Small Group Research
1–54

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DOI: 10.1177/1046496417724209
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Self-Organizing Into Winning Teams: Understanding the Mechanisms That Drive Successful Collaborations

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Abstract

Contemporary teams are self-assembling with increasing frequency, meaning the component members are choosing to join forces with some degree of agency rather than being assigned to work with one another. However, the majority of the teams literature up until this point has focused on randomly assigned or staffed teams. Thus, the purpose of the current study was to investigate how people *do* form into teams and how people *should* form into teams. Specifically, we utilized a sample of digital traces from a massively multiplayer online role-playing game (N = 1,568) to evaluate the bases for and performance implications of team self-assembly. The results indicated that self-assembled teams form via three mechanisms: homophily, familiarity, and proximity. Moreover, results of the trace data analyses indicated that successful and unsuccessful teams were homogeneous in terms of different characteristics, and successful teams formed based on friendship more often than unsuccessful teams did.

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Keywords
team self-assembly, social networks, group formation/dissolution, work groups

Increasingly, the basic unit of accomplishment in the contemporary workplace is the team rather than the individual (De Dreu & Van Vianen, 2001). This shift is the consequence of a confluence of factors, such as the substitution of technological advancements for low-skilled labor in many employment areas (e.g., Autor & Dorn, 2013), as well as the increasingly complex problems that demand collaborative solutions. In turn, this rise of team-based, cognitively demanding work in flat organizations has had implications for management practices. Traditional approaches to management, which were historically implemented successfully in vertical organizations, are now starting to cause motivational dysfunction (Pearce, 2004; Pink, 2011). One popular solution to this problem is the self-directed work group; by promoting team autonomy, employers consequently enrich jobs and empower team members (Kauffeld, 2006; Kirkman & Rosen, 2001).

Moreover, the rapid telecommunications advances that have been achieved over approximately the past 50 years—such as personal computers, the Internet, and the World Wide Web (WWW)—have made it possible for individuals to communicate at the click of a mouse, regardless of historically daunting constraints such as geographic dispersion. For example, cross-university collaborations between researchers have been sharply rising since the mid-1970s (Jones, Wuchty, & Uzzi, 2008), a phenomenon largely attributed to the proverbial *death of distance* caused by the communications revolution (Cairncross, 2001). The two aforementioned workplace trends—the rise of teams and the increase in employee autonomy—have not gone unaffected by the global technological revolution. Specifically, the intersecting phenomena of pervasive teamwork, high demand for on-the-job autonomy, and ubiquitous computing have led to the proliferation of *self-assembled teams*, or teams where members have the agency to choose their own teammates (Contractor, 2013; Edmonson, 2012).

Traditionally, the focal assembly–related issue with regard to manager-led teams has been one of staffing, or developing systematic approaches for configuring teams with optimal compositions for performance (Zaccaro & DiRosa, 2012). By analyzing how composing teams based on individual differences such as knowledge, skills, and abilities explains subsequent variance in team performance, managers can create more effective groups of workers. However—although considering the composition of all types of teams is admittedly important—there is an added dimension of complexity when considering team self-assembly. Namely, unlike staffed teammates, who were brought together based on the decisions of a manager, self-assembled teammates were attracted to one another for interpersonal reasons. Thus, an important open question about self-assembling teams is the matter of how interpersonal attraction mechanisms influence individuals to form into group—How and why do individuals self-assemble into teams?

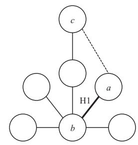
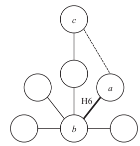
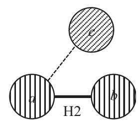
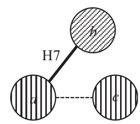
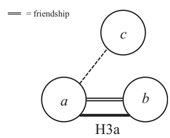
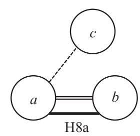
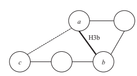
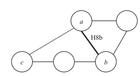
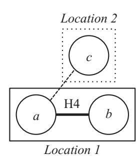
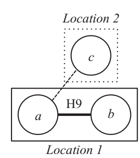
Previous research on attraction has indicated that individuals are drawn to and repelled from one another based on a wide variety of factors. However, this research has primarily studied interpersonal attraction outside of the context of teamwork. How might attraction function to coalesce teammates differently than friends or romantic partners? There are a number of ways that individuals might make sound decisions when choosing potential teammates. For instance, individuals may choose teammates who possess task-relevant characteristics such as intelligence or motivation to work for the team. However, recent evidence has suggested the existence of the team assembly bias, or a discrepancy between the criteria people *think* they use to choose their teammates and the criteria they *actually* use (Wax, Dalrymple, DeChurch, Walker, & Contractor, 2014). Thus, it is also possible that individuals commit the same errors of attraction when deciding on teammates as they do when choosing friends and romantic partners.

Attraction mistakes have different implications for self-assembled teams than they do for friends and partners in romance; namely, teammates have shared goals and a wide variety of performance-relevant outcomes that may be affected by suboptimal self-assembly. Accordingly, another unsolved issue is whether there are different performance implications of team self-assembly mechanisms; how do different mechanisms of interpersonal attraction between teammates translate into different combinations of member capabilities, emergent states, processes, and ultimately performance? The literature on team composition suggests that high-performing teams will tend to form using different attraction mechanisms than low-performing teams. For example, heterogeneous teams have been shown to be best homogeneous team on performance outcomes such as decision making (e.g., Mello & Ruckes, 2006). However, the team composition literature is largely based on samples of teams where the component members did not choose to work with one another (e.g., they were randomly assigned to a group or staffed to a team). Thus, the purpose of this study is to develop and test a theoretical model that explains how people *do* form into teams and how people *should* form into teams.

Interpersonal Attraction

Interpersonal attraction is classified as attitudinal positivity toward another person (Huston & Levinger, 1978) and is related to this basic need to belong. The attraction literature has explored a variety of ways that people are drawn

Table 1. Interpersonal Attraction Mechanism Taxonomy.

<table>
<tr><th></th><th></th><th></th><th colspan="2">Illustrative Examples of Interpersonal Attraction Mechanisms</th></tr>
<tr><th>Classification</th><th>Conceptual Variable</th><th>Operational Definition</th><th>All Teams</th><th>High-Performing Teams Only</th></tr>
<tr><td>Absolute</td><td>Popularity</td><td>Preferential Attachment</td><td>
</td><td>
</td></tr>
<tr><td>Relative</td><td>Homophily/ Heterophily</td><td>Homogeneity/ Heterogeneity⁺</td><td>
</td><td>
</td></tr>
<tr><td>Relational</td><td>Familiarity</td><td>Friendship</td><td>
</td><td>
</td></tr>
<tr><td></td><td>Balance</td><td>Closure</td><td>
</td><td>
</td></tr>
<tr><td>Situational</td><td>Proximity</td><td>Geographic Proximity</td><td>
</td><td>
</td></tr>
</table>

Note. In all illustrative examples, the team membership relationship between *a* and *b* (indicated by a thick line) is hypothesized to be highly likely based on the corresponding attraction mechanism, while the relationship between *a* and *c* (indicated by a dashed line) is hypothesized to be unlikely.
⁺Variables tested = player level, guild role, and completed quests.

to one another, and for the purposes of this research we have taxonomized these various attraction mechanisms into four categories: (a) attraction based on absolute attributes, (b) attraction based on relative attributes, (c) relational attraction, and (d) situational attraction. Table 1 displays illustrative examples of these four categories.

Attraction Based on Absolute Attributes

Certain characteristics are inherently attractive; individuals who possess these characteristics are perceived as being more attractive than others.

Status—or the relative standing of one individual to another—is one factor upon which individuals vary that has a critical impact on attractiveness, both in the real world and online (Lo, 2008). From a network perspective, high social status individuals can be distinguished from low social status individuals because the former group has more relational ties than the latter and is thus more popular. In social network theory, the phenomenon whereby individuals tend to associate themselves with the most popular individuals in the social network is termed *preferential attachment* (Barabási & Albert, 1999; Hai-Bo, Jin-Li, & Jun, 2012; Johnson & Faraj, 2005). Theoretically, preferential attachment occurs because popularity is an attractive quality (Papadopoulos, Kitsak, Serrano, Boguñá, & Krioukov, 2012); Individuals prefer others with many rather than few social connections. Preferential attachment has been observed in authorship networks (Acedo, Barroso, Casanueva, & Galán, 2006; Milojević, 2010), on discussion forums on the web (Johnson & Faraj, 2005), in trade networks (Maoz, 2012), and on Flickr (Mislove, Koppula, Gummadi, Druschel, & Bhattacharjee, 2008).

In teams. The sparse body of literature on the relationship between individual popularity/status/reputation and subsequent team self-assembly has rendered mixed results: Some studies have concluded a positive relationship (Lungeanu, Huang, & Contractor, 2014; Ruef, Aldrich, & Carter, 2003), while the results of other research were mixed (Hahn, Moon, & Zhang, 2008; Hinds, Carley, Krackhardt, & Wholey, 2000), and others still uncovered a negative relationship (Huang, Shen, & Contractor, 2013; Huang, Shen, Williams, & Contractor, 2009; Putzke, Fischbach, Schoder, & Gloor, 2010). Thus, based on aforementioned theory of interpersonal attraction based on preferential attachment, individuals with many teammate relationships will likely be perceived as more attractive teammates than individuals with fewer teammate relationships, and thus will be the preferred choices as teammates. Consequently, it is posited as follows:

> **Hypothesis 1:** Attractiveness as a teammate will be proportional to popularity as a teammate; a small number of individuals will have a disproportionately high number of teaming relationships.

Attraction Based on Relative Attributes

For most individual differences, attraction is not a matter of absolutes. Rather, individuals are attracted to one another based on their relative standing on certain characteristics. People prefer others that they perceive as similar to themselves to those that they perceive as different from themselves. This effect has been documented in a broad array of literatures and occurs in a variety of cultural contexts, including relatively homogeneous and relatively heterogeneous cultures (Schug, Yuki, Horikawa, & Takemura, 2009). Some research has even provided evidence of the direction of causality; strangers with similar demographic profiles come to like one another more than strangers with dissimilar demographic profiles (Newcomb, 1961). In sociology, scholars refer to this tendency of individuals to associate with similar others as the theory of homophily (Lazarsfeld & Merton, 1954). Specifically, "[h]omophily is the principle that a contact between similar people occurs at a higher rate than among dissimilar people" (McPherson, Smith-Lovin, & Cook, 2001, pp. 415-416). In the psychological literature, this effect is referred to as the similarity-attraction paradigm (Byrne, 1971; Byrne & Nelson, 1965).

In teams. Relative attributes as a basis for attraction have also been studied in the context of teams, but this area of the literature is still in its infancy. However, the predominant implication of the existing literature is that self-assembled teams do exhibit a homophily effect. In the context of team self-assembly, the similarity-attraction effect has been observed for a number of characteristics, including attributes at the surface level such as gender, age, and race (Hinds et al., 2000; Huang, Shen, & Contractor, 2013; Huang et al., 2009; Zhu, Huang, & Contractor, 2013), as well as those at the deep level such as experience, skill, performance, and organizational affiliation (Huang, Shen, & Contractor, 2013; Huang et al., 2009; Ruef et al., 2003; Zhu et al., 2013). Contrastingly, diversity effects have only been sporadically captured (e.g., gender diversity, Huang et al., 2009; functional diversity, Zhu et al., 2013). Therefore, based on these preliminary findings, which largely support the homophily effect in teams, in addition to prior attraction theory and research we posit the following:

> **Hypothesis 2:** Self-assembled teams will be more homophilous than would be expected by chance.

Relational Attraction

Beyond experiencing interpersonal attraction based on absolute or relative individual differences, people also are drawn to one another for relational reasons. As exemplified in Table 1, certain social configurations breed interpersonal attraction, while others maximize disdain. At a fundamental level, people's attitudes toward a stimulus tend to become more positive simply by repeatedly experiencing said stimulus; scholars have dubbed this phenomenon the mere exposure effect (Zajonc, 1968, 2001). Research has indicated that the mere exposure effect holds true for social relations, as familiarity has been shown to promote interpersonal attraction. Specifically, frequency of interaction promotes liking for virtual (Reis, Maniaci, Caprariello, Eastwick, & Finkel, 2011) as well as face-to-face interaction (Ebbesen, Kyos, & Konečni, 1976; Moreland & Beach, 1992). Furthermore, balance theory (Heider, 1958) posits that people are attracted to others whose relationships mirror their own. Specifically, because individuals are also motivated to achieve cognitive consistency in triadic relationships (Holland & Leinhardt, 1976), liking is transitive in nature; in other words, two friends of an individual are also highly likely to be friends with one another (Krackhardt & Kilduff, 1999).

In teams. Although relational attraction in teams is a burgeoning research area, there is still much work to be done on the topic. Previous research on team self-assembly has indicated that individuals prefer to work with teammates with which they are familiar (Guimerá, Uzzi, Spiro, & Amaral, 2005; Hinds et al., 2000; Lungeanu et al., 2014). Specifically, individuals tend to exhibit a preference for friends when choosing teammates (Owens, Mannix, & Neale, 1998). Furthermore, one study found that the primary attraction mechanism driving the formation of teams of open source software developers was previous collaboration ties (Hahn et al., 2008). Consequently, it is hypothesized as follows:

> **Hypothesis 3a:** Self-assembled teams will have higher levels of familiarity than would be expected by chance.

Balance—or the tendency of people to strive for relational equilibrium—has also been proposed as a mechanism that shapes team self-assembly (Contractor, 2013). Theoretically, balance occurs in team assembly when two individuals team up because they have a mutual connection. Research has indicated that two individuals who interact with a mutual third teammate are highly likely to become teammates themselves (Huang, Shen, & Contractor, 2013), providing some evidence that balance does influence team assembly patterns. In particular, the results of one study on massively multiplayer online game self-assembled teams indicated that the likelihood of transitive triplet (i.e., a specific measure of closure that only applies to directed networks) is greater than the likelihood of random tie formations (Putzke et al., 2010). In other words, people form relationships in patterns of closure more often than would be expected by chance.

We expect that for the same reasons that balance emerges in friendship networks (e.g., cohesiveness, social sanctioning, and stability), balance will also occur in team assembly networks. Component individuals in team formation networks stand to gain from patterns of closure; balanced team assembly relations mean consolidating workloads, reducing role conflict, and minimizing role overload. In other words, individuals should be driven to employ balance mechanisms in their assembly networks because developing network features such as social sanctions and Simmelian ties will facilitate teamwork in the long run. Thus, based on previous research and theory, we propose the following:

Hypothesis 3b: Self-assembled teams will have higher levels of team membership closure than would be expected by chance.

