Who Would You Like to Work With?

Use of Individual Characteristics and Social Networks in Team Formation Systems

Diego Gómez-Zará[*][†]
P. Universidad Católica de Chile
Facultad de Comunicaciones
dgomezara@uc.cl

Matthew Paras
Northwestern University
McCormick School of Engineering
mparas@u.northwestern.edu

Marlon Twyman
Northwestern University
Technology and Social Behavior
marlont2@u.northwestern.edu

Jacqueline N. Lane
Harvard Business School
Laboratory of Innovation Science
jng@hbs.edu

Leslie A. DeChurch
Northwestern University
Communication Studies
dechurch@northwestern.edu

Noshir S. Contractor
Northwestern University
McCormick School of Engineering
nosh@northwestern.edu

ABSTRACT

People and organizations are increasingly using online platforms to assemble teams. In response, HCI researchers have theorized frameworks and created systems to support team assembly. However, little is known about how users search for and choose teammates on these platforms. We conducted a field study where 530 participants used a team formation system to assemble project teams. We describe how users' traits and social networks influence their teammate searches, teammate choices, and team composition. Our results show that (a) what users initially search for differs from what they finally choose: initially they search for experts and sociable users, but they are ultimately more likely to choose their prior social connections; (b) users' decisions lead to non-diverse and segregated teams, where most of the expertise and social capital are concentrated in a few teams. We discuss the implications of these results for designing team formation systems than promote users' agency.

CCS CONCEPTS

• **Human-centered computing** → *Collaborative and social computing theory, concepts and paradigms*; *Empirical studies in HCI*.

[*]Corresponding author.
[†]Also with Northwestern University, Technology and Social Behavior.

KEYWORDS

Teams, team formation systems, people search, human capital, social capital.

1 INTRODUCTION

Team formation processes are relocating into online spaces as people and organizations look for collaborators and assemble teams through enterprise and social media platforms [5, 61]. Teams assembled online are increasing in many collaborative work environments: crowdsourcing [65], research projects [77], MOOCs [73], virtual spaces [32, 81], educational settings [2], startups [12], hackathons [76], software companies [38, 43], and other organizational contexts [46]. Since online platforms have the potential to reconfigure team formation, designers of collaborative systems are increasingly developing team formation frameworks for tailoring users interactions [50, 68, 81], incorporating recommender systems [4, 15], and augmenting users actions in online environments [65, 87].

Despite the expanding interest in online team assembly, little attention has been paid to users' behaviors when searching and choosing teammates. How members use these systems have direct consequences for the formation of their teams. Previous studies have acknowledged that ad hoc team formation processes lead to disharmony among members, lack of cohesion, organization, and diversity [9, 51, 53]. For example, unbalanced skills among team members is the third most significant contributing factor to startup failures in the U.S. [18]. Understanding how users search for and choose

teammates via online platforms can lead to rethinking technological features that enhance the assembly of teams.

In this study, we explore how users exercise their agency when looking for and choosing teammates during online team formation. We conducted a field study with 530 students who assembled 91 project teams using an online team formation system. By analyzing digital trace and survey data, we measured how users' human and social capital affected users' searches, choices, and final decisions on team formation. Additionally, we studied how users' decisions affected the distribution of human capital and social capital in resulting teams.

We found that while searching for teammates, users used the system to look for competent and social individuals. However, users ultimately relied on their prior social networks to select and accept their teammates (e.g., previous collaborators or popular individuals). We also found that teams segregated into clusters of expertise (i.e., most of the experts formed teams together), and similarly, into clusters of social connections (i.e., popular users formed teams together). Our results suggest that team formation systems that enable users' agency can lead to a high preference for teaming-up with prior social connections and also enhance disparities among teams, with some teams having the best talent and leaving other teams disadvantaged. We discuss how these results illuminate the design of future team formation systems that enable users to exercise their agency and assemble their teams.

This paper contributes to the literature by providing (1) a theoretical conceptualization of how people search for and choose teammates using online team formation systems, (2) a quantitative analysis articulating users' searches, choices, and their final team composition, and (3) a discussion of the design implications of team formation systems to promote both team diversity and user agency.

2 RELATED WORK AND BACKGROUND

We situate our work in the context of prior studies of team formation systems, team composition, and teammate selection across the HCI and organizational behavior literature.

2.1 Team formation systems

Previous studies have made efforts to understand team formation strategies in online systems. Several tools have been developed to support users' collaborative efforts for establishing groups, placing an emphasis on increasing teams' diversity [55, 66], cohesion [31, 60], and performance [44, 58, 69]. Online systems use different strategies based on the extent to which users can exercise their agency in teammate selection: from having full freedom to choose teammates, to having team structures designed by algorithms. Recent studies using computational augmentation include *flash teams*

systems –which allow the assembly of teams of experts by modularizing a project's tasks and assigning online workers to them [65]– and a system that identifies and reconfigures group structures for existing teams based on their current performance and members' experience [87].

Other team formation systems enable users to assemble their own teams by searching for teammates [39, 45]. In the study of one system, instructors selected specific criteria for teammate searching in a project-based course [42]. Students appreciated the use of rational criteria when assembling their own teams, arguing that the system reduced their stress and simplified the team formation process. However, other students disliked the search criteria selected by the instructors. Other example systems are based on filling defined team roles (e.g., sales teams [3]) and supporting "team dating" in online platforms [50], whereby users have short consecutive "dates" with other users to evaluate potential teammates. The relevance of previous connections is apparent by users' preference to choose those who they had previously "dated."

While related research has explored multiple strategies employed by team formation systems, much less is known about how users make decisions in each stage of team formation, as well as the impact of these individual decisions on the final composition of the team. Our study addresses this gap by examining users' behaviors, searches, choices, and ultimately, the final team compositions.

2.2 Team composition

Team assembly affects team effectiveness in terms of performance [82], functional diversity [20, 78], cohesion [16, 67], innovation [62], access to ideas and resources [14], as well as individual outcomes [53]. Although team success is ultimately contingent, research and practice suggest that team composition sets the stage for effective team outcomes and processes [52]. We explore important factors in the research on team composition that are affected by users' decisions on their teammates.

