                  expert and the “person” following routine. Each
                  person keeps their own similarity records
                  set max-diff to maximum difference between myself and
                  any other actor
```

```
end
```

C. calculate-groups: Calculates the group memberships that actors will have based on similarity as well as the probabilities of actors connecting to other actors.

```
to calculate-groups
     nw:set-context people links: Defines the network
     set ratio (num-people / max-diff): Normalizing factor for the
     probabilities of connecting
     ask people
          let link-memberships EMPTY LIST
          let memberships EMPTY LIST
          set link-probabilities MAKE EMPTY TABLE
          foreach expertise-diff: [expert] ->
               set link-memberships APPEND THE FOLLOWING TO
                    LIST; The person ID and normalized group
                    size (see Equation 1)
               set memberships APPEND THE FOLLOWING TO LIST; The
                    person ID, normalized group size, group
                    size raised to the power of h (see Equation 2)
          foreach memberships: [mem] ->
               table:put link-probabilities MAKE A TABLE ENTRY
                    WITH PERSON ID, AND THE PROBABILITY OF
                    CONNECTING (see Equation 3)
```

D. create-network: Contact selection where each person will draw another person at random until they have attempted to make the maximum number of contacts

```
to create-network
  ask people:
     repeat num-contact:
          choose-contacts
end
```

E. choose-contacts: A probability distribution for each agent is generated from which people are selected. Each actor has their own distribution that describes the probability of connecting with anyone else.

```
to choose-contacts
```

let prob random-float 1.0: Random number that will correspond to a value in the probability distribution assigned to a person.
let section 0
set prob-distribution MAKE EMPTY TABLE
foreach table:to-list link-probabilities: [tabs] ->
    set section (section + last tabs)
    table:put prob-distribution first tabs section
let index MATCH THE ID OF THE AGENT THAT HAS A PROBABILITY AT THE POSITION OF prob
if not out-link-neighbor? THEN CREATE A LINK TO THE PERSON THAT WAS IDENTIFIED
end

3. go: The Go procedure controls the entire logic of the simulation run.

to go
  if [complete?] of query current-query != 0 and count queries < num-queries
    generate-query: Create new problems until the maximum number of problems have been created
  if count queries with [complete? != 0] = num-queries
    stop: All problems have been completed
  find-best-team: This is the ability to search for and assess team expertise
  tick: advance to next time step
end

A. generate-query: Creates each problem by setting expertise requirements and randomly assigning it to an initial problem holder.

to generate-query
  create-queries 1:
    set current-query ID: Sets the global variable to the ID of the new problem to make inspection more straightforward
    set team turtle-set nobody: No one is on a team at initialization
    set required-expertise EMPTY LIST
    set required-expertise n-values num-expertise [i] -> SETTING EACH VALUE TO A RANDOM NUMBER DRAWN FROM A TRUNCATED NORMAL DISTRIBUTION WHERE THE MAX IS THE MAXIMUM EXPERTISE LEVEL THAT SOMEONE POSESSES IN THE NETWORK
    set holders turtle-set one-of people: Randomly select a person to be the first holder
    set complete? 0: Flag for search completing

```
        set init-holder holders: Set the global variable
        set total-holders init-holder: Everyone who ever
        receives the problem
end
```

B. find-best-team: A procedure to determine whether the current set of problem holders will make a team for the problem.

```
to find-best-team
    assess-group: calculate the qualifications and decide if new people are needed
    collaborate: Interact with other group members to decide on next problem
holders
end
```

C. assess-group: Determine the expertise of the current set of holders, then find any areas that have unfulfilled expertise.

```
to assess-group
    let top EMPTY LIST
    let scores EMPTY LIST
    foreach EXPERTISE AREA OF THE CURRENT PROBLEM: [i] ->
        set top APPEND THE PERSON WITH MAXIMUM VALUE IN THE
        AREA
        set scores APPEND THE MAXIMUM EXPERTISE VALUE IN THE
        AREA
    set unfilled-areas under-required-positions APPEND TO A
    LIST, THE AREAS THAT DO NOT MEET THE EXPERTISE REQUIREMENT
end
```

D. collaborate: When there are no unfilled parts of the problems, complete it, and stop searching. If the problem needs to continue, aggregate the group's contacts and then find to the qualified ones if they exist.

```
to collaborate
    if empty? unfilled-areas
        complete-query
        stop
    else:
```

```
            collect-contacts
            route-query
end
```

E. collect-contacts: Aggregate the contacts of the group members

```
to collect-contacts
     if "Local Search"
          set union-contacts (turtle-set DIRECT CONTACTS THAT
          ARE OUTSIDE OF THE GROUP)
     if "Broker Search"
          set first-step (turtle-set DIRECT CONTACTS THAT ARE
          OUTSIDE OF THE GROUP)
          set second-step (turtle-set DIRECT CONTACTS OF FIRST
          STEP)
          set union-contacts (turtle-set first-step second-step)
end
```

F. "Local Search" route-query: Determine whether there are contacts that are more qualified than the current set of holders and make decisions to pass or fail the problem.