Situational Attraction

In addition to the various ways that people can be attracted to one another because of individual differences and relational characteristics, certain contexts—or situations—serve to promote interpersonal attraction. The situation that has the most powerful impact on interpersonal attraction is proximity, a situation of physical closeness; "other things equal, people are most likely to be attracted toward those in closest contact with them" (Newcomb, 1956, p. 575). With few exceptions, people are more likely to form platonic and romantic connections with those who live nearby (Back, Schmukle, & Egloff, 2008; Ebbesen et al., 1976; Festinger, Back, & Schachter, 1950). The finding that physical nearness positively influences attraction is so robust, in fact, that it has even been titled the *law of proximity*. The effect of physical proximity is so powerful that it has even been demonstrated on the web; people who are geographically proximal to one another communicate more frequently online than do people who are geographically disparate (Leskovec & Horvitz, 2007, 2008).

In teams. To date, very little research has been done on the impact that proximity has on attraction in teams. One study's results indicated that individuals are more likely to choose teammates who are physically proximal than select physically distal teammates (Cummings & Kiesler, 2007). This effect has been shown to hold true even when solely considering virtual teams (Huang, Shen, & Contractor, 2013; Huang et al., 2009). Based on these preliminary findings, it is conjectured as follows:

Hypothesis 4: Self-assembled teams will exhibit a proximity effect, choosing teammates who are nearby more often than would be expected by chance.

Relative Effects

An additional goal of this research is to understand the relative impacts of assembly mechanisms on team self-assembly. Whereas the previous sections have explored the mechanisms that likely govern team formation ties, in this section we consider the relative strength of each mechanism as a force of attraction in drawing people to work together. Although little research has compared and contrasted absolute, relative, relational, and situational attraction mechanisms, one clear finding from research on attraction is the profound effect of proximity on interpersonal relationships (Back et al., 2008; Festinger et al., 1950; Priest & Sawyer, 1967). The proximity effect can even overpower other influential forces of attraction and has been shown to account for friendships that disobey similarity-attraction and balance (e.g., Nahemow & Lawton, 1975; Wimmer & Lewis, 2010). This finding implies that people's tendency to associate with nearby individuals is stronger than their tendency to form homophilous, triangulated friendships.

In teams. Very few studies have assessed the aforementioned issues in the context of team assembly patterns. However, one such study (Huang et al., 2009) used a sample of massively multiplayer online role-playing game (MMORPG) teams. The researchers used a network of team membership relationships to evaluate how absolute, relative, relational, and situational attraction mechanisms impact team assembly patterns. They determined that popularity, transitivity, and proximity all impact team assembly patterns to a degree greater than homophily. This finding is especially surprising, considering the fact that players have no discernable means of detecting one another's actual geographic locations in the virtual MMORPG world. Although this particular study did not control for the effect of familiarity, the authors suggested that perhaps player familiarity is confounded with proximity, as nearly 70% of their respondents reported playing the game with friends that they knew offline. Consequently, we hypothesize the following:

> **Hypothesis 5:** The proximity effect will be stronger than the absolute, relative, and/or relational effects on team self-assembly.

Team Composition and Outcomes

Whereas the previous hypotheses concern the mechanisms that characterize how individuals are likely to form teams, we now consider the consequences of those decisions—namely, team composition. The team composition literature centers on how team performance, cohesion, and other important outcomes can be predicted using team members' personal characteristics. Traditionally, researchers have grouped team characteristics into two general categories: compositional and configurational. Compositional—or global (Molleman, 2005)—teams are fundamentally equivalent across levels (Kozlowski & Klein, 2000). Because they manifest at the team level just as they do at the individual level, these attributes can be adequately operationalized as averages. In certain situations and/or with certain variables, however, it is not appropriate to take team-level averages (Barrick, Stewart, Neubert, & Mount, 1998). Thus, the configurational approach evaluates team composition from a different angle, using team-level variance, minimums, and maximums (Hollenbeck, DeRue, & Guzzo, 2004) to emphasize the dispersion of attributes. For the purposes of this research, we built on this established classification system to create an even broader taxonomy that is more amenable to the incorporation of both personal characteristics and relationships as building blocks of team assembly. We have grouped team characteristics into four broad categories: absolute attributes, relative attributes, relational structures, and situational attributes. Absolute attributes are certain attributes that additively impact team outcomes; in other words, the higher level of a given attribute on a team, the better the outcome. This category closely resembles the traditional compositional approach. Conversely, variance levels of relative attributes predict team outcomes; likewise, this category closely resembles the traditional compilational approach. Adding to the preexisting framework, relational structures are specific ways that teammates' relationships can be characterized—or patterned—that predict team outcomes. Finally, situational attributes are characteristics of team contexts that can be used to predict team outcomes.

Absolute Attraction and Team Outcomes

The team literature's additivity model (Hill, 1982; Tziner, 1985) suggests that certain team member characteristics combine in an additive manner with regard to their impact on group-level outcomes. Research has indicated that popularity may be one such additive attribute. In the network science literature, the term "degree" refers to the number of connections a node (i.e., a person) has to other nodes; essentially, degree represents social connectedness or popularity.

> [T]he so-called "rich-club" phenomenon . . . refers to the tendency of high-degree nodes, the hubs of the network, to be very well-connected to each other. Essentially, nodes with a large number of links, usually referred to as rich nodes, are much more likely to form tight and well-interconnected

> subgraphs (clubs) than low-degree nodes. (Colizza, Flammini, Serrano, & Vespignani, 2006, p. 110)

Furthermore, findings from empirical and meta-analytic research have suggested that teams with dense social ties outperform teams with sparse social ties (Balkundi & Harrison, 2006; Reagans & Zuckerman, 2001). It follows, then, that teams of high degree, high social status hubs will outperform teams of less popular individuals. Psychologically, assembling based on popularity and status will give teams an upper hand because they will be able to leverage the social capital afforded to them by their many relational ties (Burt, 2001) to outperform teams with fewer social connections. Thus, we hypothesize as follows:

> **Hypothesis 6:** Networks of self-assembled teams with social hubs (i.e., popular individuals) will outperform those without social hubs.

Relative Attraction and Team Outcomes

The team composition literature has also delved into the relation between the variance of surface- and deep-level attributes on a team and team performance (as well as other important team outcomes). Research on team diversity often operationalizes heterogeneous (i.e., diverse) teams as those that have a high level of variance on one or more demographic attributes, while teams that have a low level of variance on one or more demographic attributes are considered homogeneous. In general, research has shown that teams that are heterogeneous—in terms of surface- and/or deep-level attributes—have a broader array of information to draw from than homogeneous teams, and heterogeneous teams perform better than homogeneous teams when situational uncertainty and decision importance are high (Mello & Ruckes, 2006). Thus, based on this general trend, we posit the following hypothesis:

> **Hypothesis 7:** Teams that assemble based on heterophily will outperform teams that do not assemble based on heterophily.

Relational Structures and Team Outcomes

Relational structures refer to the patterns of relationships that characterize the group; teams can be described not only based on the attributes of the component individuals but also based on the relationships between teammates. Overall, prior research has indicated that familiarity facilitates team performance (e.g., Eisenhardt & Schoonhoven, 1990; Gruenfeld, Mannix, Williams,

& Neale, 1996; Harrison, Mohammed, McGrath, Florey, & Vanderstoep, 2003). Mechanistically, prior relationships increase team transactive memory and make it easier for teammates to express disagreement with one another (Katz, Lazer, Arrow, & Contractor, 2005). Furthermore, familiarity has the most beneficial effects on team performance when coordination between team members is challenging (e.g., in large teams or dispersed teams; Espinosa, Slaughter, Kraut, & Herbsleb, 2007). In particular, teams of friends tend to outperform teams of acquaintances on both decision-making tasks and motor tasks, due to higher relative levels of cooperation and commitment (Jehn & Shah, 1997). Thus, based on the extant literature, we propose the following hypothesis:

Hypothesis 8a: Teams that assemble based on familiarity will outperform teams that do not assemble based on familiarity.

The framework of balance theory (Heider, 1958), which suggests that individuals strive for consistency in their relationships with others, can be used as a basis for predicting critical team outcomes using relational structures. Triadic closure is one type of relational structure that exemplifies balance theory. Generally, triadic closure promotes the development and enforcement of norms between individuals, which in turn positively benefits performance (Reagans, Zuckerman, & McEvily, 2004). Specifically, transitivity is the "tendency that two actors who are connected to a third party form mutual relationships over time" (Batjargal, 2007, p. 998). At the group level, teams that have more transitive trust ties outperform teams with less transitive trust ties (Lusher, Kremer, & Robins, 2014). Other research has noted that teams with high levels of transitive communication ties experience stronger feelings of team cohesion, while teams devoid of such transitive communication subjectively experience a lack of cohesion (Quintane, Pattison, Robins, & Mol, 2013). Finally, one study suggested that transitivity mediates the negative relation between age diversity and knowledge transfer as well as the positive relation between educational diversity and knowledge transfer (Miao-Miao & Jun, 2013). Following findings from the extant literature, we posit the following:

Hypothesis 8b: Teams that assemble based on closure will outperform teams that do not assemble based on closure.

Situational Attributes and Team Outcomes

Teams can further be distinguished by defining characteristics of their situations or contexts. Akin to the dyadic attraction literature on the subject, proximity is an extremely powerful driver of team-level processes and outcomes. For example, research has suggested that individuals on globally distributed teams tend to identify with the subgroup in their proximal environment rather than identifying with the larger distributed team (Joshi, Labianca, & Caligiuri, 2002). This finding serves, in part, to explain why globally distributed teams' performance suffers in comparison with other types of teams. In general, distributed work groups have increased levels of conflict and experience communication breakdowns (Armstrong & Cole, 2002). Specifically, research has indicated that geographic heterogeneity negatively predicts task-relevant and task-irrelevant communication within teams (Yuan & Gay, 2006). Furthermore, geographic distance between teammates is often accompanied by differences in time zone, culture, and organizational style, all of which can make communication and coordination more challenging for distributed teams (Armstrong & Cole, 2002). Research juxtaposing proximity and virtuality concluded that globally distributed teams face greater behavioral challenges, project management challenges, and performance detriments when compared with proximally located virtual and face-to-face teams (McDonough, Kahn, & Barczak, 2001). Preliminary research on proximity and self-assembled team outcomes indicated that colocated self-assembled teams coordinate and perform better than geographically distributed self-assembled teams (Cummings & Kiesler, 2005). Specifically, proximity positively impacts the communication, coordination, mutual support, and effort facets of teamwork quality (Hoegl & Proserpio, 2004). Thus, we conjecture the following hypothesis:

> **Hypothesis 9:** Teams that assemble based on proximity will outperform teams that do not assemble based on proximity.

Relative Effects

Rarely have absolute, relative, relational, and situational facets of team composition been empirically compared and contrasted with one another. However, one clear finding from research on team composition and performance is the beneficial effect of heterophily on team performance; research has shown that teams that are heterogeneous—in terms of surface and/or deep-level attributes—have a broader array of information to draw from than homogeneous teams, and consequently, heterogeneous teams outperform homogeneous teams in important and/or uncertain situations (Mello & Ruckes, 2006). It follows that the team composition factor that contributes most expressly to the performance of self-assembled teams will be demographic heterogeneity. Thus, it is posited as follows:

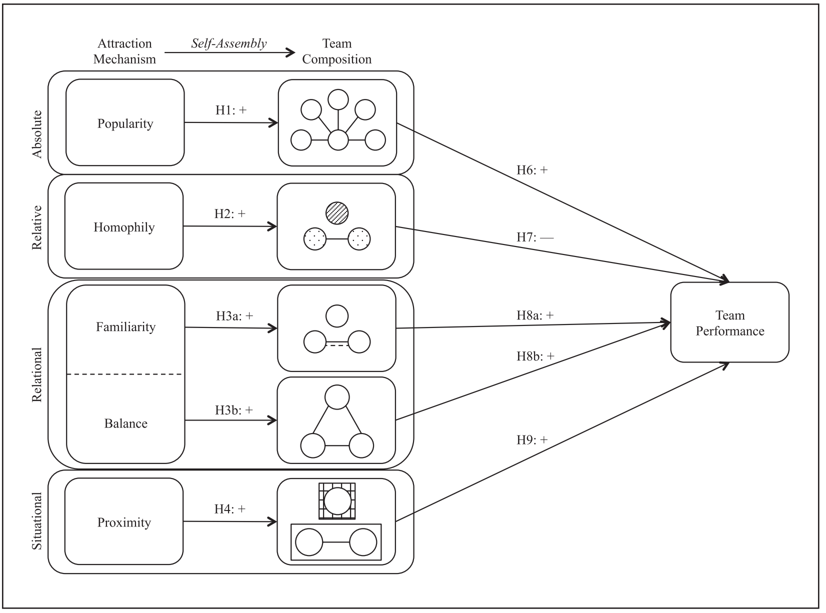


Figure 1. Theoretical model of team self-assembly and performance.

> **Hypothesis 10:** Teams that assemble primarily based on heterophily will outperform teams that assemble primarily based on absolute, relational, or situational attraction mechanisms.

Figure 1 displays a visualization of our full theoretical model, including Hypotheses 1 through 10.

Method

We tested our hypotheses using de-identified server-side data on a large sample of individuals who joined teams to play the online game Dragon Nest. Dragon Nest is a free-to-play web-based MMORPG. In the virtual, fantasy world of Dragon Nest, gameplay centers on the completion of task-based missions called quests. Importantly, players are encouraged to complete quests in teams, which range in size from two to four people.[1] Thus, making progress in Dragon Nest is contingent upon the successful self-assembly of teams. Upon the completion of a quest, teammates are rewarded with experience points that, upon accumulation, result in level advancement for each individual. Upon reaching certain milestone levels, players begin assume more advanced roles, graduating to secondary classes of characters at Level 15 and tertiary classes of characters at Level 45. Although online gameplay may appear superficially dissimilar from organizational behavior, scholars have argued otherwise (Williams, Contractor, Poole, Srivastava, & Cai, 2011). For instance, Contractor (2013) argued that “online environments are in fact the ideal ‘online laboratories’ to understand and enable how we will use the Web to assembly into teams in the foreseeable future” (p. 9; paraphrasing Reeves, Malone, & O’Driscoll, 2008), while Castronova (2006) dubbed online games “Petri dishes for social science” (p. 163).