2.2.1 Performance. Team composition leads to success or failure. Prior work has identified many determinants of success after members have assembled teams [82]. Research has empirically demonstrated that team composition influences team performance. For example, gender composition, personality, teamwork knowledge, value and belief, and cognitive ability are a few among many attributes that have been linked to team process and performance [23]. However, the factors that promote performance after the team has been formed are not necessarily generalizable to those that explain what happens at the team assembly stage [35].

2.2.2 Functional diversity. Teams' functional diversity is a consequence of members' choices. It is the degree to which

team members differ in terms of their experience or backgrounds [11, 20]. Functional diversity can facilitate atypical combination of knowledge that prompt novelty and breakthroughs [77]. In one study [78], software development teams' productivity was improved by increasing gender and tenure diversity. Despite the benefits of functional diversity, research has found that team members struggle when searching, bridging, codifying, and integrating ideas from unfamiliar domains [6]. This may lead individuals to avoid forming teams with diverse and/or unfamiliar individuals. As a consequence, the balance between similarity and diversity in teams would depend on what people look for when choosing collaborators and assembling teams [37].

2.2.3   Team cohesion. The tendency for a team to stick together and remain united in the pursuit of its instrumental objectives and/or for the satisfaction of members' affective needs is known as team cohesion [16]. The selection of certain kinds of collaborators affects team cohesion, which can be driven by looking for the most competent individuals for specific work (i.e., task-cohesion) or for those enjoyable to work with in general (i.e., social-cohesion) [67]. In this pursuit of cohesion, team members may both look for others who are inter-personally similar to them and for people with shared views and commitment to the team tasks [84]. Users' choices could however lead to less cohesive teams: for example, if they seek out the most competent individuals, this can create a team that lacks the relational ties that are needed to engage in effective teamwork [17].

2.2.4   Connectivity. Teams' connectivity or access to ideas that reside across teams is another consequence of how people look for potential collaborators. Teammates rely on shared members or team interlocks [49] to gain access to ideas, constraints, and opportunities that lie beyond their boundaries [22, 57, 72]. Teams which are well connected internally and externally are more innovative and outperform their less connected counterparts [62]. As a result, people may look to team up with influential members who have more access to resources via their connections [14].

2.3   Teammate selection: human and social capital

During team formation, users can select teammates based on specific attributes, such as similarity, familiarity, or competence [37]. Online platforms enable people to search for others across multiple purposes: looking for friendship [19, 21, 64], communities [47, 86], work collaboration [36, 85], and romantic dates [88, 89]. Users can search for others by their names or desired qualities (e.g., skills, locations, etc.) [80].

Desirable attributes for teammates can be classified as either elements of human capital or social capital [40]. Human capital refers to the knowledge, skills, abilities, and/or

experiences of individuals [8]. Social capital refers to individuals' social relationships with others [48]. Based on these two types of capital, we disaggregate four elements that can explain the search and choice of teammates: from human capital, *competence* and *warmth*, and from social capital, *bonding capital* and *bridging capital* [83].

2.3.1   Competence. Competence –or *expertise*– refers to traits related to perceived ability (e.g., intelligence, skill, and efficacy) [29],and describes a person's knowledge about a certain domain, process, or technology [7]. Competent users with relevant skills are "attractive" to work with on a project.

2.3.2   Warmth. Warmth captures traits that are related to perceived intent (e.g., friendliness, helpfulness, sincerity, trustworthiness, and morality) [29]. A person's *warmth* portends trustworthiness and allows a degree of predictability in a relationship.

2.3.3   Bonding capital. Bonding social capital characterizes the *quality* of a connection between two people. People choose close friends (strong ties) or strangers (weak ties) for different purposes. Working with prior collaborators increases the certainty of working styles, communication, and outcomes [37]. Working with weak ties increases access to novel information [33].

2.3.4   Bridging capital. Bridging social capital is characterized by occupying an advantaged position in social networks (e.g., a high popularity, brokerage, or closeness value) [13]. People who are brokers fill the structural holes between disconnected individuals, allowing more access and control over information and resources [30, 54].

Taken together, these human and social capital dimensions provide a useful conceptual lens through which to understand the characteristics that relevant for choosing collaborators and give insight into the differences that matter most in a collaborator.
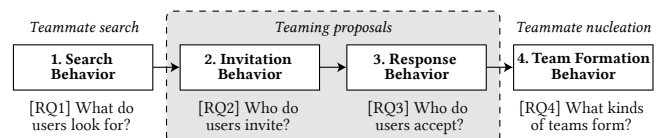
2.4   Research questions

Figure 1: Team formation stages and research questions

The studies reviewed above provide a conceptual lens to understand the characteristics that are important in team formation processes when users have agency on choosing their teammates [24]. Based on these characteristics, we delineate the social cognitive processes involved in searching for and

(a) Initial survey stage: users complete their profile, individual traits, and social network information

(b) Users search for collaborators using competence, warmth, bonding, and bridging capital attributes

(c) Invitation stage: users receive an invitation for team membership. They can accept, decline, or ignore it.
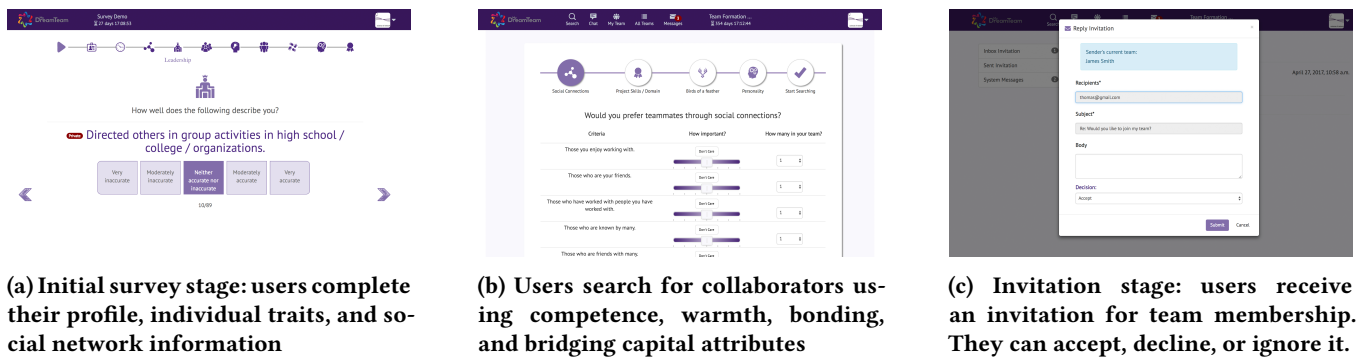
Figure 2: Interfaces of team formation system used in this study

choosing teammates via online platforms in four stages that correspond to our research questions (Figure 1).

