Assessing how Team Task Influences Team Assembly Through Network Analysis

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Abstract. What traits make users appealing as potential teammates? How do the traits that users seek out in teammates stay constant and differ as the task changes? Our study explores the social networks and skills involved in teammate selection. We performed a quasi-experimental study to analyze teammate choices for three tasks: launching a start-up, surviving in a jungle, and running an election campaign. We conducted our study in one graduate and two undergraduate classes, where students self-assembled into teams using a team recommender software. We analyzed our results using Exponential Random Graph Models (ERGMs). Our results indicate that (a) among all three tasks, prior relationships were important, while (b) the importance of certain project skills varied across the three task types when choosing potential teammates.

Keywords: Team Formation, Task Type, ERGM, Social Networks

1 Introduction

As projects become more complex and require knowledge from different fields, people organize into teams to solve challenging tasks. Organizations are encouraging their members to self-assemble teams, enabling them to search and choose the most appropriate teammates [8, 31, 27]. Research has supported that these self-assembled teams can achieve high levels of satisfaction, cohesion, and performance [28, 22, 3], but studies have been inconclusive concerning the decision-making processes. Thus, several scholars have explored how characteristics, such as competence, similarity, and familiarity [11, 2, 7] influence decisions.

While the literature on self-assembled teams is expanding among different research disciplines, little is known about how the task type—the set of shared goals that gets transformed into plans and strategies [16]—affects individuals' teammate choices. Related literature has explored the relationships between the team task with team processes and performance [25, 6, 12], but how the task-type influences individuals' teammate choices has not been deeply analyzed, which ultimately determines team composition.

Toward that aim, this paper explores the effect of the task type on the decisions that people make about whom to work with. We report a quasi-experimental study with 155 participants examining this question through a network perspective. In a three-round series, participants had to self-assemble hypothetical teams for three tasks: launching a start-up, surviving in the jungle, and running an election campaign. Participants used a digital platform to find potential teammates and invite them to form a team. We model three distinct networks, and each network represents participants' teammate choices for a task. To understand whether participants' desired traits changed or stayed constant among these three tasks, we used Exponential Random Graph Models (ERGMs) to compare the variation of structural signatures, edge-covariates, individuals' attributes, and homophily effects. Which factors remain the same over these three tasks? Which factors change?

Our contributions are twofold. First, this study sheds light on how the team task influences self-assembly team formation mechanisms, a theoretical relationship that has not been deeply explored. Second, we contribute to the complex social networks literature with an empirical case study of team assembly using network analysis. These findings crystallize how teams' goals and their context affect their participants' decision-making processes and team composition.

2 Theoretical background

Task types correspond to the specific activities, plans, and strategies in which a team works to achieve its goals [9]. Task types define to what extent the team composition, norms, resources, processes, and context fit to the teams' goals [16]. The study of task type emerged in the early small group research [10]. In the 1960s, scholars discussed performance of individuals versus groups [4]. Steiner [23] noted that comparing individuals versus teams was addressing a specific kind of task, which the performance trucks that of its best member. Steiner then identified five types of tasks for which teams can operate: *disjunctive tasks*, *conjunctive tasks*, *additive tasks*, *compensatory tasks*, and *complementary tasks* . Based on this taxonomy, individuals and groups can be more advantageous for these types of tasks. After Steiner's taxonomy, other scholars continued exploring how tasks could be classified and described. Hackman [9] identified three types of tasks: *production tasks*, *discussion tasks*, and *problem-solving tasks*. McGrath [17] presented the task circumplex model, which differentiates group activities between four main categories: generate, choose, negotiate, and execute. The model further subdivides these categories into eight sub-categories: planning tasks, creativity tasks, intellective tasks, decision-making tasks, cognitive tasks, mixed-motive tasks, contest tasks, and performance tasks. Wildman et al. [29] developed an integrated taxonomy of task types. This work presented categories that represent different types of work tasks that teams can engage in: managing others, advising others, human service, negotiation, psychomotor action, defined problem-solving, and ill-defined problem-solving. Stewart and Barrick [25] examined team task type and found significant differences between teams engaged in conceptual and behavioral tasks. Nouri et al. [18] discover that matching the task type and the task enabled cultural teams to perform better. Strauss [26] explored how communication varied among groups depending on the task type.