Participants and Materials

The Dragon Nest data set is largely comprised of digital trace data, which is a type of big data that stem from the automatic recording of information based on users’ activity within the context of a virtual system. The raw Dragon Nest trace data set included roughly 6,116,200 data points (i.e., instances of individual players questing, either by themselves or on teams) for each weeklong period. Contemporarily, computing power poses a serious limitation to the analysis of such a large data set. Thus, due to the unusually large size of the raw data, the proposed research tested the aforementioned hypotheses on a sample of Dragon Nest in-game data. Specifically, gameplay from Monday, February 6, 2012, was analyzed, because this date coincides with China’s Lantern Festival. The Lantern Festival is a holiday that marks the end of the Lunar (i.e., Chinese) New Year, when Chinese people release colorful paper lanterns and fireworks into the night sky to express their hopeful wishes for the coming year. The Lantern Festival is widely celebrated in China—so much so, in fact, that this annual burning of fireworks has a significant, negative impact on the air quality in major Chinese metropolitan areas (Wang, Zhuang, Xu, & An, 2007). For the purposes of this study, data from February 6, 2012, were selected to analyze because many Chinese schools and businesses are closed on the day of the Lantern Festival; thus, because of the holiday, more Dragon Nest players would be interacting in the virtual world throughout the course of the day. Indeed, Dragon Nest traffic was much higher on February 6 than on comparable dates in early 2012. For instance, the prior Monday had 608 less players and 265 less teams than February 6, while the subsequent Monday had 4,527 less players and 3,204 less teams.

Data Cleaning

A number of steps were taken to clean the data, identifying the portion of data that contained instances of team assembly on which the 10 hypotheses could be tested. First, 1,082,290 observations of 82,794 players were excluded because these records characterized independent play, where players did not form teams. Next, 159,949 observations of 28,735 players on 14,093 teams were removed from the data set because of variance between team members on one or more critical team-level variables, including quest success, quest performance, quest start/stop time, team size, task type, and task difficulty. Subsequently, 26 instances of single-member "teams" were removed from the data set; 343 observations of 293 players on 82 teams were excluded from analyses because the team size variable did not accurately reflect the number of team members; and 2,080 instances of 1,435 players on 200 teams were removed from the data set because these teams included more than eight members (i.e., the maximum possible amount of players on a team). Next, 5,759 observations of 923 teams were excluded because these teams' team identification codes were not unique. Overall, it is likely that these idiosyncrasies in the raw data exist for a variety of reasons. Two popular explanations are that sometimes (a) a team member intentionally quits a quest that is only partially complete, and (b) technological glitches—such as Wi-Fi interruptions—forcibly remove a teammate from a quest. Both of these justifications account for aberrations such as (a) variance between team members on team-level variables, because any member who does not complete the quest does not receive the same credit for completing the quest as the rest of her teammates, and (b) the team size variable is not accurately reflecting the number of team members, because the team's size fluctuated mid-quest due to the departure of one or more teammates. In all cases of idiosyncratic data, the entire team was removed from analyses.

Finally, teams that engaged in very high-level tasks were excluded from the sample because they systematically differed from the general population of Dragon Nest players in a number of ways, including level and team size. Specifically, Dragon Nest includes four quests that are only available to players who have successfully completed all of the other quests that the game has to offer; thus, these tasks are very challenging and allow players to form teams as large as eight (as opposed to the usual limit of four). This subset of 941 players, who formed 297 teams, was excluded from analyses.

Furthermore, to distinguish between players who selected their teammates in psychologically meaningful ways and players who joined forces using a random team generator, a given teammate relationship was only included in the sample if it occurred at least twice during the course of the 24-hr period in question. The final, clean sample included 1,568 players of the Chinese version of Dragon Nest who played on 1,744 teams, forming 929 dyadic teammate relationships. While the vast majority of individuals played with exactly one other person at least twice (n = 1,372), others played with two (n = 171), three (n = 22), and even four other players at least twice (n = 3) during the course of the day.

Individual Level

The Dragon Nest data set includes a variety of individual-level attributes, including (a) player level, (b) guild role, (c) completed quests, and (d) logins. Unless otherwise stated, data were selected from a specific time frame because it (a) predated the team membership data (from February 6, 2012); (b) was temporally proximal enough to February 6 for there to be significant overlap in terms of the players included in each sample; (c) included a substantially wide window of time, so as to capture as many players included in the February 6 team membership sample as possible; and (d) was made available to us for purposes of analysis.

Player level. Level—a variable ranging from 1 to 50—is an overall measure of a player's progress in the world of Dragon Nest. In the digital trace data set, level is recorded for each component team member upon the completion of a quest. So, team-level questing information and certain individual-level attributes (including level) are all contained in the same data set. Thus, to ensure that we had information on player level for 100% of the individuals who quested on February 6, we had to use level data from that day (as opposed to an earlier day, when less than 100% of the sample would have been playing online). To deduce each player's overall level, median level across all instances of team quests that occurred on February 6, 2012, was calculated for each player.

Furthermore, based on Huang, Ye, Bennett, and Contractor's (2013) method, level was binarized into low (29.66%) and high (70.34%). It is important to mention that the binarized version of level that we employed is a relatively static individual attribute. An appropriate metaphor would be individual age; we all grow older on a day-to-day basis, but that change is gradual to the point of being virtually unnoticeable. This point supports our decision to use level data from February 6, because minimal change occurs from one day to the next. Descriptive statistics for both versions of the variable can be seen in Table 2.

Table 2. Descriptive Statistics for Continuous Digital Trace Variables.

	M	*SD*	Minimum	Maximum
Individual level				
Control/covariate				
Average teaming frequency	2.15	0.58	2.00	14.00
Logins (raw)	62.66	61.68	1.00	744.00
Logins (transformed)	3.64	1.12	0.00	6.61
Player level (raw)	39.09	12.86	4.50	50.00
Player level (transformed)	0.70	0.46	0.00	1.00
Completed quests (raw)	162.84	136.64	1.00	873.00
Completed quests (transformed)	4.62	1.16	0.00	6.77
Dyadic level				
Control/covariate				
Teaming frequency	2.18	0.71	2.00	16.00
Proximity (raw)	918,750.20	1,208,061.00	0.00	17,339,483.00
Proximity (transformed)	0.09	0.28	0.00	1.00

Note. t (number of teams) = 1,744. n (number of individuals) = 1,568. l (number of teammate relationships) = 929.

Guild role. Guilds are official alliances between players. Guild data from January 1 to 24, 2012, were also used to determine players' guild roles. Individuals can occupy one of five potential roles within a guild: leader, manager, senior member, ordinary member, or newcomer. In instances when individuals occupied multiple roles during this time span, modal guild role was used. Of the 990 guild members in the sample, 7.07% were leaders, 11.41% were managers/deputies, 39.90% were senior members, 19.19% were ordinary members, and 22.42% were newcomers. Because guild leaders and managers/deputies are theoretically both individuals in leadership positions within their guilds, we merged these two categories into a single manager/leader category. Similarly, because guild newcomers and individuals with no guild affiliation both have yet to relationally embed themselves within a guild, we merged these two categories into a single category reflecting individuals without a role (or with a very limited role) in a guild.

Completed quests. Total number of completed quests is a player's overall quantity of successfully accomplished quests, or missions (e.g., slaying a monster). Higher numbers of completed quests lead to progress in the world of Dragon Nest. Total number of completed quests reflects the number of missions successfully accomplished per person between January 1 and February 6, 2012. Data on completed quests were missing for 39 players in the final sample. Simple random imputation was used to account for these missing data points; the R code to conduct this imputation was borrowed from Gelman and Hill (2006). Subsequently, the raw completed quests variable was transformed using a natural logarithm transformation. Additional descriptive statistics for both versions of completed quests can be seen in Table 2.

Logins. Total number of logins reflects the amount of time players have spent in the virtual world of Dragon Nest and thus is an indicator of player experience. This variable reflects the aggregate number of logins that occurred per person between January 1 and February 6, 2012. Due to its power-law distribution, logins was adjusted using a natural logarithm transformation. Descriptive statistics for both versions of logins can be seen in Table 2.

Dyadic Level

The Dragon Nest data set also includes a variety of variables at the dyadic level, including (a) friendship, (b) guild membership, (c) proximity, (d) teaming, and (e) teaming frequency.

Friendship. Dragon Nest players can add one another to friend groups (similar to the functionality of circles in Google+), thus providing documentation of familiarity at the dyadic level. Logistically, this feature in Dragon Nest allows players to easily communicate with one another via instant message. Furthermore, friendships in Dragon Nest are directed, meaning that—for example—Person A may indicate a friendship with Person B, but this does not necessarily mean that Person B indicated a friendship with Person A.

Friendship was determined by evaluating a data snapshot from January 2, 2012, which included 31 unique, directed relationships between 51 players (23 senders and 30 receivers), out of the total 1,568 players included in the sample. This specific time frame was chosen because it (a) predated the team membership data (from February 6, 2012), (b) was temporally proximal enough to February 6 for there to be significant overlap in terms of the players included in each sample, and (c) was made available to us for purposes of analysis.

Guild membership. To assess familiarity due to common guild membership, data on guild membership were used to create a binary relational matrix; in other words, common modal guild affiliations were translated into relational

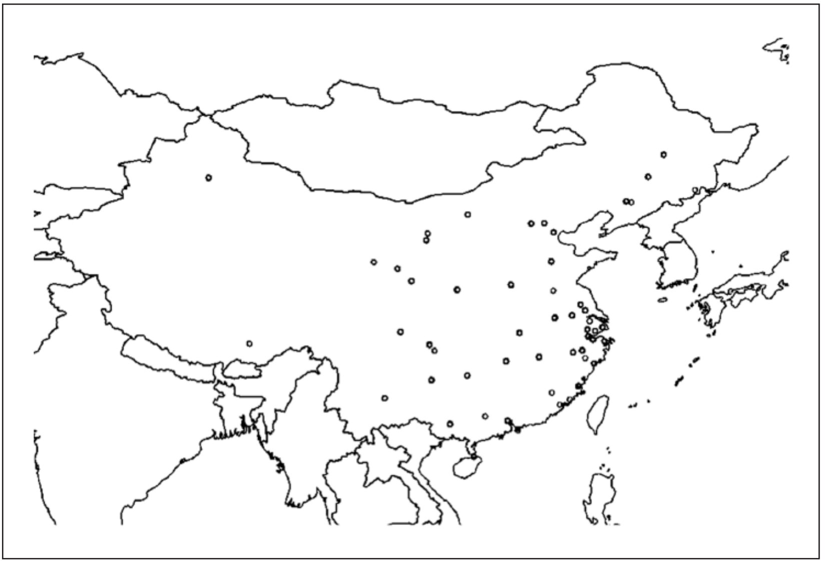


Figure 2. Chinese locations of Dragon Nest players.
Note. n (number of individuals) = 1,558.

ties. Of the full sample, 35.27% shared a guild affiliation with another player in the sample, 27.87% were isolates in terms of guild affiliation, and 36.86% had no guild affiliation. For additional details on the digital trace data used to create this variable, please see the description of guild role.

Proximity. Proximity of dyads was determined based on individual-level locations, which were determined using Internet Protocol addresses (IP addresses). IP addresses are 32-bit binary numbers that are assigned to computers, tablets, and other devices that access the Internet; they are analogous to postal addresses, expect they are used for sending and receiving information across the WWW. A sample of individual-level IP address data from January to early-/mid-February was evaluated. For individuals who logged in from more than one IP address during this time frame, modal IP addresses were used. Players' geographic location was operationalized as their coordinates (i.e., longitude and latitude). To identify players' coordinates based on their IP addresses, we used the rjson package in R (Couture-Beil, 2014) and freegeoip.net to create a database of IP addresses and associated coordinates. The vast majority of the final sample of 1,568 players (i.e., 99.36%) hailed from Mainland China. A graphical depiction of the geographic distribution of Chinese players can be found in Figure 2, which was created using the rworldmap package in R (South, 2011).

We used the package geosphere in R (Hijmans, 2014) to calculate the shortest distance between each pair of player coordinates according to the spherical law of cosines. The formula used by the package is as follows:

$$\Delta\sigma = \arccos\left(\sin\phi_1 \sin\phi_2 + \cos\phi_1 \cos\phi_2 \cos\Delta\lambda\right)\times 6{,}378{,}137.$$

In the above formula, ϕ_1, λ_1, and ϕ_2, λ_2 stand for coordinates; $\Delta\phi$ and $\Delta\lambda$ are the absolute differences of said coordinates; and $\Delta\sigma$ is the central angle between the two given points. The trigonometric function, arccos, is the inverse of cosine. The number 6,378,137 is the radius of the Earth in meters.

Furthermore, we transformed the raw proximity variable for computational purposes. Specifically, we applied the following transformation:

$$\text{Transformed proximity} = \exp\left(\frac{-\text{Raw proximity}}{50{,}000}\right).$$

This equation is based on two pieces of information. First, a number of researchers have proposed that the probability of a tie forming between two nodes is a negative exponential function of geographic distance (Kleinberg, 2000). Second, the raw proximity distances were divided by 50,000 because it has been suggested that 50,000 meters (or 50 kilometers) is a reasonable base distance to measure close geographic proximity (Huang, Shen, & Contractor, 2013).

Teaming. In Dragon Nest, team membership is recorded for every instance that a group of players assembles to complete a quest. In addition, teams can be identified and differentiated by their unique team identification codes. For the purposes of this study, teaming was operationalized at the dyadic level. In other words, if two players joined forces at least twice on February 6, 2012, it was inferred that they had a teaming relationship. These dyadic relationships were used to create the binary outcome network of teaming relationships.

Teaming frequency. Although dyads had to work together at least twice in a 24-hr period to be included in the sample, some pairs joined forces far more frequently—as many as 16 times throughout the course of the day. Descriptive statistics for teaming frequency can be found in Table 2.

Performance. Team questing performance was measured via quest success. Quest success is a binary variable indicating whether a team successfully completed their mission or not. For analytic purposes, dyads were categorized into three performance groups: one group consisting of dyads that only succeeded when questing, one group consisting of dyads that only failed, and a third group consisting of dyads that both succeeded and failed (i.e., the mixed group). Furthermore, steps were taken to ensure that all of the performance groups were truly independent. First, 55 individuals were excluded from the performance analyses because they appeared in more than one performance group. Second, 57 individuals were excluded from the performance analyses because they shared at least one common team membership with a player in a different performance group. Therefore, 1,456 players constituted the sample that was analyzed to assess performance-related hypotheses; 1,027 individuals were in the successful group, 337 were in the mixed group, and 92 were in the unsuccessful group. Table 3 displays detailed descriptive statistics for all variables of interest for each performance group.

Analytic Approach

To test our hypotheses, we used exponential random graph models (ERGMs). In an ERGM, the observed network is the relational dependent variable that the user is interested in modeling. The pattern of ties present in the observed network is conceptualized as just one potential configuration out of many, many potential configurations of ties. ERGMs allow users to estimate model parameters based on this observed network; in other words, users can determine whether structural characteristics of interest in the observed network likely occurred by chance or not (Robins, Pattison, Kalish, & Lusher, 2007). Parameter estimates can be based on node attributes (i.e., individual differences) and relational configurations present in the observed network (Anderson, Wasserman, & Crouch, 1999). Furthermore, ERGMs allow users to predict relational dependent variables using relational independent variables (Robins et al., 2007). The analyses produce effect estimates and associated significant levels, and thus are suitable for testing hypotheses. Furthermore, ERGMs can be applied to very large networks; the maximum number of nodes that can be run in a single estimation is approximately 1,000 to 2,000 (Lusher, Koskinen, & Robins, 2013). The statnet package in R (Handcock et al., 2014) was used to test the proposed hypotheses using ERGMs.