In the first stage, we aim to understand what people seek out from others [RQ1]. In the second stage, we aim to analyze which individuals are more likely to receive an invitation [RQ2]. Then, in the third stage, we aim to understand the fundamental factors for accepting or declining an invitation [RQ3]. Finally, we assess the composition of teams at the end of the entire process [RQ4].

3 METHOD

Based on our research questions, we designed a field study to observe team assembly in an online setting. To facilitate our study, we developed an online team formation system where users assemble teams by searching, inviting, and accepting (or declining) invitations from others. We analyzed all four team formation stages based on the human and social capital dimensions explored. The first three stages use behavioral data generated during team assembly from an online team formation system and the fourth stage is analyzed using behavioral data as well their responses to a survey.

3.1 Participants

In total, 530 individuals participated across 9 independent case studies at universities in the United States between 2016 and 2018. Students organized into 91 teams in order to complete a required course project. We conducted our study in five undergraduate courses taught by several professors in three universities. 314 undergraduate students participated and their nationality breakdown is as follows: 61% were Americans, 32% were international, and 7% did not report. As part of undergraduate students' assignments, they assembled teams to complete a course project. Similarly, 216 graduate students at one university in the United States participated in this study, spread across four graduate courses. Regarding their nationalities, 60% were Americans, 34% were international, and 6% did not report it. Graduate

students self-assembled into teams to analyze case studies and participate in discussion groups.

In each case study, all students were asked to self-organize into teams for their term project. Students did not participate in more than one class and worked on more than one team either. The topics of these projects ranged from consulting teams to app development. The sample includes an equal distribution of males and females, and average age ranged from 20 to 31 years. Participation in this study and the use of the team formation system was voluntary and consented. They could withdraw their consent at any time during the case study. The research team provided manuals, help elements, and a video tutorial to explain the overall process of the research to all students. We explained to the students that the use of this system will not affect their grades for the course.

3.2 Initial survey

The first task for participants was completing a public user profile. They identified themselves using their real names and completed profiles by replying to a set of open-ended questions about their backgrounds, skills, favorite things to do, and motivation to take the course. This information was available for other participants to view.

Next, as part of registration in the team formation system, participants completed a survey assessing human and social capital. This survey included questions relating to their demographic information, creativity, leadership experience, psychological collectivism, social skills, personality, project skills, and relationships to others in the network (Figure 2a). This information was used to provide results in response to users' searches. Participants were allowed up to two weeks to complete this survey. After all participants completed the survey, they were able to search for and invite users to their team.

3.2.1 Demographic information. As control variables, we asked participants their gender, age, and nationality. We also

controlled whether they were undergraduate or graduate students.

3.2.2 Competence. To assess this human capital dimension, participants answered six items regarding their expertise on skills relevant to the team project. These items were adapted for each project, often considered a set of computational, statistical, communication, and research skills. The main distinction was determined by the type of course (under-graduate or graduate). While the former used the same set of skills (3 technical expertise skills and 3 communication skills), the latter used specific skills related to the course's project. These items were assessed on a 5-point Likert scale [63], which ranged from "Not at all skilled" to "Extremely skilled."

3.2.3 Warmth. We defined creativity, leadership experience, psychological collectivism, social skills, and personality as part of warmth skills:

Creativity. Creativity is a dimension of *warmth* because a creative mindset relates to a person's self-efficacy and ability to have positive and affective relationships [75]. We asked participants about their ability to produce creative outcomes and be creative in their work roles. We used [75]'s three-item scale to measure this trait. For each participant, we averaged these three items in one score (α=.86).

Leadership experience. We used the Adolescent Leadership Activities Scale [56] with slight modifications to reflect that participants could have participated in leadership in both high school and college. Participants answered eight items relating to previous leadership behaviors on a 5-point Likert scale of how well each statement described them ranging from "very inaccurate" to "very accurate." For each partici-pant, we averaged these eight items in one score (α=.83).

Psychological collectivism. To assess the extent to which participants valued teamwork and team's success, we used each of the five facets of psychological collectivism in the form of 15 questions in this study [41]. These questions were assessed on a 5-point Likert scale, which ranged from "strongly disagree" to "strongly agree." We averaged the fif-teen items in one score per participant (α=.89).

Social skills. We used the Political Skill Inventory [28] to target four key dimensions of desired political behaviors: social astuteness, interpersonal influence, networking ability, and apparent sincerity. Participants answered seven items, which corresponded to each of the four facets. We assessed these items on a 7-point Likert scale, which ranged from "strongly disagree" to "strongly agree." These items were also averaged per participant (α=.85).

Personality. The mini-International Personality Item Pool (IPIP) scales were used to assess all Big Five personality traits [26]. Participants responded to 20 items on a 5-point Likert scale about how well each statement describes them ranging from "very inaccurate" to "very accurate." For each user, we averaged the four questions for each of the five traits: agreeableness, conscientiousness, extraversion, neuroticism, and openness (α=.79).

3.2.4 Bonding capital. Participants were asked three ques-tions: "Who on this list do you know?", "Who have you worked with on projects?", "With whom on this list do you enjoy working?". Based on their answers, we created three different directed networks: Contact network, Collaboration network, and Friendship network, corresponding to each question respectively. If they nominated another person for any of the questions, a relation was formed in the corre-sponding network.

3.2.5 Bridging capital. Based on the previous three social networks, we operationalized four network metrics for each user to calculate their bridging capital [79]:

Popularity: Users' indegree as the sum of how many people mentioned them as a contact / collaborator / friend.

Activity: Users' outdegree as the sum of how many they nominated another as a contact / collaborator / friend.