Finally, several computer science scholars have model task types as a combination of skills in order to find teams that satisfy the task's goals (e.g., [15]).

Although research on task types has been conducted for more than 60 years, less is known about how the task type influences team formation. Understanding the link between team formation and task types could leverage individuals' decisions for choosing more suitable teammates for the task, as well as enhancing the composition of the team [19, 30]. We study this relationship through a network lens arising at the individual, relational, and structural signature levels by analyzing individuals' choices as a network. Our research questions are:

RQ1. When individuals are choosing potential teammates, what are the decision-making factors that stay constant among different task-types?
RQ2. When individuals are choosing potential teammates, what are the decision-making factors that change among different task-types?

3 Methodology

To answer these research questions, we performed a study at one university in the US with one undergraduate class in 2019 (C_1), one graduate class in 2019 (C_2), and one undergraduate class in 2020 (C_3). All classes were related to team studies and taught by the same instructor. For each class, participants had to assemble teams for three different tasks. This exercise was carried out in a single session during their class. All courses required participants to assemble into teams of approximately five members. In total, 155 students attended these classes ($N_{C_1} = 444$, $N_{C_2} = 70$, $N_{C_3} = 41$), 101 were female ($N^{fem}_{C_1} = 25$, $N^{fem}_{C_2} = 57$, $N^{fem}_{C_3} = 19$). The mean age was 23.50 (SD=7.94), and 28.39% were international students ($N^{int}_{C_1} = 15.91\%$,$N^{int}_{C_2} = 50.00\%$,$N^{int}_{C_3} = 4.88\%$). Students participated voluntarily and provided informed consent. No incentives were provided.

3.1 Procedure

To understand to what extent the task-type influences participants' teammate choices, we asked them to choose their team members for three different tasks. Since participants would not be performing the task itself, we chose tasks that relied mostly on generating ideas and plans, rather than their execution and outputs. In three rounds, participants were asked to form teams for the following tasks: (1) launch a start-up, (2) survive in the jungle, and (3) run an election campaign. According to McGrath's circumplex model, the first task corresponds to a *planning* task since the team's goal is to generate plans and cooperate together in an endeavor. The second task is classified as a *performance* task since the team is expected to succeed in their goals and without any rivals. Finally, the third task is classified as a *competitive* task since the team must defeat rivals who are competing for the same position.

We conducted this experiment using a team formation system called *My-DreamTeam* [5] to track their teammate choices. On the platform, participants first create profiles, search for others, and send invitations that can be accepted or rejected until teams are formed. Participants completed the following steps:

Initial survey Participants were asked to populate a profile on the platform. The platform enabled participants to display public information in their profiles, such as their background, hobbies, and motivations. Participants also answered a survey to assess their personality, social networks, project skills, leadership experience, and creativity. These answers were confidential but used by the team formation system to generate recommendations of potential teammates.

Search stage After participants completed their profiles and surveys, they filled out a search query to find potential teammates. The query prompted participants to provide their preferences for potential teammates on the attributes collected in the initial survey on a 7-point Likert scale, ranging from “Not important at all” (-3), to “Don’t care” (0), and “Yes, for sure.” (+3). The platform used all of the preferences included in the search query and rank-ordered all potential teammates based on their match to the query and displayed them in a list.

Team formation stage After browsing potential teammates’ profiles, participants sent invitations to others to join their teams. For each course, participants had 10 minutes to assemble their teams for each task. The recipient had a choice between accepting, rejecting, or ignoring invitations. If the recipient accepts the invitation, the sender and the recipient will form a team. If the recipient or sender were already part of a team, their teams would merge if the final team size was no greater than the maximum size allowed. At the end, some students could not have found a teammate.