An analogy can be drawn between ERGM and logistic regression; although the latter assumes independence of observations and the former does not, there are many similarities between the two methods. Logistic regression involves predicting a binary outcome from multiple independent variables, with model parameters (i.e., regression coefficients) indicating the relative importance of predictors. Similarly, ERGM involves predicting the presence/

Table 3. Descriptive Statistics, Grouped by Performance.

	Successful (t = 1,100, n = 1,027, l = 580) AIC = 6,037 BIC = 6,171				Mixed (t = 362, n = 337, l = 191) AIC = 1,356 BIC = 1,463				Unsuccessful (t = 130, n = 92, l = 56) AIC = 298.90 BIC = 368.70			
	M	*SD*	Minimum	Maximum	*M*	*SD*	Minimum	Maximum	*M*	*SD*	Minimum	Maximum
Individual-level control												
Average teaming frequency	2.10	0.36	2.00	7.00	2.18	0.39	2.00	4.00	2.53	1.81	2.00	14.00
Logins (raw)	59.55	59.81	1.00	744.00	64.57	63.08	1.00	622.00	73.30	66.34	1.00	385.00
Logins (transformed)	3.57	1.15	0.00	6.61	3.69	1.08	0.00	6.43	3.85	1.06	0.00	5.95
Individual level												
Player level (raw)	38.41	13.09	4.50	50.00	39.31	12.95	9.00	50.00	41.16	12.41	12.00	50.00
Player level (transformed)	0.70	0.46	0.00	1.00	0.67	0.47	0.00	1.00	0.66	0.48	0.00	1.00
Quests (raw)	168.80	143.32	1.00	873.00	145.14	120.94	1.00	736.00	141.57	126.18	2.00	848.00
Quests (transformed)	4.65	1.16	0.00	6.77	4.52	1.14	0.00	6.60	4.47	1.18	0.69	6.74
Dyadic-level control												
Teaming frequency	2.11	0.40	2.00	7.00	2.18	0.40	2.00	4.00	2.71	2.29	2.00	16.00
Dyadic level												
Proximity (raw)	9.01e+5	1.09e+6	0.00	1.56e+7	1.09e+6	1.69e+6	0.00	1.52e+7	6.84e+5	5.02e+5	0.00	2.05e+6
Proximity (transformed)	0.10	0.29	0.00	1.00	0.09	0.28	0.00	1.00	0.09	0.27	0.00	1.00

Note. t = number of teams; n = number of individuals; l = number of teammate relationships; AIC = Akaike information criterion; BIC = Bayesian information criterion.

Table 4. Individual-Level Pearson's Correlation Coefficients.

	1.	2.	3.	4.
1. Player level (transformed)	—			
2. Completed quests (transformed)	.16***	—		
3. Logins (transformed)	.65***	.47***	—	
4. Average teaming frequency	.02	.05	.04	—

Note. n (number of individuals) = 1,568.
*** p < .001.

absence of a network tie (i.e., a binary outcome) from multiple independent variables (i.e., network configurations), with model parameters indicating the relative importance of each configuration to the presence of a tie (Lusher et al., 2013).

Results

We tested our 10 hypotheses using four ERGMs—one for attraction-related hypotheses and three for performance-related hypotheses. The presentation of results is as follows: (a) correlations among focal variables, (b) attraction-related ERGM, and (c) performance-related ERGMs.

Correlations Among Focal Variables

Table 4 presents individual-level correlation coefficients[2] for variables of interest in the current study. One interesting pattern that emerged was that player level, completed quests, and logins were all positively correlated with one another; rs ranged from .16 to .65, $p < .001$. The robust relation between these variables is unsurprising, as they are all strongly related to experience playing Dragon Nest. Over time, players who login more will likely have higher cumulative numbers of completed quests than those who login less, and this progress results in level promotions.

The Quadratic Assignment Procedure (QAP) is a technique that is commonly used to correlate social network data (Krackhardt, 1987). The sna package in R (Butts, 2014) was used to calculate QAP coefficients for the current study's three social networks. All networks were treated as undirected to accurately reflect subsequent analyses. As visible in Table 5, friendship, guild membership, and team membership all correlated positively with one another; QAP coefficients ranged from .06 to .22, $p < .001$.

Table 5. QAP Coefficients.

	Friendship	Guild membership	Team membership
Friendship	—		
Guild membership	.11***	—	
Team membership	.06***	.22***	—

Note. Average *p* values were used. *n* (number of individuals) = 1,568. QAP = Quadratic Assignment Procedure.
***$p < .001$.

Interpersonal Attraction in Teams

Hypotheses 1 through 5 were quantitatively tested using a single ERGM, the results of which can be seen in Table 6. In addition to the parameter estimates used to test hypotheses, we also included three control parameters in this model: (a) number of relationships, (b) average teaming frequency, and (c) main effects. First, edges is a crucial control variable that accounts for the number of relationships in the network expected to occur by chance and must be included in every ERGM. Second, average teaming frequency[3] was included in all models as a node attribute covariate to control for individual differences among players in terms of the tendency to repetitively team up with one or more other players. Although dyads had to work together a minimum of 2 times to be included in the sample, some pairs quested together as many as 16 times throughout the course of the day. To account for this variability in individuals' teaming activity, we included this control variable in all models at the individual level; in other words, each player's teaming frequencies across all of her teammate relationships were averaged and included as vertex covariates. This enabled us to control for the fact players who were more active teamers were also more likely, just by chance, to team with more players.

Third, main effects of player level and guild role were controlled for so that similarity-attraction parameter estimates for these variables would be valid to interpret. For each of these categorical main effects, a base argument was omitted from the model; "[t]o include all attribute values is usually not a good idea, because the sum of all such statistics equals twice the number of edges and hence a linear dependency would arise in any model also including edges" (Morris, Handcock, & Hunter, 2008, p. 5). The base argument for player level was low level, and for guild role was newcomers/individuals without a guild affiliation.

Table 6. ERGM Revealing the Self-Assembly Mechanisms That Predict Team Membership.

	Effect estimate	*SE*	Odds ratio
Controls/covariates			
Number of relationships (edges)	−15.46***	0.84	—
Average teaming frequency (nodecov)	−0.12	0.16	0.89
Main effects (nodefactor)			
Player level[a]	−0.07	0.23	0.93
Ordinary member	0.34	0.27	1.40
Senior member	0.14	0.24	1.15
Manager/leader	−0.38	0.35	0.68
H1: Absolute attraction (popularity)			
Antipreferential attachment (gwdegree)	9.52***	0.57	13,629.61
H2: Relative attraction (similarity)			
Player level[a] (nodematch)	0.26**	0.10	1.30
Guild role (nodematch)	0.26**	0.09	1.30
H3a: Relational attraction (familiarity)			
Friendship (edgecov)	1.59	1.04	4.90
Guild membership (edgecov)	5.74***	0.18	311.06
H3b: Relational attraction (balance)			
Closure (gwesp)	3.15***	0.13	23.34
H4: Situational attraction (proximity)			
Proximity[a] (edgecov)	2.31***	0.09	10.07

Note. ERGM = exponential random graph models; *t* (number of teams) = 1,744; *n* (number of individuals) = 1,568; *l* (umber of teammate relationships) = 929; edges = parameter that accounts for the number of relationships in the network expected to occur by chance; gwdegree = parameter that accounts for preferential avoidance (i.e., antipreferential attachment); gwesp = parameter that accounts for alternating *k*-triangles; edgecov = parameter that accounts for relational covariates; nodefactor = parameter that indicates the number of times that a node with a given attribute appears in an edge in the network, used to control for the main effects of categorical variables; nodematch = parameter that counts of the number of edges (*i, j*) for which attribute (*i*) = attribute (*j*), used to test for homogeneity for categorical variables; Outcome network = team membership; Akaike information criterion (AIC) = 13,213; Bayesian information criterion (BIC) = 13,478.
[a]The transformed version of the variable was used.
$^{**}p < .01$. $^{***}p < .001$.

Absolute attraction. Hypothesis 1 predicted that attractiveness as a teammate would be proportional to one's popularity—In other words, there would be a popularity effect in the team membership network. To test this premise, the team membership network was modeled using gwdegree, a preferential *avoidance* (i.e., antipreferential attachment) structural parameter. A positive, significant gwdegree coefficient signifies that the network exhibits preferential avoidance; essentially, this means that low-degree or unpopular nodes (i.e., individuals with relatively few social connections) are more likely to gain new edges than high-degree nodes (i.e., individuals with relatively many social connections; Hunter, 2007). The results testing Hypothesis 1 are presented in Table 6. The gwdegree parameter was estimated as 9.52, $p < .001$, meaning that individuals were over 13,600 times more likely to team up with a low-degree player than a high-degree player. This is opposite to the preferential-attachment mechanism that was proposed in Hypothesis 1; in effect, unpopular individuals were far more attractive as teammates than popular individuals were. Players' degree was much more uniformly distributed in the observed network than it was in the comparable random network. Thus, Hypothesis 1 was not supported.

Relative attraction. Hypothesis 2 posited that self-assembled teams would be more homogeneous than would be expected by chance. As visible in Table 6, the nodematch ERGM term—which counts the number of relationships (i, j) for which individual difference (i) = individual difference (j)—was used to test for homogeneity. Homogeneity was estimated for player level and guild role.[4] In support of Hypothesis 2, the homogeneity effect for player level was significant (0.26, $p < .01$). Furthermore, the homogeneity effect for guild role was also significant (0.26, $p < .01$). In other words, the odds of two players with similar levels/roles teaming up were 1.30 greater than the odds of two players with dissimilar levels/roles teaming up. Overall, Hypothesis 2 was supported.

Relational attraction. To test Hypothesis 3a—that self-assembled teams would form based on familiarity more often than would be expected by chance—the observed network of team membership ties between individuals was modeled by estimating a friendship edge covariate parameter and by estimating a guild membership edge covariate parameter. As seen in Table 6, the effect of common guild memberships on teaming relationships was significant (5.74, $p < .001$); players were over 311 times more likely to team up with a fellow guild member than they were to join forces with a stranger. The effect of friendship of teaming relationships was not significant (1.59, *ns*). Altogether, Hypothesis 3a was partially supported.

Hypothesis 3b postulated that self-assembled teams would form based on closure more often than would be expected by chance. To test this proposition, the observed team membership network was modeled using gwesp. A positive, significant gwesp coefficient signifies evidence of triadic closure. In the current sample, the effect of triadic closure was significant (3.15, $p < .001$). Practically, what this means in the current sample is that if Person A teamed up with Person B, and Person B teamed up with Person C, then Person C was 23.34 times more likely to team up with Person A. Accordingly, Hypothesis 3b was supported.

Situational attraction. Hypothesis 4 predicted that self-assembled teams would exhibit a proximity effect, choosing teammates who were nearby more often than would be expected by chance. To test this hypothesis, the observed network of team membership ties between individuals was modeled by estimating a proximity edge covariate parameter. This was accomplished first by calculating (and transforming) the distance between every pair of players in the sample and then translating those calculations into a weighted adjacency matrix. As seen in Table 6, the proximity edge covariate was estimated as 2.31, $p < .001$. This model reflects decrease in distance rather than the typical increase in distance because the raw proximity scores were transformed using a negative exponential function, thus reversing the interpretation of the proximity parameter estimate. In other words, individuals were more likely to team up with spatially proximal individuals than with distal individuals. Therefore, Hypothesis 4 was supported.

Relative effects of attraction on assembly. Hypothesis 5 posited that the proximity effect would be stronger than the effects of popularity, similarity-attraction, familiarity, or balance on team self-assembly. As seen in Table 6, the antipreferential-attachment effect had the strongest impact on teaming (estimate = 9.52, $p < .001$), followed by the effects of guild membership (estimate = 5.74, $p < .001$), balance (estimate = 3.15, $p < .001$), proximity (estimate = 2.31, $p < .001$), and similarity-attraction (estimate = 0.26, $p < .01$). Consequently, Hypothesis 5 was not supported.

Team Composition and Performance

Hypotheses 6 through 10 were also quantitatively tested using a single ERGM, the results of which can be seen in Table 7. To test these remaining hypotheses, which posit that certain assembly mechanisms are associated with better/worse team performance, we first needed to determine whether systematic differences between performance groups existed; if disparities emerged, they would need to be controlled for in all subsequent models, to ensure that these disparities did not influence the outcome of the tests of Hypotheses 6 through 10. Accordingly, Levene's tests were conducted to evaluate the appropriateness of Kruskal–Wallis one-way ANOVAs versus

Table 7. ERGMs Revealing the Absolute, Relative, Relational, and Situational Attraction Mechanisms that Predict Team Tie Formation, Grouped by Performance.

	Successful (t = 1,100, n = 1,027, l = 580) AIC = 6,037 BIC = 6,171			Mixed (t = 362, n = 337, l = 191) AIC = 1,356 BIC = 1,463			Unsuccessful (t = 130, n = 92, l = 56) AIC = 298.90 BIC = 368.70		
	Effect estimate	*SE*	Odds ratio	Effect estimate	*SE*	Odds ratio	Effect estimate	*SE*	Odds ratio
Controls/covariates									
Number of relationships (edges)	−17.19***	1.99	—	−16.62***	3.01	—	−11.85***	3.25	—
Average teaming Frequency (nodecov)	−0.31	0.40	0.73	−0.06	0.49	0.94	−0.55*	0.23	0.58
Number of logins[a]	0.13	0.16	1.14	−0.06	0.31	0.94	0.26	0.48	1.30
Main effects									
Player level[a] (nodefactor)	−0.41	0.36	0.66	−0.54	0.63	0.58	0.18	1.08	1.20
Completed quests[a] (nodecov)	0.15	0.13	1.16	0.14	0.22	1.15	−0.28	0.28	0.76
H6: Absolute composition (popularity)									
Antipreferential attachment (gwdegree)	10.85***	0.97	51,534.15	11.92***	2.10	150,241.61	13.12***	3.96	498,819.71
H7: Relative composition (similarity)									
Player level[a] (nodematch)	0.35**	0.11	1.42	0.36*	0.17	1.43	0.26	0.34	1.30
Completed quests[a] (absdiff)	0.02	0.07	1.02	−0.22	0.13	0.80	−0.58**	0.21	0.56

(continued)

Table 7. (continued)

	Successful (t = 1,100, n = 1,027, l = 580) AIC = 6,037 BIC = 6,171			Mixed (t = 362, n = 337, l = 191) AIC = 1,356 BIC = 1,463			Unsuccessful (t = 130, n = 92, l = 56) AIC = 298.90 BIC = 368.70		
	Effect estimate	*SE*	Odds ratio	Effect estimate	*SE*	Odds ratio	Effect estimate	*SE*	Odds ratio
H8a: Relational structure (familiarity)									
Friendship (edgecov)	4.81***	1.04	122.73	−1.31	1.38	0.27	—	—	—
Guild membership (edgecov)	5.54***	0.20	254.68	6.66***	0.33	780.55	7.46***	1.10	1,737.15
H8b: Relational structure (balance)									
Closure (gwesp)	3.24***	0.19	25.53	3.10***	0.30	22.20	2.69***	0.48	14.73
H9: Situational attributes (proximity)									
Proximity[a] (edgecov)	2.08***	0.12	8.00	2.83***	0.20	16.95	2.12***	0.36	8.33

Note. ERGM = exponential random graph models; t = number of teams; n = number of individuals; l = number of teammate relationships; AIC = Akaike information criterion; BIC = Bayesian information criterion; edges = parameter that accounts for the number of relationships in the network expected to occur by chance; gwdegree = parameter that accounts for preferential avoidance (i.e., antipreferential attachment); gwesp = parameter that accounts for alternating k-triangles; edgecov = parameter that accounts for relational covariates; nodefactor = parameter that indicates the number of times that a node with a given attribute appears in an edge in the network, used to control for the main effects of categorical variables; nodematch = parameter that counts the number of edges (i, j) for which attribute (i) = attribute (j), used to test for homogeneity for categorical variables; absdiff = sum of absolute difference for attribute (i) − attribute (j), for all edges in the network; Outcome network = team membership.