Betweenness: User's brokerage as the number of shortest paths between participants that pass through the user.

Closeness: The inverse of the sum of the length of the shortest paths between that user and all other participants.

3.3 Search for teammates

Once all participants completed the survey, they were able to search for and select teammates. Users searched for team-mates using queries (Figure 2b). A query in the system is a set of search preferences explicitly made by a user, represent-ing considerations for potential teammates based on human and social capital. In each query, users had to select at least two criteria and rate the importance of these criteria using a 7-point scale, ranging from "Not important at all" (-3) to "Yes, for sure!" (+3), including "Don't care" (0). By default, all the criteria were set in 0 and the user had to manually change the criteria's importance to create a query.

The system computed a score for each potential teammate j matching searcher i's queries according to the following formula: $S_{ij} = \sum_{k \in K} \alpha_k s_{ijk}$, where α_k is the importance of the criteria k in the query. Then, each score of s_{ijk} considers the potential teammate j's score of the criterion k in relation to the searcher i. The formulas for each s_{ijk} are listed in Table 1. Finally, the system used the S_{ij} scores to display a rank-ordered list of the potential teammates that best fit the user i's query. The system paginated all the results – ordered according to the user's query– in pages with ten profiles. For each potential teammate, the system displayed their picture, the percentage of how well their matched with the user's query, a link to their full public profile (containing

the responses to open-ended questions described above), and an invite button.

Users also had the option to directly specify others' names in order to see their profiles directly and potentially send an invitation. Here again, the system provided a picture of each potential teammate, a brief description, a button that links to their full public profile, and an invite button.

Table 1: Search preferences available on the system

Attribute	Label displayed	Formula
Competence		
Project Skill #1	Project Skill #1	User j's project skill #1 score
Project Skill #2	Project Skill #2	User j's project skill #2 score
Project Skill #3	Project Skill #3	User j's project skill #3 score
Project Skill #4	Project Skill #4	User j's project skill #4 score
Project Skill #5	Project Skill #5	User j's project skill #5 score
Project Skill #6	Project Skill #6	User j's project skill #6 score
Warmth		
Psychological collectivism	Those who have strong team values	User j's p. collectivism overall score
Creativity	Those with a creative mind	User j's creativity overall score
Social skills	Those who have good social skills	User j's social skills overall score
Leadership experience	Those with good leadership experience	User j's leadership experience overall score
Similar personality	Those who have a similar personality to you	Cosine similarity between users across personality features
Bonding capital		
Worked within the past	Those you have worked within the past	User i mentioned user j as a co-worker
Friendship	Those who are your friends	User i mentioned user j as a friend
Shared collaborators	Those who have worked with people you have worked with	If user i have worked with user j, and user k with user j, then user k is displayed.
Bridging capital		
Social network brokers	Those who can introduce you to many	Users' betweenness
Work popularity	Those who have worked with many	Users' indegree
Know popularity	Those who are known by many	Users' indegree
Friend popularity	Those who are friends with many	Users' indegree

3.4 Team Assembly

Users sent invitations asking other users to join their teams. When a user sent an invitation, a pre-populated message pop-up opened, and the user could either use the default message or add personalized text to the invitation (Figure 2c). Each invitation message also contained the sender's profile. The receiver of the invitation had the choice to accept, decline, or ignore the invitation. If a user not on a team accepts an invitation from another user not in a team, the system creates a new team with them. If two users who are on two existing teams accept to work together, both pre-existing teams will merge and establish a unique team only if and only the final team size is less than or equal to the maximum team size allowed. The system does not designate a leader of the team; as a result, any person on the team has the ability to invite new members or merge teams, and any member on another team who has been invited may choose to accept the invite

and merge the teams. Users also had the option to leave a team. The system offered them an option to share with their former teammates their motives for leaving the team. Once a team was finalized, they were not be able to accept any new members. When the team assembly deadline was reached, students started working on their respective course projects over a 10-week period. If some students were unable to assemble into a team by the deadline, the class' instructor assigned them to a team using the system. Overall, team sizes ranged from 4 to 6 members (M=5.13, SD=.93).

3.5 Analytic approach

We conducted separate descriptive analyses and statistical models to explain participants' searches, invitations, acceptances, and the final teams compositions. To examine RQ1 –What do individuals look for?– we analyzed the number of search preferences used in each query to see whether users had a strong preference for competence, warmth, bonding capital, and bridging capital.

To respond to RQ2 –Who do individuals invite based on their current team formation stage?– we analyzed the likelihood of an invitation from one to another user. Similarly, to respond to RQ3 –Who do individuals accept based on their current team formation stage?– we analyzed the likelihood of accepting a user's invitation. We first operationalized the "team formation stages" according to the current state of users' teams (i.e., the number of users in the team at any given point) since the nine case studies had different spans of team formation, and participants' behavior changed over time as team size changed [70, 71]. To define these team formation stages, we checked the flow of invitations between users according to their teams' size. Teams' size was computed at the time that one of their members accepted or declined an invitation, which might have been different from when the invitation was extended. Figure 3a indicates the percentage of total invitations sent based on the number of individuals in the sending team and receiving team. Based on this analysis, we defined three invitational stages:

(i) *Initiating a team* (60.8% of the total number of invitations) were invitations sent between users who were not yet on a team.

(ii) *Growing a team* (27.6%) were invitations sent from users who are either not yet on a team or on a small team of 2-3 people, to recipients on any size team, excluding invites found in the first group.

(iii) *Finalizing a team* (11.6%) were invitations from users who are on a large team of 4, 5, or 6 people sent to users of any team size, looking to fill the remainder of their group.