3.2 Network Modeling

We use Exponential Random Graph Models (ERGMs) to identify the individual, relational, and network-level variables that explain participants’ motivations behind team member selection. ERGMs are a type of stochastic model that provide an appropriate analytic methodology to test multi-theoretical multilevel network hypotheses [21]. This statistical model estimates the likelihood of the observed network structures emerging from all possible network configurations generated based on certain hypothesized self-organizing principles. Like logistic regressions, ERGM uses Maximum Likelihood Criterion (MLC) to estimate the network statistics’ coefficients. Positive and significant coefficients indicate that the corresponding independent variable is more likely to influence invitations being extended than by chance. We use Markov-Chain Monte Carlo (MCMC) to identify maximum likelihood estimates (MLE) for parameter values. MCMC simulates thousands of random networks fitting the model’s quantifiable properties. Once the ERGM and its coefficients are estimated, we test whether the observed network is likely to be observed within the distribution of simulated networks. Analyses were carried out using the *ergm* package [13] on R 3.6.0 [20].

To study participants’ teammate decisions for each task, we gathered invites sent by participants and modeled a network. To study the effect among the courses, we created an adjacency matrix for each course and combined them in a block diagonal matrix. We specified structural zeros in the other entries of the block diagonal matrix to disallow the possibility of participants from different courses forming ties. We created an invitation network from each block diagonal matrix, composed of nodes (representing participants) with attributes (representing individual traits) and edge-covariates (representing their prior social relationships), directed edges pointing from the sender node of an invitation to its receiver node. After populating each of the invitation network's nodes with their respective attribute values, it was passed into an ERGM, yielding log-odds estimations for the likelihood of ties forming between two nodes as a function of the estimates. We modeled three ERGMs, one for each task (Figure 1).

To measure the fit of the estimated ERGMs to the observed data, we use the Goodness of Fit (GoF) test from the *ergm* package. We sample one network out of every 1,000, spread across 10 million iterations, and compare the characteristics of generated networks to the statistics of the observed networks.

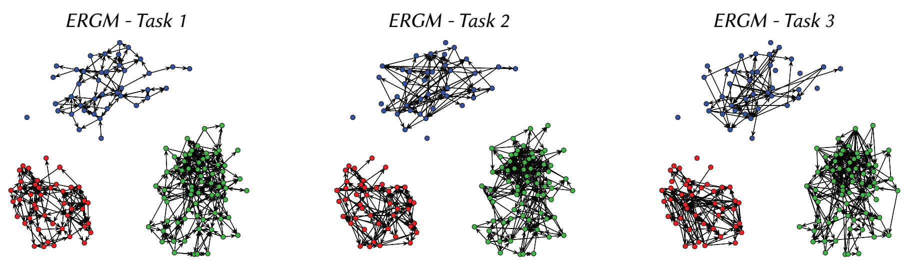

Fig. 1. Each network represents participants assembling teams for a specific task. A directed tie represents an invitation between two individuals.

3.3 Variables and Measurements

Based on ERGM statistical coefficients, we controlled to what extent individual, relational, and network-level variables influenced participants' teammate choices. We modeled these measurements using the *ergm* package. The variables were used as nodal covariates for senders (out-links) and receivers (in-links).

Structural effects *Popularity.* We measured the likelihood that a participant will receive a disproportionate number of invitations compared to others. We included the geometrically weighted indegree term (i.e., the weighted count of invitations they received), which models participants' in-degree distribution and estimates how concentrated are the received invitations in certain participants. A significantly positive estimate implies a less centralized network that has more middle-degree participants, and invitations are homogeneously distributed. A negative estimate reflects the presence of hubs, who received a lot more invitations. Popularity was modeled using the *gwidegree* term.