[a]The transformed version of the variable was used.

*p < .05. **p < .01. ***p < .001.

ANOVAs; Kruskal–Wallis one-way ANOVAs are nonparametric and can be used when the assumptions of ANOVA are not met. Of the variables tested,[5] only average teaming frequency had a statistically significant Levene's test result, $F(2) = 24.62$, $p < .001$, indicating inequality of variances across groups. Subsequently, a Kruskal-Wallis one-way ANOVA was conducted for average teaming frequency, while ANOVAs were conducted for the other variables. Out of all the tested variables, only two surfaced as being significantly different between groups: average teaming frequency, $\chi^2(2) = 44.25$, $p < .001$, and total number of logins, $F(2, 1453) = 3.45$, $p < .05$. In other words, unsuccessful teams tended to have the highest average teaming frequencies and the most logins, while successful teams tended to have the lowest average teaming frequencies and the least logins. Consequently—in addition to edges and main effects—average teaming frequency (which was previously included as a node covariate in the models testing Hypotheses 1 through 5) and logins were included as control variables in the models testing Hypotheses 6 through 10.

Absolute composition and performance. Hypothesis 6 postulated that networks of self-assembled teams with social hubs (i.e., popular individuals) would outperform networks of self-assembled teams without social hubs. As presented in Table 7, the team membership networks for successful, mixed, and unsuccessful dyads were modeled using gwdegree to test this premise. In the successful sample, gwdegree was estimated as 10.85, $p < .001$; in the mixed sample, gwdegree was estimated as 11.92, $p < .001$; and in the unsuccessful sample, gwdegree was estimated as 13.12, $p < .001$. Therefore, although all three groups exhibited preferential avoidance effects, the group with the effect of the lowest magnitude was the unsuccessful individuals, opposite to the direction proposed by Hypothesis 6. Thus, Hypothesis 6 was not supported.

Relative composition and performance. Hypothesis 7 predicted that teams that assembled based on heterophily would outperform teams that did not assemble based on heterophily. Heterophily was estimated for player level and completed quests (see Note 4). As presented in Table 7, player-level homophily was estimated as 0.35, $p < .01$, in the successful sample; as 0.36, $p < .05$, in the mixed sample; and as 0.26, *ns*, in the unsuccessful sample. In other words, the successful and mixed groups exhibited homophily effects in terms of player level, while the unsuccessful group did not exhibit a significant effect. Furthermore, completed quest homophily was estimated as 0.02, *ns*, in the successful sample; as −0.22, *ns*, in the mixed sample; and as −0.58, $p < .01$, in the unsuccessful sample. In other words, the unsuccessful group exhibited a homophily effect in terms of completed quests, while the other groups did not exhibit significant effects. Accordingly, Hypothesis 7 was partly supported (in terms of relative quest completion, but not relative player level).

Relational composition and performance. To test Hypothesis 8a—that teams assembled based on familiarity would outperform teams that did not assemble based on familiarity—the observed networks of team membership ties between individuals for two of the three performance groups were modeled by estimating a friendship edge covariate parameter. An effect estimate was not produced to test this hypothesis for the unsuccessful performance group because there were no friendship ties available to model in that network. As seen in Table 7, the effect of friendship on team self-assembly in the successful sample was estimated as 4.81, $p < .001$, and in the mixed group was estimated as −1.31, *ns*. The large magnitude of the friendship effect estimate for the successful performance group combined with the sheer lack of friendship ties in the unsuccessful group jointly provide support for this hypothesis. In addition, the observed networks of team membership ties were modeled for all performance levels by estimating a guild membership edge covariate parameter. The effect of shared guild membership on team self-assembly was estimated in the successful sample as 5.54, $p < .001$; in the mixed sample as 6.66, $p < .001$; and in the unsuccessful sample as 7.46, $p < .001$. Overall, Hypothesis 8a was partially supported (by the relationships between friendship and team self-assembly, but not by the relationships between guild membership and team self-assembly).

Hypothesis 8b predicted that teams that assembled based on closure would outperform teams that did not assemble based on closure. As presented in Table 7, the team membership networks for successful, mixed, and unsuccessful dyads were modeled using gwesp to test this proposition. [G]wesp was estimated as 3.24, $p < .001$, in the successful sample; as 3.10, $p < .001$, in the mixed sample; and as 2.69, $p < .001$, in the unsuccessful sample. Therefore, because all three performance groups exhibited statistically significant effects of transitivity of similar magnitudes, Hypothesis 8b was not supported.

Situational composition and performance. Hypothesis 9 posited that teams that assembled based on proximity would outperform teams that did not assemble based on proximity. To test this hypothesis, the observed network of team membership ties between individuals was modeled for all three performance groups by estimating proximity as an edge covariate, just as was accomplished in the analysis testing Hypothesis 4. As seen in Table 7, the effect of proximity on team self-assembly was estimated as 2.08, $p < .001$, in the successful sample; as 2.83, $p < .001$, in the mixed group; and as 2.12, $p < .001$,

Table 8. Hypothesized and Supported Relations.

Hypothesis No.	Proposition	Supported?
What are the drivers of team self-assembly?		
1	Popularity	No
2	Homophily	Yes
3a	Familiarity	Yes[a]
3b	Balance	Yes
4	Proximity	Yes
Which driver of team self-assembly is the most powerful?		
5	Proximity	No
Which drivers of team self-assembly lead to high team performance?		
6	Popularity	No
7	Heterophily	Yes[a]
8a	Familiarity	Yes[a]
8b	Balance	No
9	Proximity	No
Which driver of team self-assembly has the most powerful impact on team performance?		
10	Heterophily	No

Note. Please see the "Results" section for additional details.
[a]Hypothesis was partially supported.

in the unsuccessful group. This pattern indicates that players from all three performance groups tended to team up with geographically proximal players, and that this effect was most extreme for the mixed performance group. Thus, the results failed to support Hypothesis 9.

Relative effects of composition on performance. Hypothesis 10 postulated that teams that assembled primarily based on heterophily would outperform teams that assembled primarily based on absolute, relational, or situational attraction mechanisms. However, as seen in Table 7, the successful performance group did not evidence any tendency of self-assembling based on heterophily but did appear to use homophily (in terms of player level and guild membership) as a mechanism of self-assembly. Based on this evidence, Hypothesis 10 was not supported. Table 8 displays an overview of all hypothesized and supported relations.

Goodness of Fit

There are three primary ways to assess goodness of fit for ERGMs: (a) Akaike information criterion (AIC) and Bayesian information criterion (BIC) values,

(b) Markov chain Monte Carlo (MCMC) model diagnostics, and (c) goodness-of-fit plots. In general, it is optimal to take a holistic approach to assessing goodness of fit; by considering different pieces of evidence, the most accurate possible understanding of model fit can be achieved. First, AIC and BIC values reflect how well a model fits a particular data set; higher values indicate worse fit, while lower values indicate better fit. However, AIC and BIC values only approximate the fit of an ERGM and are relatively imprecise (Hunter, Goodreau, & Handcock, 2008). Specifically, AIC values worsen as the number of model parameters increases, and BIC values worsen as the number of observations increases (Lusher et al., 2013), leading to the conclusion that these criteria lend themselves to cross-model fit comparisons as opposed to direct interpretations of fit (Harris, 2014). As visible in Table 5, for the full sample, AIC and BIC values were 13,213 and 13,478, respectively. As visible in Table 7, the successful performance group had an AIC value of 6,037 and a BIC value of 6,171; the mixed performance group had an AIC value of 1,356 and a BIC value of 1,463; and the unsuccessful performance group had an AIC value of approximately 299 and a BIC value of approximately 369.

MCMC model diagnostics "can help determine whether the estimating algorithm has converged or there are degeneracy problems and if the model itself or the estimation settings need adjustment" (Harris, 2014, p. 74). However, similar to AIC and BIC values, it is critical to consider this diagnostics in conjunction with other information on convergence/goodness of fit rather than in a vacuum (Cowles & Carlin, 1996). Statistics fluctuating stochastically around a mean of 0 indicate that a model has converged. Overall, the MCMC model diagnostics for the ERGMs presented in Tables 5 and 7 indicated model convergence.

Goodness-of-fit plots provide a comparison between the proportion of nodes in the observed network with a given characteristic and the proportion of nodes in the simulated network with the same characteristic. In terms of interpretation, the thick black line that appears on each plot represents the observed network, while the two thin gray lines represent the 95% confidence interval of the simulated network; if the black line falls between the gray lines, this is an indication of good fit (Harris, 2014). Overall, the goodness-of-fit plots for the ERGMs presented in Tables 5 and 7 indicated good model fit.[6]

Discussion

An interesting implication of the shift toward empowered work teams is that individuals have increasing autonomy not only in choosing how to work together but also in choosing whom to work with. This change raises the question, "What are the interpersonal mechanisms of attraction in teams?" "What factors influence individuals' decisions of whom to work with?" These decisions have important implications for the resulting skill mix present within the team, the quality of members' teamwork interactions, and the ultimate success or failure of the team in reaching valued goals. Thus, the purpose of this study was twofold: to investigate how people *do* form into teams and how people *should* form into teams.

The results of this research support a number of the proposed hypotheses. First, several patterns emerged regarding the attraction mechanisms that drive team performance. Self-assembled teams formed based on homophily, familiarity, closure, and proximity more often than would be expected by chance. Based on these results, it is reasonable to conclude that relative, relational, and situational attraction mechanisms are crucial in driving the self-assembly process of MMORPG teams. Furthermore, teams that self-assembled based on surface-level homophily (i.e., homophily in terms of player level) and/or friendship outperformed teams that assembled based on deep-level homophily (i.e., homophily in terms of completed quests). Accordingly, it follows that relative and relational attraction mechanisms also have important implications for self-assembled team performance outcomes.

Interpersonal Attraction in Self-Assembled Teams

Hypothesis 1, which predicted that attractiveness as a teammate would be proportional to popularity as a teammate, was ultimately not supported. In fact, a very strong, highly significant preferential avoidance effect was observed in the team membership network. There are several reasons why this may be the case. First, it is possible that certain MMORPGs are unlikely to incur popularity effects. A few studies have assessed preferential avoidance in large MMORPG networks, and the results have largely trended toward preferential avoidance (e.g., Huang, Shen, & Contractor, 2013; Huang et al., 2009). Interestingly, one study assessed other outcome networks in an MMORPG data set apart from team membership, such as networks with ties based on being in the same virtual location or instant message history. Based on these alternative outcome networks, the researchers discovered significant effects of preferential attachment (Huang et al., 2009). Similar research has noted that high-level, expert players are disproportionately likely to receive communications from other players (Huffaker et al., 2009). These patterns of results indicate that popularity is likely a reality in Dragon Nest but perhaps is not reflected in the self-assembled team membership network.

Another explanation for the Hypothesis 1 result is that very popular Dragon Nest players are likely very high level, and therefore only engage in extremely challenging tasks, which were excluded from analyses. This possibility is probable, given that famous gamers generally tend to be very experienced and accomplished (Armelin, 2012); specifically, this is true for famous Chinese gamers (Hu & Sørensen, 2011). Still another conceivable explanation for the results is that many of the well-known players are trolls or individuals that make provocative comments and/or behave annoyingly to incite negative reactions. Trolls, while notorious, are not typically well-liked; it follows that famous trolls would be unpopular teammates, thus explaining the lack of a popularity effect in the observed data.

To evaluate the impact of relative attraction mechanisms on self-assembled team membership, Hypothesis 2 was tested using two variables: player level and guild role. Results for both variables supported the hypothesis. To evaluate the impact of relational attraction mechanisms on self-assembled team membership, Hypotheses 3a and 3b were tested. First, Hypothesis 3a posited that self-assembled teams would form based on familiarity more often than would be expected by chance, and was supported by the results for the guild membership network but was not supported by the results for the friendship network, although the two predictor networks were significantly correlated (as seen in Table 4). However, when the guild membership network was removed from the model described in Table 5, the impact of friendship on team self-assembly was rendered significant. This patterning of results indicates that the small, nonsignificant effect of friendship on team membership is likely a consequence of multicollinearity, due to the friendship and guild membership networks being largely redundant. In support of this line of reasoning, previous research has indicated that dramatic ERGM parameter estimate shifts are a symptom of multicollinearity (Lubell, Scholz, Berardo, & Robins, 2012). In addition, Hypothesis 3b, that self-assembled teams would form based on closure more often than would be expected by chance, was fully supported.

To assess the effect of situational attraction on self-assembled team membership, Hypothesis 4—which predicted that the self-assembled teams would exhibit a proximity effect—was tested and was supported. This finding buttresses similar research on team membership networks, which indicated a strong player preference for geographically proximal teammates (Huang et al., 2009). In other words, the Internet is not necessarily the great equalizer it is purported to be; although individuals have the opportunity to communicate across large distances, they still tend to abide by the law of proximity.

Finally, to compare and contrast the relative effects of absolute, relative, relational, and situational attraction on team self-assembly, Hypothesis 5, which posited that the proximity effect would be stronger than the other effects, was tested but was not supported. In reality, an absolute attraction mechanism (i.e., preferential avoidance) had the most profound effect of teaming tendencies, followed by relational attraction mechanisms (i.e., familiarity and closure), followed by the hypothesized strongest influence, a situational attraction mechanism (i.e., proximity).