```
to route-query
     let next-group turtle-set nobody
     let new-team turtle-set nobody
     let finalist turtle-set nobody
     if any? union-contacts
          foreach EXPERTISE AREA OF THE PROBLEM [i] ->
               if member? i unfilled-areas
                    set finalist IDENTIFY THE MOST QUALIFIED
                    CONTACT IN THE AREA
                    if (EXPERTISE OF finalist IS GREATER THAN
                    THE MAXIMUM EXPERTISE OF GROUP IN THE AREA)
                         set next-group (turtle-set next-group
                         finalist)
                    else:
                         set next-group (turtle-set next-group
                         PERSON WITH MAXIMUM EXPERTISE IN THE
                         AREA ALREADY IN GROUP)
```

```
                    set new-team (turtle-set new-team MEMBERS
                    OF next-group and holders WITH MAXIMUM
                    EXPERTISE IN THE AREA)
               else:
                    set new-team (turtle-set new-team PERSON
                    WITH MAXIMUM EXPERTISE IN THE AREA ALREADY
                    IN GROUP)

     else:
          fail-query: Fail if there are no people
     if ([holders] of query current-query = new-team) and (not
     empty? unfilled-areas)
          fail-query:  The problem is failed if there is no better qualified team
          and there are still unfilled requirements
     else:
          pass-query new-team: If there is a new team, and there are unfilled
          requirements, then pass the problem to the new team.
end
```

G. "Broker Search" route-query: Determine whether there are contacts that are more qualified than the current set of holders and make decisions to pass or fail the problem. There are two-steps of contacts considered.

```
to route-query
     let next-group turtle-set nobody
     let new-team turtle-set nobody
     let finalist turtle-set nobody
     let first-final turtle-set nobody
     let second-final turtle-set nobody
     if any? union-contacts
          foreach EXPERTISE AREA OF THE PROBLEM [i] ->
               if member? i unfilled-areas
                    set first-final IDENTIFY THE MOST QUALIFIED
                    first-step CONTACT IN THE AREA
                    if (EXPERTISE OF first-final IS GREATER
                    THAN THE MAXIMUM EXPERTISE OF GROUP IN THE
                    AREA)
                         set finalist first-final
                    else:
                         if any? second-step
```

```
                set second-final IDENTIFY THE
                MOST QUALIFIED second-step
                CONTACT IN THE AREA
                set finalist second-final
            else:
                fail-query
                stop
        if member? finalist first-step
            if (EXPERTISE OF finalist IS GREATER
            THAN THE MAXIMUM EXPERTISE OF GROUP IN
            THE AREA)
                set next-group (turtle-set next-
                group finalist)
            else:
                set next-group (turtle-set next-
                group PERSON WITH MAXIMUM
                EXPERTISE IN THE AREA ALREADY IN
                GROUP)
        else:
            if (EXPERTISE OF finalist IS GREATER
            THAN THE MAXIMUM EXPERTISE OF GROUP IN
            THE AREA): Finalist is now in second-step
                set next-group (turtle-set next-
                group A DIRECT CONTACT OF THE
                finalist in SECOND-STEP THAT HAS
                THE HIGHEST EXPERTISE): Next group
                has a first-step contact that will serve as a
                broker and connect to second-step finalist.
        set new-team (turtle-set new-team next-
        group): Add the finalist to the new team, the finalist is
        either a first-step contact that has more expertise than
        anyone currently in the team, or is a first-step contact that is
        connected to the second-step finalist and will broker the
        connection in the next step of the search.
            else:
                set new-team (turtle-set new-
                team PERSON WITH MAXIMUM
                EXPERTISE IN THE AREA ALREADY IN
                GROUP)
else:
    fail-query: Fail if there are no people
if ([holders] of query current-query = new-team) and (not
empty? unfilled-areas)
```

```
fail-query: The problem is failed if there is no better qualified team
            and there are still unfilled requirements
    else:
            pass-query new-team: If there is a new team, and there are unfilled
            requirements, then pass the problem to the new team.
end
```

H. pass-query: Determine the next group of problem holders and then assign them to the appropriate problem variable.

```
to pass-query [group]
    ask query current-query
        set total-holders (turtle-set total-holders holders) :
        Add the current group of problem holders to a set of all people who have
        held the problem.
        set num-hops num-hops + 1: Count the number of steps
        set holders group: Set the holders variable to the new group of
        holders
end
```

I. complete-query: When expertise requirements are met, a member of a team is assigned to address each expertise area. The problem is completed.

```
to complete-query
    ask query current-query
        if count holders > 1:
        foreach AREA OF EXPERTISE OF PROBLEM [i] ->
            set team (turtle-set min-one-of holders with
            EXPERTISE GREATER THAN OR EQUAL TO THE EXPERTISE
            REQUIRMENT)
        else:
            set team holders
        set complete? true
        set total-holders (turtle-set total-holders team)
end
```

J. fail-query: Sets the complete status to failure, and then does not return a team

```
to fail-query
  ask query current-query
    set complete? false
```

```
      set team turtle-set nobody
      set holders init-holder
  stop
end
```