We repeated this grouping method in order to also analyze acceptance and decline behavior, however now we considered the number of teammates at the moment of acceptance

(a) Number of invitations sent with respect to team size (1,066 in total)

(b) Number of invitations accepted with respect to team size (357 in total)

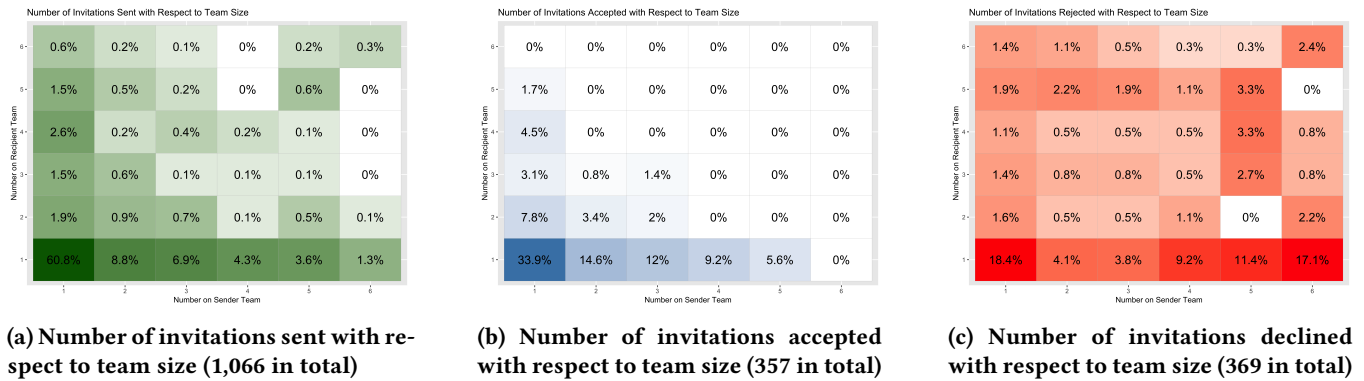(c) Number of invitations declined with respect to team size (369 in total)

Figure 3: Distribution of invitations sent and responded

(Figure 3b) and decline (Figure 3c). These responses are then grouped into three-team formation stages:

(i) *Initiating a team* contains (26.0% of the total responded invitations) only invitations accepted and declined between users who are not yet on a team.

(ii) *Growing a team* (59.2%) contains invitations accepted and declined from users who on any size team, to recipients on a small team of 2-3 people.

(iii) *Finalizing a team* (14.8%) contains invitations from users on any size that were accepted and declined by users who are on a large team of 4, 5, or 6 people.

Once we defined the team formation stages, we employed Hierarchical Logistic Models to explain users' decisions and account for the differences between the nine case studies [10]. HLM is an advanced form of logistic regression that allows us to examine the effects of independent variables (i.e., individual traits, social networks, and dyad relationships) on dependent variables (i.e., likelihood of receiving an invitation and accepting an invitation), considering potential correlations across the case studies (level-1) and the team formation stage (level-2). To calculate these HLMs, we use Generalized Linear Mixed Effects Models (GLM) using the binomial family (which, we coded 1 when an invitation was sent/accepted, otherwise, as 0). We normalized all numerical coefficients and verified that the calculated models meet the assumptions of linear regressions and have no overdispersion.

Finally, to respond RQ4 –What kinds of teams form?– we computed the distribution of participants' skills and network centrality measures of team members using *k*-means [74], which partitions the teams' users skills and degrees into *k*-clusters. The method calculates the mean squared value of each team and classifies it according to the nearest cluster's center. This analysis was done for 3, 4 and 5 clusters. We validated the consistency within clusters –their cohesion and separation– by calculating the Sum of Squared Error (SSE) of each cluster and the average silhouette coefficient over all teams' data. Three clusters was determined to be the best

number of clusters for human capital (SSE=70, S.C.=0.24) and social capital (SSE=201, S.C.=0.42), which captures appropriately the segmentation of these teams and were theoretically better supported.

4 RESULTS

4.1 Users' initial survey

Across the nine case studies (N=530 users), users had an average of 8.74 (SD=6.64) contacts, 4.81 (SD=4.36) collaborators, and 5.62 (SD=5.38) friends. These social networks were skewed: while 50% of the users were mentioned by less than 6 others as a contact, only 10% of them were mentioned by more than 25 users. These numbers are even more dispersed on the collaboration network and in the friendship network: in both cases, 50% of the people were mentioned by less than 4 users, and only 10% were mentioned by more than 11 users. By checking the popularity distributions, the contact and friend networks followed a power-law (γ=2.17 and γ=2.64). 62 students were not mentioned as a contact by any others, while 33 were not mention prior collaborations, and 33 not mentioned as friends. We calculated Gini coefficients of users' traits to check the distribution of users' skills among the case studies. We found that all traits were distributed equally among users: creativity (M=5.6, SD=.96, Gini=.09), leadership experience (M=3.87, SD=.71, Gini=.10), social skills (M=5.22, SD=.87, Gini=.09), psychological collectivism (M=3.65, SD=.51, Gini=.08), and project skills (M=3.62, SD=.64, Gini=.10). Users' personality scores were normally distributed, and each trait's means were marginally above the middle of the scale (2.5): the lowest was openness score with 2.55 (SD=.46) and the highest was agreeableness with 3.04 (SD=.37).

4.2 Search behavior

In response to RQ1, we analyzed how users search for forming teams. 71.5% of the users made searches on the platform.

61.7% of the users used the search preferences to find others and 16.8% directly specified names to find others. Users made 1,138 queries in total. The mean user performed 3.48 queries (SD=7.00), where 44.3% of these users made between 2 and 5 queries. The mean query used 9.61 (SD=4.80) search preferences, where 54.7% of the queries used between 5 to 14 attributes.
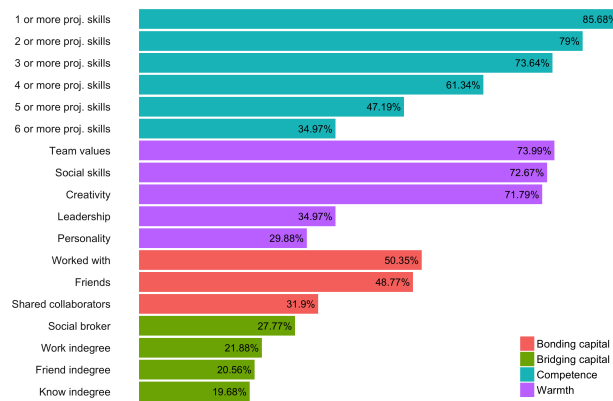

Figure 4: Search Preferences in Users' Search Queries

Figure 4 shows the most used search preferences across all users. Users preferred competence and warmth over bonding capital and bridging capital when they searched for potential teammates. Results suggest that users valued teammate characteristics on pairs with project skills. Users searched for at least one skill in 85.7% of the queries. Team values (74.0%), social skills (72.7%), and creativity (71.8%) were frequently searched by users. Users also searched for past collaborators (50.4%), friendship (48.8%), and shared collaborators (31.9%) over people's bridging capital.