Self-Assembled Team Composition and Performance

To evaluate the impact of absolute composition on self-assembled team performance, Hypothesis 6, which posited that networks of self-assembled teams with social hubs (i.e., popular individuals) would outperform networks of self-assembled teams without social hubs, was tested but was not supported by the data. To understand why the observed self-assembled team membership network exhibited such a complete lack of preferential attachment, it is important to understand how popularity effects are differentially applicable to different types of social networks. In the first place, it is clear that certain types of networks are prone to exhibiting popularity effects. For instance, one study found evidence that the formation process for Broadway musical teams was driven, at least in part, by preferential attachment. These teams emerged from a large, densely connected network of Broadway musical professionals, where a small number of celebrities acted as brokers between different groups of people (Guimerá et al., 2005). However, individuals embedded in more mundane network structures are given fewer opportunities to associate with others outside of their own clusters (Aldrich & Kim, 2007). Accordingly, it is possible that the tendency of the Dragon Nest team membership network to exhibit preferential avoidance is simply an inherent property of the type of network that it is. Especially when only considering dyads that engage in repetitive teaming, it follows that networks of online gamers will be much more likely to repeat interactions within their individual clusters without venturing to forge new relationships, and thereby will have more uniform degree distributions than networks akin to the Broadway musical team network. Alternatively, it is possible that the overarching lack of preferential attachment among Dragon Nest players was strategically driven. Previous research has suggested that decentralized network structures enhance team performance (Grund, 2012; Mehra, Smith, Dixon, & Robertson, 2006; Rulke & Galaskiewicz, 2000). In the current study, we observed a powerful effect of preferential avoidance among high-performing teammates and—given that preferential avoidance is associated with network decentralization—our results support those of prior research on the topic and suggest that Dragon Nest players may experience a competitive advantage by staying decentralized.

To assess the impact of relative composition on self-assembled team performance, Hypothesis 7 was tested using two variables: player level and completed quests. Interestingly, successful teams were more likely to assemble based on surface-level homogeneity (i.e., homogeneity based on level), while unsuccessful teams were more likely to assemble based on deep-level homogeneity (i.e., homogeneity based on completed quests); thus, due to the deep-level results, Hypothesis 7 was partially supported. However, in the case of player level, the successful group actually exhibited a homophily effect, while the other two performance groups did not. Thus, dyads that are relatively homogeneous in terms of level tend to outperform dyads that are disparate in terms of level. On one hand, this may be because homogeneous dyads engage in quests that are appropriately difficult for both players, and consequently, each individual is equally incentivized to expend effort to complete the task. On the other hand, for level-heterogeneous dyads questing undoubtedly involves a task that is either too easy for one player or too difficult for the other; the former situation may lead to poor performance on the part of the expert as a result of lack of motivation or boredom, while the latter situation will undoubtedly lead to poor performance on the part of the novice.

To gauge the impact of relational self-assembled team composition on performance, Hypotheses 8a and 8b were tested. First, Hypothesis 8a, which predicted that teams that assembled based on familiarity would outperform teams that did not assemble based on familiarity, was tested. Out of all the performance groups, the effect of friendship on team membership was the most pronounced for the high performers. Contrastingly, the unsuccessful performance group had no reported friendships, whatsoever. Accordingly, these results partially supported Hypothesis 8a. However, Hypothesis 8b, which proposed that teams that assembled based on closure would outperform teams that did not assemble based on closure, was not supported, due to the fact that all performance groups exhibited similar levels of transitivity. Some researchers argue that closure is not as integral to performance as once thought; for example, several studies have indicated that structural holes may be the more critical structural drivers of success (Soda, Usai, & Zaheer, 2004; Zaheer & Bell, 2005). Thus, perhaps there are simply other relational network structures that are far more influential on performance outcomes than is closure.

To evaluate the impact of situational composition on self-assembled team performance, Hypothesis 9—which posited that teams that assembled based on proximity would outperform teams that did not assemble based on proximity—was tested but was not supported by the data. Based on these results, it appears that the use of geographic proximity as a mechanism of team self-assembly simply does differentiate high performers from low performers, perhaps due to the fact that the effect of proximity is universally prevalent.

Especially when considering individuals collaborating virtually via the Internet, physical proximity may not be fundamental to the successful completion of a task. Specifically in the context of MMORPGs, a player's location in the virtual world of Dragon Nest may have more of an influence on their team member selection decisions and subsequent performance levels than their actual, physical location.

Finally, to compare and contrast the relative effects of absolute, relative, relational, and situational self-assembled team composition on performance, Hypothesis 10—which postulated that teams that assembled primarily based on heterophily would outperform teams that assembled primarily based on other attraction mechanisms—was tested but was not supported. For successful dyads, an absolute attraction mechanism (i.e., preferential avoidance) had the most profound effect of teaming tendencies, followed by three relational attraction mechanisms (i.e., friendship, shared guild membership, and closure), followed by a situational attraction mechanism (i.e., proximity), followed by a relative attraction mechanism (i.e., player-level homophily). For unsuccessful dyads, an absolute attraction mechanism (i.e., preferential avoidance) had the most profound effect of teaming tendencies, followed by two relational attraction mechanisms (i.e., shared guild membership and closure), followed by a situational attraction mechanism (i.e., proximity), followed by another relative attraction mechanism (i.e., completed quest homophily).

Generalizability

This article has two primary issues of generalizability: Are the teaming mechanisms and their consequences that were found in this study generalizable to teams in the workplace and/or teams that interact offline?

Workplace generalizability. The first issue of generalizability is as follows: Do this study's findings on teammate attraction and its consequences extend to teams that would be found in typical work settings? The self-assembled teams in Dragon Nest are just that—Groups of individuals who, of their own accord, joined forces to interdependently achieve collective goals. However, they differ from similarly ephemeral virtual work teams—such as teams of software developers or cyber security teams that rapidly assemble in response to a specific threat—in a few key ways. First, MMORPGs are leisure activities. With the notable exception of gold farmers (i.e., players who engage in gameplay to earn real-world money; Ahmad, Keegan, Srivastava, Williams, & Contractor, 2009), most MMORPG players are intrinsically motivated to achieve in-game goals (Dickey, 2007; Ryan, Rigby, & Przybylski, 2006). Consequently, as the current study employed a sample of self-assembled teams working together for enjoyment rather than the typical extrinsic motivators associated with work (e.g., a paycheck), it is possible that the patterning of reported results is specific to the situation of intrinsically motivated self-assembled teams. For instance, the findings that homophily and familiarity drive team self-assembly may be due to the fact that the task at hand was purely for pleasure. In an actual work situation, when the stakes are higher, individuals may be (a) less prone to team up with their friends, who may or may not be the best suited for the task at hand and (b) more prone to create diverse teams/capitalize on complementary skills.

Second, in the grand scheme of things, Dragon Nest teams are relatively short-lived, with membership that is in a constant state of flux. Importantly, transient, flexible teams like this *do exist* in the real world; as Edmonson (2012) implied, contemporary teams are increasingly fluid and less stable than the traditional, well-established teams of the past. However, the vast majority of workplace teams are still traditionally staffed groups of employees. This discrepancy does not impact the findings of this research, per se, but it is important to acknowledge it when interpreting the study's findings. For instance, results indicated no effect of popularity on teaming; in fact, there was an antipopularity effect. However, it is possible that popularity would drive team self-assembly in work groups with longer tenures. As people grow increasingly familiar with one another's knowledge, skills, and abilities, they may come to a common understanding of who the high-performing individuals are, which may result in these high performers becoming popular teammate choices.

Moreover, an additional issue of workplace generalizability stems from the fact that online gamers tend to be disproportionately young and educated, so the results of this study may not generalize to older, less educated groups of people. For instance, it may be the case that younger and older workers differ in their teammate selection rules; over time, as individuals choose teammates and then witness the consequences of those decisions, they may refine their implicit policies, affecting the types of factors they consider important in a teammate.

Offline generalizability. The second issue of generalizability is as follows: Do the current study's results surrounding teammate attraction and its consequences generalize to teams that form and interact offline? First, the Internet affords users a large degree of anonymity, which makes it relatively difficult to discern the characteristics of other users. Thus, it is possible that face-to-face teams rely more heavily on attraction mechanisms that hinge on stimuli that are salient in face-to-face contexts. For instance, individuals in the real world may be more prone to self-assembling based on similarity-attraction because of the face-to-face salience of surface-level characteristics. Moreover, there is clear evidence to suggest that online anonymity is a factor that facilitates behavioral disinhibition, which manifests in a variety of ways, including antisocial, benign, and prosocial (Hughes & Louw, 2013; Suler, 2004). So, considering the fact that individuals systematically act less inhibited online than they do offline, it follows that some of the current study's results may be specific to the online context. For instance, perhaps individuals are more willing to self-assemble into homogeneous teams online, a context where they feel distanced from societal norms that value diversity. Finally, one highly logistical point is that the effect of proximity on self-assembly will likely be stronger in face-to-face teams than virtual teams, due to the fact that the former are colocated and the latter are geographically distributed. It follows that Hypothesis 5, which posited that proximity would be the most powerful driver of team self-assembly, may hold true in contexts outside the virtual realm.

The intrinsic value of understanding virtual worlds. Although virtual and real-world teaming may not perfectly map on to one another, online teaming behaviors are inherently important to understand, regardless of their ability to generalize to other types of behaviors. Millions of people play MMORPGs and the economies of certain virtual worlds (such as EverQuest's Norrath) are comparable in size with the economies of large, real-world countries (such as Russia; Castronova, 2001, 2002) Thus, it is possible to consider virtual behaviors in a vacuum, as these human tendencies are becoming increasingly fundamental. Furthermore, as our world progresses to a state of ubiquitous computing, MMORPGs are being used by more people and in wider variety of venues (such as in the classroom; Susaeta et al., 2010). Therefore, as our virtual lives complexify and become richer, the demand to understand them will only increase.

Limitations

There are several important limitations of this study. First, the current study was entirely descriptive in nature. To regard the conclusions of this research with the highest degree of confidence, caution was taken to ensure that independent variables temporally preceded the dependent variable and that potential confounds were controlled for. Even so, causality cannot really be determined without conducting a true experiment (i.e., including an experimental manipulation, random assignment, and a control group). Furthermore, although the Dragon Nest data set is very large and includes a variety of different variables, we did not have access to many subject variables. In terms of evaluating certain questions, such as the impact of homophily on team self-assembly, knowledge of individuals' social identities would have been optimal.

One final limitation of this study is the possibility that aspects of the Dragon Nest context and game design drive some of the findings about teammate attraction and its consequences. As an example, Dragon Nest provides players with a party (i.e., team) creation interface, which allows them to generate and join teams with strangers. Some of the participants in this study may have used the party creation interface, negating meaningful inferences that assume individual agency when choosing teammates. Because the digital trace data set does not make it apparent which teams were groups of strangers who joined forces using the party creation interface and which were preexisting groups, we attempted to control for this feature of the game by only including dyads that worked together at least twice over the course of the day. Our reasoning behind this decision was that players who choose to continue working with one another must be psychologically driven to do so, and therefore it can be inferred that an attraction mechanism is motivating their teaming. However, it is also possible that individuals continue playing in teams of strangers that they formed using the party creation interface for completely arbitrary reasons. For instance, perhaps an individual is playing with a group of complete strangers and simply does not want to take the time or effort to use the matchmaking system again, so she repetitively teams with the same group. Thus, although this study operated under the inference that the Dragon Nest teaming relationships are psychologically meaningful, these ties may be weaker than was previously assumed.

Future Research

Future research could test the hypotheses set forth in this study with more experimental rigor by conducting a large-scale, virtual quasi-experiment with the goal of collecting digital traces. This type of big data methodology is still relatively rare but is increasingly being embraced by researchers of various disciplines so as to maximize internal validity (e.g., Aral, Muchnik, & Sundararajan, 2009; Aral & Walker, 2012). In addition, future research could address the hypotheses of the primary study using a mixed methods approach. Collecting and analyzing both digital trace and self-report data would provide a more holistic view of the team self-assembly process. The administration of a self-report survey in conjunction with big data collection would allow future researchers to test hypotheses related to a variety of subject variables—such as personality variables—that are not easily deduced via digital traces. Moreover, in the future, scholars could carry out field research to evaluate team self-assembly in populations who do not routinely use the Internet, such as older people in the United States.

Future research could also evaluate reciprocity as a potential relational attraction mechanism by measuring and assessing a directed team assembly outcome network. Another possibility would be for scholars to gauge the impact of temporal proximity on team self-assembly in two different ways. First, researchers could use a mixed methods approach and ask participants to self-report their schedules. Second, a team assembly network from an area with a wide variety of time zones could be analyzed. Finally, future research could use valued ERGMs to conduct research on valenced outcome networks (Krivitsky, 2012).

Scientific Advancements

The study of self-assembled teams is yet in its infancy, and this study made an important contribution to the growing body of scholarly knowledge regarding the attraction mechanisms that influence the formation of self-assembled teams. Specifically, the results of the primary study of this research revealed that individuals tend to self-assemble into teams that are homogeneous at the surface level and also tend to form teams based on prior friendship, closure, and geographic proximity. Furthermore—deviating from hypothesized outcomes—results also suggested that attractiveness as a teammate is not proportional to popularity as a teammate and situational attraction mechanisms are not the most influential on team self-assembly. This study also made a significant contribution to the growing body of scholarly knowledge regarding the performance of self-assembled teams. Specifically in terms of performance analyses, a number of significant differences between performance groups were evidenced: Unsuccessful teams were more homogeneous at the deep level than successful teams were, successful teams were more homogeneous at the surface level than unsuccessful teams were, and successful teams formed based on friendship more often than unsuccessful teams did.

One of the main theoretical contributions of this research was to evaluate which theories of interpersonal attraction may be applicable to the context of teaming. Based on the results, similarity-attraction (Byrne, 1971; McPherson et al., 2001), familiarity-attraction (Zajonc, 1968, 2001), closure (Heider, 1958), and proximity (Festinger et al., 1950; Newcomb, 1956) theories all seem suitable to apply to the workplace, while preferential attachment appears to be less appropriate. However, it may also be possible to apply the results of this study back to the context of interpersonal attraction. The interpersonal attraction literature has largely centered on the impact of exogenous variables (e.g., individual differences) on friendship and romance. Endogenous predictors, on the contrary, are not independent of the relational structure of the network but are defined by the structure of relationships, for example, closure (Hunter, Handcock, Butts, Goodreau, & Morris, 2008). While popular in the context of network science, exogenous predictors tend to be removed from the scholarly discussion of the psychology of attraction. The results of this study imply that endogenous variables are indeed important to consider when predicting team self-assembly ties. For instance, across many different models, one clear conclusion of this research is that dyads who share a common teammate are much more likely to be teammates themselves than dyads who do not share a common teammate. Based on these robust findings, it is clear that endogenous variables should be considered as potential predictors of interpersonal attraction, as well as teaming relationships.