Activity. We measured the likelihood that a participant will send a disproportionate number of invitations. We included the geometrically weighted outdegree term (i.e., the weighted count of invitations they sent), which models participants' outdegree distribution and estimates how concentrated are the sent invitations in certain users. A significantly positive coefficient implies a less centralized network and a homogeneous distribution of senders. Users' activity was modeled using the *gwodegree* term.

Two-path Invitations. We measure to what extent participants who did not send invitations were potentially connected through third-participants. This term was measured by calculating the directed geometrically weighted frequency of non-edgewise shared partners (i.e., *dgwnsp*), representing the likelihood of participants inviting people who, in turn, also invite a shared third person.

Transitive Invitations. Conversely, we measured to what extent two participants, one inviting the another, were also potentially connected through third-participants. This term was measured by calculating the directed geometrically weighted frequency of edgewise shared partners (i.e., *dgwesp*).

Edge covariates *Prior-collaborations.* We asked participants who they had worked with to represent the prior collaboration network. We consolidated each participant's responses by assigning a relationship between two participants if at least one participant reported a connection to the other [14]. We modeled this term using the *edgecov* term.

Friendship. Similarly, we asked participants which people they had enjoyed socializing with to represent a friendship network. We consolidated each participant's responses by assigning a relationship between two participants if at least one participant reported a connection to the other. We modeled this term using the *edgecov* term.

Node attributes effects *Gender.* In the initial survey, participants self-reported their gender identity as "Male," "Female," or "Other." *International/National.* We asked participants "Which is your country of origin?" and they answered using a list of countries provided. American participants were classified as national.

Project skills. To assess participants' level of competence at skills relevant to the task, we asked them to report their proficiency in nine areas relevant to the tasks. Participants' skill level was reported on a 5-point Likert scale ranging from "Not at all skilled" to "Extremely skilled." We averaged these six scores to get a competence score for each person.

Personality. We used mini-IPIP scales which assessed the Five-Factor Model attributes of agreeableness (Cronbach's $\alpha = .74$), conscientiousness ($\alpha = .68$), extroversion ($\alpha = .76$), neuroticism ($\alpha = .67$), and openness ($\alpha = .70$). Participants responded to 20-items (four per trait), and the items were then averaged for each trait.

Leadership experience. We measured individuals' prior leadership experience using the 8-item Adolescent Leadership Activities Scale. As the items showed acceptable reliability ($\alpha = .84$), they were averaged into one leadership experience score.

Creativity. We assessed participants' creative self-efficacy. The 3-item scale measured participants' belief in their own ability to complete creative goals. Observing acceptable reliability ($\alpha = .57$), we computed a creativity score for each person by averaging the items.

Homophily effects We controlled homophily among categorical variables (i.e., gender, international) using the *nodematch* term. This term counts how many nodes connected in the network share the same value for that categorical attribute. As a result, a positive and significant effect means that participants were more likely to form a tie with another person with the same characteristics. Lastly, we controlled for homophily among numerical variables (i.e., project skills, leadership, creativity, personality traits) using *absdiff*. In contrast to *nodematch*, this term measures the absolute difference of an attribute between two participants. A smaller difference means that participants with similar values among that attribute are likely to form a tie. A negative and significant effect means that participants are likely to form a tie when they have similar scores in that attribute.

3.4 Results

Across the three courses ($N = 155$), participants had an average of 17.95 ($SD = 10.28$) prior collaborators and 17.87 ($SD = 16.90$) friends. We analyzed the relationship networks and found similar patterns among all 3 classes. In the prior collaboration network, 50% of the people had worked with less than 15 participants, and only 10% worked with more than 30 participants. Similarly, in the friendship network, 50% of the people had less than 10 friends, and only 10% had more than 30 friends. Most project skills were uniformly distributed. The highest variance was found in Skill 7, sports ($M = 3.72, SD = 1.46$), and the lowest was in Skill 5, social integration ($M = 3.96, SD = 0.87$). Participants' creativity ($M = 5.52, SD = 0.79$), leadership experience ($M = 3.93, SD = 0.71$), and project skills ($M = 3.68, SD = 0.52$) were measured. Users' personality traits' means were marginally above the middle of the scale (2.5): the lowest was openness score with 2.74 ($SD = 0.47$). The highest personality traits' score was for agreeableness with 3.11 ($SD = 0.40$).