We examined whether users' prior collaborations affected their use of social (bridging and bonding) capital search preferences. We found that users without any prior collaborations used bridging capital search preferences more times than users with prior collaborations: 64.9% versus 43.2% of the time in their queries. These results suggest that the search of brokers and popular users was a real alternative for those who were not well connected with others in these classes. Graduate and undergraduate students differed significantly in their bonding capital search behavior: undergraduates relied on friendship networks, whereas graduate students relied on work networks.

4.3 Invitation behavior

In response to RQ2, we examined factors that influenced their invitation behavior (who they decided to invite to team-up with them). Across all case studies, 282 users (53.2% of

the sample) extended a total of 1,066 invitations. Users sent an average of 3.78 invitations (SD=3.29). Table 2 reports the factors influencing the sending of invitations during each of the three stages. These are described in the following sections.

4.3.1 Initiating a team. While initiating a team, individuals were more likely to extend invitations to those they knew (β=.04, p<.001), had previously collaborated with (β=.08, p<.001), or with whom they were friends (β=.1, p<.001) . Senders who scored high on the trait of psychological collectivism were more likely to send an invite (β=.005, p<.01). Recipients who rated themselves highly as leaders were more likely to receive an invite (β=.006, p<.01). In addition, senders who rated themselves highly on project skills were more likely to send an invite (β=.01, p<.05). Interestingly, users who reported a high number of friends (β=-.02, p<.001) or collaborators (β=-.02, p<.001) were less likely to send an invite. Users who others reported collaborating with were also less likely to send an invite (β=-.01, p<.001).

4.3.2 Growing a team. At the second, growing a team stage, prior collaborations and existing social connections continued to positively influence whether an invite was sent: being a contact (β=.04, p<.001), prior collaborator (β=.08, p<.001), and being friends with the individual (β=.03, p<.05). Unlike the initiating team stage, users with a lot of friends no longer less likely to extend invitations but those with a higher number of reported contacts (β=-.01, p<.001) or reported prior collaborations (β=-.01, p<.001) were less likely to send an invite.

4.3.3 Finalizing a team. Once again, bonding capital proved to be impactful in users' choices: being a prior collaborator (β=.05, p<.001) or friends (β=.06, p<.001) were positively significant. In this finalizing stage, however having higher bringing capital resulted in a lower likelihood of acceptance: users frequently reported as collaborators by others were less likely to receive an invitation (β=-.02, p<.001). Females were more likely to receive an invitation (β=.001, p<.05) as well as creative users (β=.009, p<.01). Senders who scored high on the psychological collectivism trait were more likely to send an invite (β=.007, p<.05). Finally, users reporting high leadership experience were less likely to receive an invite (β=-.007, p<.05).

4.4 Responding behavior

Next, in response to RQ3, we analyzed the factors influencing users' distribution of received invitations. We removed from this analysis invitations for which they were no responses. 407 users (76.8% of the sample) received at least one invitation. The rest had to wait until the end of the team assembly phases when instructor of the course assigned them

Table 2: Sending Behavior HLM
D.V. = Likelihood of sending an invitation

	1. Initiating a team	2. Growing a team	3. Finalizing a team
Fixed Effects	β(S.E.)	β(S.E.)	β(S.E.)
Competence			
[S] Project skills sum	.018 (.008)	-	-
Warmth			
[S] Psych. Collectivism	.006 (.001)	-	.007 (.003)
[R] Creativity	-	-	.009 (.003)
[R] Leadership	.007 (.002)	-	-.007 (.003)
Bonding capital			
Contacts	.04 (.009)	.04 (.009)	-
Collaborators	.08 (.007)	.08 (.007)	.05 (.013)
Friends	.13 (.009)	.03 (.008)	.06 (.012)
Bridging capital			
[S] Contact activity	-	-.01 (.002)	-
[S] Friendship activity	-.02 (.003)	-	-
[S] Collab. Popularity	-.01 (.004)	-	-
[S] Collab. activity	-.02 (.003)	-.02 (.004)	-
[R] Collab. popularity	-	-	-.024 (.005)
Demographics			
[R] Gender (Female)	-	-	.01 (.005)
Random Effects	σ^2	σ^2	σ^2
Project (Intercept)	.0003	.0001	.0002
Residual	.03	.02	.027
REML	-5,126.9	-9,303.8	-2,801
N. of Observations	14,305	11,156	4,170

Note: We display only the fixed-effects terms and coefficients that were statistically significant (p < .05). [R] Recipient and [S] Sender.

Table 3: Accepting Behavior HLM
D.V. = Likelihood of accepting an invitation

	1. Initiating a team	2. Growing a team	3. Finalizing a team
Fixed Effects	β(S.E.)	β(S.E.)	β(S.E.)
Competence			
[S] Project skills sum	-.39 (.18)	-	-
Warmth			
[S] Social skills	-	-	.14 (.06)
[S] Extraversion	-.08 (.04)	-	-.08 (.04)
[S] Agreeableness	-	-	-.09 (.04)
[S] Openness	-	-	.09 (.04)
Bonding capital			
Contacts	-	.19 (.06)	-
Collaborators	-	-.12 (.06)	-
Bridging capital			
[S] Contact Activity	-.17 (.05)	-	-
[S] Collab. Activity	.21 (.08)	.11 (.06)	-
[S] Friend. Activity	-	-	.13 (.05)
[R] Collab. Popularity	-	.13 (.06)	-
[R] Friend. Popularity	-.24 (.11)	-	.19 (.08)
Timing			
[S] Has a team	-	-	-.33 (.17)
[S] 1st invitation sent	.22 (.09)	-	-
[R] Pending invitations	-.06 (.029)	-.06 (.01)	-
Random Effects	σ^2	σ^2	σ^2
Project (Intercept)	.000	.015	.008
Residual	.15	.13	.07
REML	346.6	581.7	187.3
N. of Observations	189	430	107

Note: We display only the fixed-effects terms and coefficients that were statistically significant (p < .05). [R] Recipient and [S] Sender.

in other teams. Table 3 reports the factors influencing the responses to invitations during each of the three stages. These are described in the following sections.