Implications for Practice

Based on the results of this research, a couple of recommendations for teaming are clear. First, the results of the trace data analyses indicated that unsuccessful teams were more homogeneous than successful teams in terms of completed quests (i.e., a measure of deep-level experience). This finding supports the notion that deep-level homogeneity is bad for performance. Therefore, individuals should be wary of their natural predilections to team up with similarly skilled others, as this may result in inferior performance. In other words, having a variety of ability levels on a team may be good for performance. Second, the results indicated that successful teams formed based on friendship more often than unsuccessful teams did. Therefore, it appears that prior familiarity is an effective mechanism for team self-assembly, and one that most people are already cognizant of using, which may make it easier to harness.

Conclusion

It has been suggested that MMORPGs are the online laboratories that will mold the skills of the future leaders of tomorrow (Reeves et al., 2008). This study explored this suggestion; how might online relationships help explain offline relationships? Specifically, this study investigated the attraction mechanisms that guide teaming in the virtual world, the performance implications of said attraction mechanisms, and the potential similarities and differences of the virtual and real worlds. The results indicated that self-assembled teams form via three assembly mechanisms: homophily, familiarity, and proximity. Moreover, results of the trace data analyses indicated that successful and unsuccessful teams were homogeneous in terms of different characteristics, and successful teams formed based on friendship more often than unsuccessful teams did.

Acknowledgments

We are grateful to Benjamin Herndon, Bruce Walker, and Rustin Meyer for their insightful comments on earlier drafts of this article, and to Yun Huang for providing his input on our analyses. Finally, we thank Yunjie (Calvin) Xu and Yifan Li for their help recruiting participants and collecting data in China, and the Fudan University School of Management for supporting this project.

Declaration of Conflicting Interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding

The author(s) disclosed receipt of the following financial support for the research, authorship, and/or publication of this article: This research was supported by a grant from the National Science Foundation (East Asia and Pacific Summer Institutes Award No. 1414978) and a grant from the Army Research Office (W911NF-14-10686).

Notes

1. Three Dragon Nest quests for very high-level players that have maximum team sizes of eight are exceptions to this rule.
2. The Hmisc package in R (Harrell, 2014) was used to calculate these Pearson's correlation coefficients.
3. Exponential random graph models (ERGMs) were run with and without this control variable, and there were no qualitative changes in the pattern of results supported/not supported. In the end, we decided to retain this variable because of its conceptual importance as a control.
4. The decision to test for homogeneity effects using these particular variables was made based on the quality of the model fit and the ability to reach convergence; see subsequent section titled "Goodness of Fit" for further details.
5. For additional details on these variables and test results, please contact the corresponding author.
6. Markov chain Monte Carlo (MCMC) diagnostics and goodness-of-fit plots are available upon request; please contact the corresponding author for details.

References

Acedo, F. J., Barroso, C., Casanueva, C., & Galán, J. L. (2006). Co-authorship in management and organizational studies: An empirical and network analysis. *Journal of Management Studies*, *43*, 957-983. doi:10.1111/j.1467-6486.2006.00625.x

Ahmad, M. A., Keegan, B., Srivastava, J., Williams, D., & Contractor, N. (2009, August). Mining for gold farmers: Automatic detection of deviant players in MMOGs. In *CSE'09: International Conference on Computational Science and Engineering, 2009* (Vol. 4, pp. 340-345). New York, NY: IEEE. doi:10.1109/CSE.2009.307

Aldrich, H. E., & Kim, P. H. (2007). Small worlds, infinite possibilities? How social networks affect entrepreneurial team formation and search. *Strategic Entrepreneurship Journal*, *1*, 147-165. doi:10.1002/sej.8

Anderson, C. J., Wasserman, S., & Crouch, B. (1999). A *p** primer: Logit models for social networks. *Social Networks*, *21*, 37-66. doi:10.1016/S0378-8733(98)00012-4

Aral, S., Muchnik, L., & Sundararajan, A. (2009). Distinguishing influence-based contagion from homophily-driven diffusion in dynamic networks. *Proceedings of the National Academy of Sciences*, *106*, 21544-21549. doi:10.1073/pnas.0908800106

Aral, S., & Walker, D. (2012). Identifying influential and susceptible members of social networks. *Science*, *337*, 337-341. doi:10.1126/science.1215842

Armelin, L. (2012). Fame and celebrity within a virtual world: A case study of World of Warcraft (Unpublished master's thesis). Stockholm University, Stockholm, Sweden.

Armstrong, D. J., & Cole, P. (2002). Managing distances and differences in geographically distributed work groups. In S. E. Jackson & M. Ruderman (Eds.), *Diversity in work teams* (pp. 167-186). Washington, DC: American Psychological Association.

Autor, D. H., & Dorn, D. (2013, August). How technology wrecks the middle class. *The New York Times*, p. 24. Retrieved from http://opinionator.blogs.nytimes.com/2013/08/24/how-technology-wrecks-the-middle-class/

Back, M. D., Schmukle, S. C., & Egloff, B. (2008). Becoming friends by chance. *Psychological Science*, *19*, 439-440. doi:10.1111/j.1467-9280.2008.02106.x

Balkundi, P., & Harrison, D. A. (2006). Ties, leaders, and time in teams: Strong inference about network structure's effects on team viability and performance. *Academy of Management Journal*, *49*, 49-68. doi:10.5465/AMJ.2006.20785500

Barabási, A. L., & Albert, R. (1999). Emergence of scaling in random networks. *Science*, *286*, 509-512. doi:10.1126/science.286.5439.509

Barrick, M. R., Stewart, G. L., Neubert, M. J., & Mount, M. K. (1998). Relating member ability and personality to work-team processes and team effectiveness. *Journal of Applied Psychology*, *83*, 377-391. doi:10.1037/0021-9010.83.3.377

Batjargal, B. (2007). Network triads: Transitivity, referral and venture capital decisions in China and Russia. *Journal of International Business Studies*, *38*, 998-1012.

Burt, R. S. (2001). Structural holes versus network closure as social capital. In R. S. Burt, K. Cook & N. Lin (Eds.), *Social capital: Theory and research* (pp. 31-56). New York, NY: Aldine de Gruyter.

Butts, C. (2014). sna: Tools for social network analysis (Version 2.3-2) [R package]. Retrieved from http://CRAN.R-project.org/package=sna

Byrne, D. (1971). *The attraction paradigm*. New York, NY: Academic Press.

Byrne, D., & Nelson, D. (1965). Attraction as a linear function of proportion of positive reinforcements. *Journal of Personality and Social Psychology*, *1*, 659-663. doi:10.1037/h0022073

Cairncross, F. (2001). *The death of distance: How the communications revolution is changing our lives*. Boston, MA: Harvard Business Press.

Castronova, E. (2001, December). *Virtual worlds: A first-hand account of market and society on the cyberian frontier* (CESifo Working Paper Series No. *618)*. Retrieved from https://ssrn.com/abstract=294828

Castronova, E. (2002, July). *On virtual economies* (CESifo Working Paper Series No. *752)*. Retrieved from https://ssrn.com/abstract=338500

Castronova, E. (2006). On the research value of large games: Natural experiments in Norrath and Camelot. *Games and Culture*, *1*, 163-186. doi:10.1177/1555412006286686

Colizza, V., Flammini, A., Serrano, M. A., & Vespignani, A. (2006). Detecting rich-club ordering in complex networks. *Nature Physics*, *2*, 110-115. doi:10.1038/nphys209

Contractor, N. (2013). Some assembly required: Leveraging Web science to understand and enable team assembly. *Philosophical Transactions of the Royal Society of London A: Mathematical, Physical and Engineering Sciences*, *371*, Article 20120385. doi:10.1098/rsta.2012.0385

Couture-Beil, A. (2014). rjson: JSON for R. (Version 0.2.14) [R package]. Retrieved from http://CRAN.R-project.org/package=rjson

Cowles, M. K., & Carlin, B. P. (1996). Markov chain Monte Carlo convergence diagnostics: A comparative review. *Journal of the American Statistical Association*, *91*, 883-904.

Cranmer, S. J., & Desmarais, B. A. (2011). Inferential network analysis with exponential random graph models. *Political Analysis*, *19*, 66-86. doi:10.1093/pan/mpq037

Cummings, J. N., & Kiesler, S. (2005). Collaborative research across disciplinary and organizational boundaries. *Social Studies of Science*, *35*, 703-722. doi:10.1177/0306312705055535

Cummings, J. N., & Kiesler, S. (2007). Coordination costs and project outcomes in multi-university collaborations. *Research Policy*, *36*, 1620-1634. doi:10.1016/j.respol.2007.09.001

De Dreu, C. K., & Van Vianen, A. E. (2001). Managing relationship conflict and the effectiveness of organizational teams. *Journal of Organizational Behavior*, *22*, 309-328. doi:10.1002/job.71

Dickey, M. D. (2007). Game design and learning: A conjectural analysis of how massively multiple online role-playing games (MMORPGs) foster intrinsic motivation. *Educational Technology Research and Development*, *55*, 253-273. doi:10.1007/s11423-006-9004-7

Ebbesen, E. B., Kyos, G. L., & Konečni, V. J. (1976). Spatial ecology: Its effects on the choice of friends and enemies. *Journal of Experimental Social Psychology*, *12*, 505-518. doi:10.1016/0022-1031(76)90030-5

Edmonson, A. C. (2012). Teamwork on the fly: How to master the new art of teaming. *Harvard Business Review*, *90*, 72-80.

Eisenhardt, K. M., & Schoonhoven, C. B. (1990). Organizational growth: Linking founding team, strategy, environment, and growth among U.S. semiconductor ventures, 1978-1988. *Administrative Science Quarterly*, *35*, 504-529. doi:10.2307/2393315

Espinosa, J. A., Slaughter, S. A., Kraut, R. E., & Herbsleb, J. D. (2007). Familiarity, complexity, and team performance in geographically distributed software development. *Organization Science*, *18*, 613-630. doi:10.1287/orsc.1070.0297

Festinger, L., Back, K. W., & Schachter, S. (1950). *Social pressures in informal groups: A study of human factors in housing*. Redwood City, CA: Stanford University Press.

Gelman, A., & Hill, J. (2006). Missing-data imputation. In A. Gelman & J. Hill (Eds.), *Data analysis using regression and multilevel/hierarchical models* (pp. 529-544). Cambridge, UK: Cambridge University Press.

Gruenfeld, D. H., Mannix, E. A., Williams, K. Y., & Neale, M. A. (1996). Group composition and decision making: How member familiarity and information distribution affect process and performance. *Organizational Behavior and Human Decision Processes*, *67*, 1-15. doi:10.1006/obhd.1996.0061

Grund, T. U. (2012). Network structure and team performance: The case of English Premier League soccer teams. *Social Networks*, *34*, 682-690. doi:10.1016/j.socnet.2012.08.004

Guimerá, R., Uzzi, B., Spiro, J., & Amaral, L. A. N. (2005). Team assembly mechanisms determine collaboration network structure and team performance. *Science*, *308*, 697-702. doi:10.1126/science.1106340

Hahn, J., Moon, J. Y., & Zhang, C. (2008). Emergence of new project teams from open source software developer networks: Impact of prior collaboration ties. *Information Systems Research*, *19*, 369-391.

Hai-Bo, H., Jin-Li, G., & Jun, C. (2012). Modeling online social networks based on preferential linking. *Chinese Physics B*, *21*, Article 118902.

Handcock, M. S., Hunter, D. R., Butts, C. T., Goodreau, S. M., Krivitsky, P., Bender-deMoll, S., . . .Morris, M. (2014). statnet: Software tools for the statistical modeling of network data (Version 2014.2.0) [R package]. Retrieved from http://cran.r-project.org/web/packages/statnet/index.html

Harrell, F. E., Jr. (2014). Hmisc: Harrell miscellaneous (Version 3.14-6) [R package]. Retrieved from http://CRAN.R-project.org/package=Hmisc

Harris, J. K. (2014). *An introduction to exponential random graph modeling*. Thousand Oaks, CA: SAGE.

Harrison, D. A., Mohammed, S., McGrath, J. E., Florey, A. T., & Vanderstoep, S. W. (2003). Time matters in team performance: Effects of member familiarity, entrainment, and task discontinuity on speed and quality. *Personnel Psychology*, *56*, 633-669. doi:10.1111/j.1744-6570.2003.tb00753.x

Heider, F. (1958). *The psychology of interpersonal relations*. New York, NY: John Wiley.

Hijmans, R. J. (2014). geosphere: Spherical trigonometry (Version 1.3-11) [R package]. Retrieved from http://CRAN.R-project.org/package=geosphere

Hill, G. W. (1982). Group versus individual performance: Are N + 1 heads better than one? *Psychological Bulletin*, *91*, 517-539. doi:10.1037/0033-2909.91.3.517

Hinds, P. J., Carley, K. M., Krackhardt, D., & Wholey, D. (2000). Choosing work group members: Balancing similarity, competence, and familiarity. *Organizational Behavior and Human Decision Processes*, *81*, 226-251. doi:10.1006/obhd.1999.2875

Hoegl, M., & Proserpio, L. (2004). Team member proximity and teamwork in innovative projects. *Research Policy*, *33*, 1153-1165. doi:10.1016/j.respol.2004.06.005

Holland, P. W., & Leinhardt, S. (1976). The statistical analysis of local structure in social networks. In D. R. Heise (Ed.), *Sociological methodology* (pp. 1-45). San Francisco, CA: Jossey-Bass.

Hollenbeck, J. R., DeRue, D. S., & Guzzo, R. (2004). Bridging the gap between I/O research and HR practice: Improving team composition, team training, and team task design. *Human Resource Management*, *43*, 353-366. doi:10.1002/hrm.20029

Hu, Y., & Sørensen, O. J. (2011). Innovation in virtual networks: Evidence from the Chinese online game industry. *Journal of Knowledge-Based Innovation in China*, *3*, 198-215. doi:10.1108/17561411111167863

Huang, Y., Shen, C., & Contractor, N. S. (2013). Distance matters: Exploring proximity and homophily in virtual world networks. *Decision Support Systems*, *55*, 969-977. doi:10.1016/j.dss.2013.01.006

Huang, Y., Shen, C., Williams, D., & Contractor, N. S. (2009, August). Virtually there: Exploring proximity and homophily in a virtual world. In *Proceedings from CSE'09: International Conference on Computational Science and Engineering, 2009*. New York, NY: IEEE. doi:10.1109/CSE.2009.471

Huang, Y., Ye, W., Bennett, N., & Contractor, N. S. (2013). Functional or social? Exploring teams in online games. In *Proceedings from CSCW'13*. New York, NY: Association for Computing Machinery. doi:10.1145/2441776.2441822

Huffaker, D., Wang, J., Treem, J., Ahmad, M. A., Fullerton, L., Williams, D., . . . Contractor, N. S. (2009, August). The social behaviors of experts in massive multiplayer online role-playing games. In *CSE'09: International Conference on Computational Science and Engineering* (Vol. 4, pp. 326-331). New York, NY: IEEE. doi:10.1109/CSE.2009.13

Hughes, M., & Louw, J. (2013). Playing games: The salience of social cues and group norms in eliciting aggressive behaviour. *South African Journal of Psychology*, *43*, 252-262. doi:10.1177/0081246313482629

Hunter, D. R. (2007). Curved exponential family models for social networks. *Social Networks*, *29*, 216-230. doi:10.1016/j.socnet.2006.08.005

Hunter, D. R., Goodreau, S. M., & Handcock, M. S. (2008). Goodness of fit of social network models. *Journal of the American Statistical Association*, *103*, 248-258. doi:10.1198/016214507000000446

Hunter, D. R., Handcock, M. S., Butts, C. T., Goodreau, S. M., & Morris, M. (2008). ergm: A package to fit, simulate and diagnose exponential-family models for networks. *Journal of Statistical Software*, *24*, 1-29.