Using a one-way among subjects ANOVA test, we checked whether there were significant differences in participants' individual traits, social networks, and invitations among the three classes. Normality and homogeneity assumptions were satisfied before performing these tests. Overall, we found that the only significant differences ($p < 0.05$) among the three groups were participants' leadership experience, persuasion skills, networking skills, technical skills, social integration skills, political interest, and entertainment interest score. We then conducted the Tukey Post Hoc test, which measured where the significant differences of the ANOVA results lie. We found that significant differences occurred between the 2019 undergraduate class and the graduate class, while there were no significant differences between the two undergraduate classes. From these results, we were able to conclude that the graduate class was responsible for the significant differences.

Regarding the three team-formation exercises, participants sent 1,467 invitations: 545 for Task 1, 480 for Task 2, and 442 and for Task 3. Overall, 25.49% of the invitations were accepted by the sender, while 3.77% were rejected, and 70.74% were ignored.

3.5 ERGM Results

Table 1 shows the ERGM results for each task-type. The GoF test determined that all observed networks' statistics were well explained by the ERGM models, lying within 95% of the confidence interval. We then analyze the results:

When participants chose teammates, a variety of factors stayed constant across each task type. For structural effects, we found it was unlikely to observe indirect connections. For edges, we found that among all three tasks, prior collaborations and friendships were highly valued. For receiver effects, we observed that recipients with high creativity, persuasion, technical skills, and those skilled or marginally skilled in strategic thinking received invitations. For sender effects, we found that it was significant or marginally significant that those uninterested in sports and politics sent invitations. For homophily effects, we observed that among all three tasks, participants sending and receiving invitations valued those with the same international status.

When participants chose teammates, certain factors varied between each task type. Looking at structural effects, we found that a few participants were responsible for most invitations for Task 2 ($\beta = -0.58$) and 3 ($\beta = -1.19$). We observed that for Task 3 there was even distribution of invitations ($\beta = 0.67$), and users were likely to be connected through third participants for Task 1 ($\beta = 0.6$) and 2 ($\beta = 0.6$). For receiver effects, we found that males ($\beta = -0.38$) and those with networking ($\beta = 0.2$) and adaptability skills ($\beta = 0.27$) were likely to receive invites for Task 3. Those not skilled in finance ($\beta = -0.11$), politics ($\beta = -0.11$), and entertainment ($\beta = -0.11$), while those interested in sports ($\beta = 0.19$) were more likely to be invited for Task 2. For sender effects, we found that for Task 2, males ($\beta = -0.31$), those who lacked networking abilities ($\beta = -0.14$), and those who do not easily adapt ($\beta = -0.18$) sent invitations. Those with high levels of strategic thinking ($\beta = 0.14$), but those who do not easily adapt ($\beta = -0.21$) were likely to send invites for Task 1. Those with high creativity in Task 2($\beta = 0.15$) and in Task 3 ($\beta = 0.21$) were likely to send invitations. When observing homophily effects, we found that those with different levels of strategic thinking ($\beta = 0.18$) and political interest ($\beta = 0.12$), while those with similar levels of financial interest ($\beta = -0.21$) sent and received invites to one another for Task 1. Those with similar levels of sports interest for Task 1 ($\beta = -0.2$) and 2 ($\beta = -0.18$) and those of the same gender for Task 1 ($\beta = 0.26$) and 2 ($\beta = 0.36$) sent and received invitations to one another.

Table 1. ERGM Results for the three Tasks. Results are separated in Structural effects, edge covariates, Receiver effects (i.e., the participant who received the invitation), Sender effects (i.e., the participant who sent the invitation), and Homophily effects.