4.4.1 Initializing a team. When initializing a team, users were more likely to accept the first invitation that they received (β=.22, p<.05), and less likely to accept an invitation if they had many other pending invitations to choose among (β=-.06, p<.05). Users were less likely to accept (or conversely, more likely to decline) invitations from individuals who scored high on the extraversion trait (β=-.08, p<.05). Previous social connections were also significant in impacting decision making in the early stage of team formation: users were more likely to accept invitations from users who have collaborated with many people in the past (β=.21, p<.01), but were more likely to decline invitations from users who knew many people (β=-.17, p<.01). Users were also more likely to decline invitations if many others cited them as friends (β=-.24, p<.05). Interestingly, competence had a negative effect: users were more likely to decline invitations from senders who reported possessing a large number of the skills required for the project.

4.4.2 Growing a team. During the growing a team stage, the users were more likely to accept an invitation from somebody who they already knew (β=.19, p<.01), but curiously they were less likely to accept an invitation from somebody with whom they had previously collaborated (β=-.12, p<.01). Users were more likely to accept invitation if they reported collaborating with many in the past (β=.13, p<.05) or if others reported collaborating with them (β=.10, p<.01).

4.4.3 Finalizing a team. In the finalizing team stage, users were more likely to decline an invitation from a user who was already on a team (β=-.33, p<.05). Users were more likely to accept invites from senders with higher social skills (β=.13, p<.05) and those scoring higher on the openness trait (β=.09, p<.05). On the other hand, users were more likely to decline invites from users scored high on the extraversion (β=-.08, p<.05) and agreeableness (β=-.09, p<.05) traits. Prior social connections were also important: users were more likely to accept invitations from those who were cited as friends by many (β=.19, p<.05), and those who reported having many friends (β=.13, p<.05).

4.5 Team composition

Finally, in response to RQ4, we examined how individuals' search, invitation, and response behaviors aggregated to emergent outcomes on team composition. In total, users formed 91 teams: 93.4% were self-assembled completely by users, 5.5% required the intervention of the instructor (adding one or more members to the team), and 1.1% were assembled manually by the instructor.

Many teams were formed based, at least in part, on existing social connections. In 64.7% of teams, each user knew at least one other person in the team, in 36.5% of teams each user had previously collaborated at least one other team member, and in 48.2% of teams, each person was a friend with at least one team member. That said, 3.5% of teams were formed where nobody in knew each other, 12.9% were formed where

(a) Clusters based on Human Capital
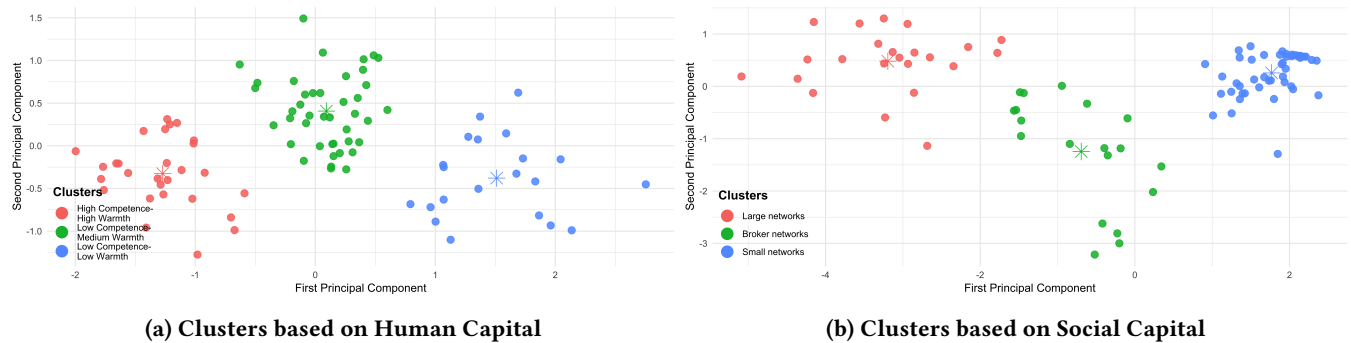
(b) Clusters based on Social Capital

Figure 5: Clusters detected according to the 91 assembled teams

nobody had collaborated with one another, and 9.4% were formed where nobody was friends with one another. To assess the distribution of human capital and social capital we clustered teams based on the users' responses to competence and warmth attributes as well as their social connections in the initial survey. We discuss these results next.

4.5.1 Human capital. We found that the teams belong to one of 3 clusters based on users' responses to competence and warmth attributes (Figure 5a). The first cluster, compromising 32% of the teams, were composed of members who were on average high on competence and warmth. The second group, compromising 44% of the teams, were composed who were average on warmth skills but below average on competence. Finally, the third cluster compromising 25% of the teams, were composed of members who were high on competence but low on warmth.

4.5.2 Social capital. We found that teams belong to one of three clusters (Figure 5b) based on their bridging capital attributes (i.e., popularity, activity, brokerage, and closeness). The first cluster, compromising 31% of the teams, teams were composed of members with high popularity (indegree), activity (outdegree), and closeness scores that were far above the average across all their social networks (i.e., contact, collaboration, friends). The second cluster, compromising 20% of the teams, teams were composed of members who had averages scores on popularity, activity, and closeness, but high scores on betweenness. These teams composed of members who, despite having modest sized networks, were especially adroit brokers. Finally, the third cluster, compromising 49% of the teams, were composed of users with below average bridging capital across all networks.

5 DISCUSSION

In this study, we analyzed users' behaviors on an online team formation system to search for and choose teammates. During the teammate search stage, users' queries included mostly competence and warmth attributes (RQ1): 86% of the

queries included at least one project skill and 74% of them asked for members who valued teamwork. Regardless bridging and bonding capital were used in less than 50% of the queries, we found users' bridging capital and bonding capital were the most important factors for choosing a teammate.