Huston, T. L., & Levinger, G. (1978). Interpersonal attraction and relationships. *Annual Review of Psychology*, *29*, 115-156. doi:10.1146/annurev.ps.29.020178.000555

Jehn, K. A., & Shah, P. P. (1997). Interpersonal relationships and task performance: An examination of mediating processes in friendship and acquaintance groups. *Journal of Personality and Social Psychology*, *72*, 775-790. doi:10.1037/0022-3514.72.4.775

Johnson, S. L., & Faraj, S. (2005). Preferential attachment and mutuality in electronic knowledge networks. In *Proceedings of the 26th International Conference on Information Systems* (pp. 287-299). New York, NY: Association for Computing Machinery.

Jones, B. F., Wuchty, S., & Uzzi, B. (2008). Multi-university research teams: Shifting impact, geography, and stratification in science. *Science*, *322*, 1259-1262. doi:10.1126/science.1158357

Joshi, A., Labianca, G., & Caligiuri, P. M. (2002). Getting along long distance: Understanding conflict in a multinational team through network analysis. *Journal of World Business*, *37*, 277-284. doi:10.1016/S1090-9516(02)00094-9

Katz, N., Lazer, D., Arrow, H., & Contractor, N. (2005). The network perspective on small groups. In M. S. Poole & A. B. Hollingshead (Eds.), *Theories of small groups: Interdisciplinary perspectives* (pp. 277-312). Thousand Oaks, CA: SAGE.

Kauffeld, S. (2006). Self-directed work groups and team competence. *Journal of Occupational and Organizational Psychology*, *79*, 1-21. doi:10.1348/096317905X53237

Kirkman, B. I., & Rosen, B. (2001). Powering up teams. *Organizational Dynamics*, *28*, 48-66. doi:10.1016/S0090-2616(00)88449-1

Kleinberg, J. (2000). The small-world phenomenon: An algorithmic perspective. In *Proceedings from the Thirty-Second Annual ACM Symposium on Theory of Computing*. New York, NY: Association for Computing Machinery. doi:10.1145/335305.335325

Kozlowski, S. W. J., & Klein, K. J. (2000). A multilevel approach to theory and research in organizations: Contextual, temporal, and emergent processes. In K. J. Klein & S. W. J. Kozlowski (Eds.), *Multilevel theory, research and methods in organizations: Foundations, extensions, and new directions* (pp. 3-90). San Francisco, CA: Jossey-Bass.

Krackhardt, D. (1987). QAP partialling as a test of spuriousness. *Social Networks*, *9*, 171-186. doi:10.1016/0378-8733(87)90012-8

Krackhardt, D., & Kilduff, M. (1999). Whether close or far: Social distance effects on perceived balance in friendship networks. *Journal of Personality and Social Psychology*, *76*, 770-782. doi:10.1037/0022-3514.76.5.770

Krivitsky, P. N. (2012). Exponential-family random graph models for valued networks. *Electronic Journal of Statistics*, *6*, 1100-1128. doi:10.1214/12-EJS696

Lazarsfeld, P. F., & Merton, R. K. (1954). Friendship as a social process: A substantive and methodological analysis. *Freedom and Control in Modern Society*, *18*, 18-66.

Leskovec, J., & Horvitz, E. (2007). *Worldwide buzz: Planetary-scale views on an instant-messaging network*. Redmond, WA: Microsoft Research, Technical Publication.

Leskovec, J., & Horvitz, E. (2008, April). Planetary-scale views on an instant-messaging network. In *Proceedings of the 17th International Conference on World Wide Web* (pp. 915-924). New York, NY: Association for Computing Machinery.

Lo, S. (2008). The impact of online game character's outward attractiveness and social status on interpersonal attraction. *Computers in Human Behavior*, *24*, 1947-1958. doi:10.1016/j.chb.2007.08.001

Lubell, M., Scholz, J., Berardo, R., & Robins, G. (2012). Testing policy theory with statistical models of networks. *Policy Studies Journal*, *40*, 351-374. doi:10.1111/j.1541-0072.2012.00457.x

Lungeanu, A., Huang, Y., & Contractor, N. S. (2014). Understanding the assembly of interdisciplinary teams and its impact on performance. *Journal of Informetrics*, *8*, 59-70. doi:10.1016/j.joi.2013.10.006

Lusher, D., Koskinen, J., & Robins, G. (Eds.). (2013). *Exponential random graph models for social networks: Theory, methods, and applications*. Cambridge, UK: Cambridge University Press.

Lusher, D., Kremer, P., & Robins, G. (2014). Cooperative and competitive structures of trust relations in teams. *Small Group Research*, *45*, 3-36. doi:10.1177/1046496413510362

Maoz, Z. (2012). Preferential attachment, homophily, and the structure of international networks, 1816-2003. *Conflict Management and Peace Science*, *29*, 341-369. doi:10.1177/0738894212443344

McDonough, I. I. I., Kahn, K. B., & Barczak, G. (2001). An investigation of the use of global, virtual, and colocated new product development teams. *The Journal of Product Innovation Management*, *18*, 110-120. doi:10.1111/1540-5885.1820110

McPherson, M., Smith-Lovin, L., & Cook, J. M. (2001). Birds of a feather: Homophily in social networks. *Annual Review of Sociology*, *27*, 415-444. doi:10.1146/annurev.soc.27.1.415

Mehra, A., Smith, B. R., Dixon, A. L., & Robertson, B. (2006). Distributed leadership in teams: The network of leadership perceptions and team performance. *The Leadership Quarterly*, *17*, 232-245. doi:10.1016/j.leaqua.2006.02.003

Mello, A. S., & Ruckes, M. E. (2006). Team composition. *Journal of Business*, *79*, 1019-1039. doi:10.1086/500668

Miao-Miao, L., & Jun, W. (2013). The role of transitivity on the intra-team knowledge transfer. In *Proceedings of the20th International Conference on Management Science and Engineering* (pp. 1341-1348). New York, NY: IEEE. doi:10.1109/ICMSE.2013.6586446

Milojević, S. (2010). Modes of collaboration in modern science: Beyond power laws and preferential attachment. *Journal of the American Society for Information Science and Technology*, *61*, 1410-1423. doi:10.1002/asi.21331

Mislove, A., Koppula, H. S., Gummadi, K. P., Druschel, P., & Bhattacharjee, B. (2008, August). Growth of the Flickr social network. In *Proceedings of the First*

Workshop on Online Social Networks (pp. 25-30). New York, NY: Association for Computing Machinery. doi:10.1145/1397735.1397742

Molleman, E. (2005). The multilevel nature of team-based work research. *Team Performance Management*, *11*, 113-124. doi:10.1108/13527590510606316

Moreland, R. L., & Beach, S. R. (1992). Exposure effects in the classroom: The development of affinity among students. *Journal of Experimental Social Psychology*, *28*, 255-276. doi:10.1016/0022-1031(92)90055-O

Morris, M., Handcock, M. S., & Hunter, D. R. (2008). Specification of exponential-family random graph models: Terms and computational aspects. *Journal of Statistical Software*, *24*, 1548-7660.

Nahemow, L., & Lawton, M. P. (1975). Similarity and propinquity in friendship formation. *Journal of Personality and Social Psychology*, *32*, 205-213. doi:10.1037/0022-3514.32.2.205

Newcomb, T. M. (1956). The prediction of interpersonal attraction. *American Psychologist*, *11*, 575-586. doi:10.1037/h0046141

Newcomb, T. M. (1961). *The acquaintance process*. New York, NY: Holt, Rinehart & Winston.

Owens, D. A., Mannix, E. A., & Neale, M. A. (1998). Strategic formation of groups: Issues in task performance and team member selection. *Research on Managing Groups and Teams*, *1*, 149-165.

Papadopoulos, F., Kitsak, M., Serrano, M. Á., Boguñá, M., & Krioukov, D. (2012). Popularity versus similarity in growing networks. *Nature*, *489*, 537-540. doi:10.1038/nature11459

Pearce, C. L. (2004). The future of leadership: Combining vertical and shared leadership to transform knowledge work. *The Academy of Management Executive*, *18*, 47-57. doi:10.5465/AME.2004.12690298

Pink, D. H. (2011). *Drive: The surprising truth about what motivates us*. New York, NY: Penguin.

Priest, R. F., & Sawyer, J. (1967). Proximity and peership: Bases of balance in interpersonal attraction. *American Journal of Sociology*, *72*, 633-649. doi:10.1086/224400

Putzke, J., Fischbach, K., Schoder, D., & Gloor, P. A. (2010). The evolution of interaction networks in massively multiplayer online games. *Journal of the Association for Information Systems*, *11*, 69-94.

Quintane, E., Pattison, P. E., Robins, G. L., & Mol, J. M. (2013). Short- and long-term stability in organizational networks: Temporal structures of project teams. *Social Networks*, *35*, 528-540. doi:10.1016/j.socnet.2013.07.001

Reagans, R., Zuckerman, E., & McEvily, B. (2004). How to make the team: Social networks vs. demography as criteria for designing effective teams. *Administrative Science Quarterly*, *49*, 101-133. doi:10.2307/4131457

Reagans, R., & Zuckerman, E. W. (2001). Networks, diversity, and productivity: The social capital of corporate R&D teams. *Organization Science*, *12*, 502-517. doi:10.1287/orsc.12.4.502.10637

Reeves, B., Malone, T. W., & O'Driscoll, T. (2008). Leadership's online labs. *Harvard Business Review*, *86*, 58-66.

Reis, H. T., Maniaci, M. R., Caprariello, P. A., Eastwick, P. W., & Finkel, E. J. (2011). Familiarity does indeed promote attraction in live interaction. *Journal of Personality and Social Psychology*, *101*, 557-570. doi:10.1037/a0022885

Robins, G., Pattison, P., Kalish, Y., & Lusher, D. (2007). An introduction to exponential random graph (*p**) models for social networks. *Social Networks*, *29*, 173-191. doi:10.1016/j.socnet.2006.08.002

Ruef, M., Aldrich, H. E., & Carter, N. M. (2003). The structure of founding teams: Homophily, strong ties, and isolation among U.S. entrepreneurs. *American Sociological Review*, *68*, 195-222.

Rulke, D. L., & Galaskiewicz, J. (2000). Distribution of knowledge, group network structure, and group performance. *Management Science*, *46*, 612-625. doi:10.1287/mnsc.46.5.612.12052

Ryan, R. M., Rigby, C. S., & Przybylski, A. (2006). The motivational pull of video games: A self-determination theory approach. *Motivation and Emotion*, *30*, 344-360. doi:10.1007/s11031-006-9051-8

Schug, J., Yuki, M., Horikawa, H., & Takemura, K. (2009). Similarity attraction and actually selecting similar others: How cross-societal differences in relational mobility affect interpersonal similarity in Japan and the USA. *Asian Journal of Social Psychology*, *12*, 95-103. doi:10.1111/j.1467-839X.2009.01277.x

Soda, G., Usai, A., & Zaheer, A. (2004). Network memory: The influence of past and current networks on performance. *Academy of Management Journal*, *47*, 893-906. doi:10.2307/20159629

South, A. (2011). rworldmap: Mapping global data [R package]. Retrieved from http://cran.r-project.org/web/packages/rworldmap/index.html

Suler, J. (2004). The online disinhibition effect. *CyberPsychology & Behavior*, *7*, 321-326. doi:10.1089/1094931041291295

Susaeta, H., Jimenez, F., Nussbaum, M., Gajardo, I., Andreu, J. J., & Villalta, M. (2010). From MMORPG to a classroom multiplayer presential role playing game. *Educational Technology & Society*, *13*, 257-269.

Tziner, A. (1985). How team composition affects task performance: Some theoretical insights. *Psychology Reports*, *57*, 1111-1119. doi:10.2466/pr0.1985.57.3f.1111

Wang, Y., Zhuang, G., Xu, C., & An, Z. (2007). The air pollution caused by the burning of fireworks during the lantern festival in Beijing. *Atmospheric Environment*, *41*, 417-431. doi:10.1016/j.atmosenv.2006.07.043

Wax, A., Dalrymple, K. M., DeChurch, L. A., Walker, B. N., & Contractor, N. S. (2014, February). *Interdisciplinary design teams: Self-organization and performance*. Paper presented at the 34th Annual International Network for Social Network Analysis Sunbelt Conference, St. Petersburg, FL.

Williams, D., Contractor, N., Poole, M. S., Srivastava, J., & Cai, D. (2011). The virtual worlds exploratorium: Using large-scale data and computational techniques for communication research. *Communication Methods and Measures*, *5*, 163-180. doi:10.1080/19312458.2011.568373

Wimmer, A., & Lewis, K. (2010). Beyond and below racial homophily: ERG models of a friendship network documented on Facebook. *The American Journal of Sociology*, *116*, 583-642. doi:10.1086/653658

Yuan, Y. C., & Gay, G. (2006). Homophily of network ties and bonding and bridging social capital in computer-mediated distributed teams. *Journal of Computer-Mediated Communication*, *11*, 1062-1084. doi:10.1111/j.1083-6101.2006.00308.x

Zaccaro, S. J., & DiRosa, G. A. (2012). The process of team staffing: A review of relevant studies. In G. P. Hodgkinson & J. K. Ford (Eds.), *International review of industrial and organizational psychology* (Vol. 27, pp. 197-229). Hoboken, NJ: John Wiley.

Zaheer, A., & Bell, G. G. (2005). Benefiting from network position: Firm capabilities, structural holes, and performance. *Strategic Management Journal*, *26*, 809-825. doi:10.1002/smj.482

Zajonc, R. B. (1968). The attitudinal effects of mere exposure. *Journal of Personality and Social Psychology, Monograph Supplement*, *9*, 1-27. doi:10.1037/h0025848

Zajonc, R. B. (2001). Mere exposure: A gateway to the subliminal. *Current Directions in Psychological Science*, *10*, 224-228. doi:10.1111/1467-8721.00154

Zhu, M., Huang, Y., & Contractor, N. S. (2013). Motivations for self-assembling into project teams. *Social Networks*, *35*, 251-264. doi:10.1016/j.socnet.2013.03.001

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