Parameter	**Task 1 (Start-up)**	**Task 2 (Jungle)**	**Task 3 (Election)**
Structural effects			
Edges	-6.24 (1.56)***	-8.51 (1.65)***	-11.22 (1.88)***
Popularity	0.52 (0.33)	0.34 (0.31)	0.67 (0.32)*
Activity	-0.32 (0.29)	-0.58 (0.28)*	-1.19 (0.28)***
Two-path invitations	-0.22 (0.02)***	-0.18 (0.02)***	-0.21 (0.03)***
Transitive invitations	0.6 (0.08)***	0.6 (0.09)***	0.11 (0.11)
Edge covariates			
Prior collaborations	1.35 (0.11)***	1.06 (0.12)***	0.83 (0.12)***
Friendships	1.58 (0.12)***	1.32 (0.13)***	1.04 (0.13)***
Receiver effects			
Gender (F)	-0.1 (0.12)	0.05 (0.13)	-0.38 (0.15)*
International	0.07 (0.11)	-0.09 (0.13)	0.16 (0.13)
Leadership Experience	0.01 (0.08)	0.14 (0.09)	0.18 (0.11)†
Creativity score	0.23 (0.07)***	0.23 (0.07)**	0.24 (0.08)**
Project Skill 1: Strategic Thinking	0.14 (0.06)*	0.13 (0.07)*	0.11 (0.07)†
Project Skill 2: Persuasion	0.25 (0.07)***	0.21 (0.07)**	0.53 (0.09)***
Project Skill 3: Networking	0.08 (0.06)	-0.04 (0.06)	0.2 (0.08)**
Project Skill 4: Technical Skills	0.13 (0.05)**	0.15 (0.05)**	0.15 (0.05)**
Project Skill 5: Adaptability	0 (0.06)	0.05 (0.07)	0.27 (0.08)**
Project Skill 6: Finance	-0.06 (0.04)	-0.11 (0.04)*	-0.04 (0.05)
Project Skill 7: Sports	-0.07 (0.04)*	0.19 (0.05)***	-0.07 (0.04)
Project Skill 8: Politics	-0.03 (0.04)	-0.11 (0.05)*	-0.01 (0.05)
Project Skill 9: Entertainment	-0.01 (0.05)	-0.11 (0.06)†	0.09 (0.07)
Sender effects			
Gender (F)	-0.02 (0.11)	-0.31 (0.12)*	-0.22 (0.13)†
International	-0.06 (0.11)	0.08 (0.12)	0.13 (0.12)
Leadership Experience	-0.02 (0.08)	-0.04 (0.09)	0.13 (0.09)
Creativity score	0.02 (0.07)	0.15 (0.07)*	0.21 (0.07)**
Project Skill 1: Strategic Thinking	0.14 (0.06)*	0.07 (0.06)	0.02 (0.06)
Project Skill 2: Persuasion	0.11 (0.07)	0.08 (0.07)	0.15 (0.08)†
Project Skill 3: Networking	-0.03 (0.06)	-0.14 (0.06)*	-0.11 (0.07)
Project Skill 4: Technical Skills	0.08 (0.05)†	0.05 (0.05)	0.03 (0.05)
Project Skill 5: Adaptability	-0.21 (0.06)***	-0.18 (0.06)**	-0.07 (0.07)
Project Skill 6: Finance	-0.05 (0.04)	-0.03 (0.04)	-0.04 (0.04)
Project Skill 7: Sports	-0.17 (0.04)***	-0.16 (0.05)**	-0.07 (0.04)†
Project Skill 8: Politics	-0.08 (0.04)†	-0.09 (0.04)*	-0.11 (0.05)*
Project Skill 9: Entertainment	0 (0.05)	0 (0.05)	0 (0.06)
Homophily effects			
Gender (nodematch)	0.26 (0.11)*	0.36 (0.12)**	0.09 (0.13)
International (nodematch)	0.29 (0.11)**	0.4 (0.12)**	0.57 (0.13)***
Leadership Experience(absdiff)	0.02 (0.1)	-0.03 (0.1)	0.09 (0.11)
Creativity score(absdiff)	-0.11 (0.08)	0.05 (0.08)	0.07 (0.09)
Project Skill 1 (absdiff): Strategic Thinking	0.18 (0.07)**	-0.09 (0.07)	0.06 (0.07)
Project Skill 2 (absdiff): Persuasion	0.12 (0.07)†	0.09 (0.07)	0.04 (0.08)
Project Skill 3 (absdiff): Networking	0.08 (0.07)	0.11 (0.07)†	0.08 (0.08)
Project Skill 4 (absdiff): Technical Skills	0.09 (0.06)	0 (0.06)	-0.06 (0.06)
Project Skill 5 (absdiff): Adaptability	-0.05 (0.07)	-0.03 (0.07)	-0.13 (0.08)
Project Skill 6 (absdiff): Finance	-0.21 (0.05)***	-0.08 (0.05)	-0.06 (0.05)
Project Skill 7 (absdiff): Sports	-0.2 (0.04)***	-0.18 (0.05)**	-0.07 (0.05)
Project Skill 8 (absdiff): Politics	0.12 (0.05)*	0.06 (0.05)	0.09 (0.06)
Project Skill 9 (absdiff): Entertainment	-0.05 (0.06)	0.08 (0.06)	0 (0.07)
AIC	2821.85	2762.31	2727.77
BIC	3250.77	3191.22	3156.69