Users' initial searches for competent and warm individuals were not translated to their final teammate selections. Despite the high importance of competence and warmth during the search stage, bonding capital was ultimately determinant in inviting others (RQ2). Even though the system provided multiple search choices sorted by expertise and social skills, users were more likely to invite someone with who they were more familiar. Less-connected users took advantage of using bridging capital search preferences; they searched for "social network brokers" and popular individuals more than highly-connected users. In terms of sending invitations, prior connections were dominant factors across all three team formation stages (i.e., initiating, growing, and finalizing), while some users' traits were relevant at the beginning (e.g., leadership experience) and others at the end (e.g., creativity and gender).

Users' decisions to accept or decline invitations relied on bonding capital and bridging capital: prior collaborations and popular users were more likely to be accepted, while neither competence nor warmth were significant factors across all three team formation stages of initiating, growing, and finalizing (RQ3). One explanation may be the lack of information provided to the invitee about the invitations' sender and, if any, about others on the sender's team. Although recipients were able to see senders' profiles on the platform, only a minority of recipients opened the profiles of the users who sent them invitations (<10%). This shows an asymmetry with the senders, who had more information about the person they were inviting based on specific preferences they used to search for others. In addition to social capital, the need for a teammate also explained the acceptance of several of the invitations. Users were more likely to accept an invitation when they were looking for their first teammate, and when

they only had a few options to choose from. Users who were alone (not in a team) or in a partial team with just a few others were more likely to accept invitations from a larger partial team. They relied mostly on the (smaller) size of their current team, rather than focusing on the potential senders' skills or expertise.

Finally, we found that users' search, invite, and response behaviors aggregated perniciously to create emergent teams that were segregated by users' human capital and social capital (RQ4): while most of the expertise and warm skills were concentrated in a small number of teams, a considerable number of teams were formed by novice users or less sociable individuals [17]. Similarly, the most connected users were concentrated in a small number of teams, and the majority of the teams had members with few social connections.

5.1 Augmenting team formation processes

In this study, we designed an experience that promoted users' agency to select their teammates and the outcomes were not inconsistent with the literature on team formation: social connections are fundamental for teammate selection [37]. Considering this dependency on prior social connections, we question how future team formation systems can enable users to consider other factors beyond their prior social connections, such as the balance and diversity of their skills or backgrounds [66].

Computational augmentation can facilitate users' team formation processes when they have agency to self-assemble [1, 24, 72]: systems can learn from users' traits and social networks to provide feedback in their searches and choices, detecting the strengths and weaknesses of each user [87], and reduce the bias produced by the use of competence and warmth at the search phase, as well as the bias produced by bonding and bridging capital in the invitation and response phases. Future systems can provide users with the option to simulate the formation of their teams [3]. For example, the system might ask users to provide their ideal teammates or needed skills. Users can visualize and plan balanced and skilled teams, in order to understand what are the missing skills or resources needed in their groups. This simulation approach would allow the system to understand how each user would form their own team if they were able to dictate their circumstances.

Finally, systems could interact with the users as social agents in these search and choice processes [27, 59]. Since users' interactions were asynchronous, the system can become an agent who interacts with each user and become a social broker. Systems can be also part of these negotiation stages between users, offering suggestions or making new connections in order to increase the likelihood of diverse teams.

5.2 Emergence of segregated teams

A key, and disturbing takeaway, from this study is that platforms designed to flatten the playing field for team formation can unintentionally enable greater segregation. The concentration of human capital and social capital in a small number of teams reveals one of the main issues with allowing users' agency for choosing teammates. Users' choices led to the social exclusion of certain users, where many teams were filling missing members just to complete the team size requirement. Additionally, those who received many invitations had more potential teammates to choose from, and therefore, greater influence in the final team composition, creating an imbalance in the equation of team formation among all users [34]. The design of team formation systems can hinder the emergence of functional diversity [11, 20], which brings different domains of knowledge and experiences in a single team, as well as the teams' connectivity [57, 72], which provides access to different networks and resources [51]. Future systems should include mechanisms that enable the formation of teams with balanced skills and social connections [78]. For instance, systems can offer potential teammates diversity metrics in terms of skills, traits, and connectivity.

The design of team assembly platforms have the inevitable trade-off: on one hand systems can form teams by optimizing users' expertise and qualities but without considering users' preferences; on the other, systems can grant users full agency for choosing their teammates but without considering the macro-level outcomes. The extent to which users can exercise personal agency challenges the formation of functionally diverse teams. HCI researches must consider how this team formation pipeline aims to maximize the probability of assembling functional teams by allowing users to search and invite others. Future systems can complement both approaches by offering dynamic interfaces: for example, the system might consider reconfiguring teams as the team formation process advances [87], providing enhanced alternatives to its users [25], and involving instructors or managers to be part of the team formation processes [42].

5.3 Limitations and future work

One important limitation of this study is the participation of only students in the U.S., who are may not be representative of other demographic groups. More case studies in other environments would contribute to assess the generalizability of team assembly factors identified in this study. Second, users' self-reported skills may not be realistic: in future, peer-evaluations should confirm others' expertise. Third, we acknowledge that our system configuration and design affected users' searches and team formation processes. The system likely induced certain search preferences and decisions, precluding alternatives that in other contexts they

would have considered. Fourth, we did not control students' interactions during the lectures and outside of them: some teams may have formed because students agreed to do so offline, but that was not possible to measure. Fifth, we cannot infer cause-and-effect relationships among users' traits, their final teammates' choices, and the use of team search systems. Future experimental designs should test our RQs to infer causality. Finally, we did not measure teams' performance after they were assembled. There are indeed valuable questions to be asked surrounding how people adjust their assembly strategies based on past team performance. Future research should consider using ratings of project outcomes, rubrics, standardized non-graded tests, exit surveys, and other metrics to link team formation processes with team performance.

6 CONCLUSION

This study reveals the high relevance of competence and warmth as factors that drive users' searches. However, bonding capital was the most important factor in choosing a teammate. Users' behaviors led to segregated teams. We gained insight into people's underlying decision rules and how they shift according to their team composition. We envision new designs for team formation systems that augment users' capacity for assembling more functional, cohesive, and connected teams that take into consideration users' skills, traits, and social connections.

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