Significance codes: $p < 0.001$(***), $p < 0.01$(**), $p < 0.05$(*), $p < 0.1$(†).

4 Discussion

In response to our first research question regarding which factors stay constant when choosing teammates for certain tasks, we found that prior collaboration and friendship networks were influential when choosing teammates. Additionally, competence in persuasion, creativity, strategic thinking, and technical skills were important for all task types. Also, having the same international status affected teammate selection. Our results show that even when the task type varies, certain attributes stay valuable when choosing teammates to complete various tasks.

In response to our second research question about how teammate choices differ in relation to certain tasks, we found that task type influences what factors are important to consider when choosing teammates to complete tasks. For planning tasks, prior collaborations and friendships as well as competence in strategic thinking and similar levels of financial interests were important when it came to inviting and accepting invitations. While for performance tasks, being a male and having an interest in sports were influential factors. For competitive tasks, being of male gender and having skillfulness in adaptability and networking yielded a higher invitation outcome. Much of the current research being conducted examines the team formation process surrounding one task. Our study gives further insight into how teams are formed among three different task types. Our results are consistent with the findings that prior friendship and collaboration networks are a significant factor in choosing teammates [2, 1, 11]. However, our research goes beyond other studies to show that while people do look for teammates similar to them [8], they also value diverse abilities in order to form cohesive teams [24]. Our findings show that certain factors do stay valuable across various tasks but considerations of certain skills and traits are important depending on the task and the desired outcomes.

Our results must be interpreted cautiously because of the following limitations. First, the characteristics of our context and participants place important boundary conditions on the findings. More case studies with a broader population and different organizational contexts could assess the generalizability of the team assembly factors identified in this study. Second, we relied on users' self-reported skills, which may not be accurate. Future studies may consider peer-evaluations as a way to confirm others' expertise. Third, many design features of the team formation platform were likely to affect participants' behavior. Fourth, since the teams were fictitious, we did not study the performance of these teams. Future studies could explore how the task influences team performance. Lastly, we did not control students' interactions during the sessions and outside the platform, meaning some teams may have formed because students agreed to do so offline, but that was not possible to measure.

To summarize, we conducted a study of team assembly through a network analysis by studying the patterns of 155 students. We were able to gain insight into how teammate decisions change depending on the task at hand. We are able to conclude that the influence of prior relationships and individual abilities are considered when choosing teammates for various task types.

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