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Antecedents of student team formation in higher education

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A R T I C L E I N F O

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S T R U C T U R E D A B S T R A C T

Background: Students often form project teams by themselves rather than impose pre-defined teams because it leads to better study outcomes. However, few scholars have investigated the mechanisms driving the formation of self-organized groups.
Aims: We examine three underlying and interrelated antecedents of project team formation: friendships, familiarity with fellow team members due to prior co-working experiences, and similarity of team members regarding gender, academic achievement, and preferred collaborators.
Sample: The data encompasses 70 first-year university students asked to self-form teams to carry out a semester project.
Methods: We utilize Exponential Random Partition Models. This new method allows us to model how friendships, familiarity, and similarity affect self-organized group compositions while accounting for each factor's relative importance.
Results: The results show that friends are more likely to end up in the same team than non-friends. Similarity is also an important antecedent for team formation: Students with the same gender and similar grades are more likely to end up in the same team. Familiarity and preferred collaboration showed negligible effects.
Conclusions: Our findings emphasize that educators must consider academic and non-academic factors when allowing students to self-organize in teams, depending on what goal educators strive to achieve with team projects.

In small-group teaching curricula, teachers – or educators in general – often ask students to select fellow students to form project teams by themselves rather than impose pre-defined teams (e.g., through a random assignment). Such a self-organizing approach is frequently preferred over random assignments because it can lead to better outcomes, such as achieving better the team's goals, fostering pride in the collective outcome, limiting conflicts, and increasing the levels of students' enjoyment (Chapman et al., 2006; Chen & Gong, 2018). Yet, while prior research shows that the composition of a team is critical for its efficiency (Bell, 2007; Mathieu et al., 2008), research on how and why specific team configurations come about – notwithstanding recent advances (Bailey & Skvoretz, 2017; Bercovitz & Feldman, 2011; Contractor, 2013; Kaven, Kaven, Gómez-Zará, DeChurch, & Contractor, 2021; Zhu et al., 2013) – is scant. Currently, most zoom in on one factor contributing to team formation or do not inspect the relative importance of several mechanisms driving the team composition (Bailey & Skvoretz, 2017; Bercovitz & Feldman, 2011; Contractor, 2013). For example, a contributing factor of team formation is similarity in academic achievement, the strength of this effect may depend on other factors, such as friendships or familiarity. Moreover, most studies rely on network models to inspect team formation in the absence of appropriate statistical tools (Kaven et al., 2021; Zhu et al., 2013). Network models are designed to study the antecedents of network formation but are limited when studying team formation. There is, to our knowledge, no study that examines the combination of different mechanisms (friendship, familiarity, and similarity) affecting team formation in higher education and statistically test them simultaneously, using an appropriate statistical tool to model team formation.

Students exhibit varying approaches toward team formation (Bailey & Skvoretz, 2017; Bercovitz & Feldman, 2011; Kaven et al., 2021). Some students adopt a result-oriented approach and prioritize forming teams with high-grade or (perceived) collaborative students. Conversely,

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others may optimize team formation based on other factors unrelated to academic performance. Students may, for example, prioritize convenience or social signaling. Students may also choose to team up with friends or familiar others for reasons beyond academic performance, such as wanting to spend time with them. For example, Bailey and Skvoretz (2017) note that positive past experiences, the mere presence of a friendly face, similarity in attributes (e.g., gender, competence, interests, attitudes), and popularity may influence the choice of teammates. Indeed, there are abundant reasons to join project teams. We aim to provide insights that can inform educational practices, policies, and outcomes in institutions of higher learning in which self-organized teams play a role. In doing so, we explore the most studied variables that affect the composition of self-organized teams in the higher education context: Friendships, familiarity, and similarities in gender, academic achievement, and collaboration popularity.

1. Friendships: Teaming up with friends

Friendship plays an essential role in shaping students' academic lives. Friends help each other, provide each other with social support, and share personal information. Dunbar (2018, p. 32) notes that "friends provide moral and emotional support, as well as protection from external threats and the stresses of living in groups, not to mention practical and economic aid when the need arises." Friendships are usually formed based on 'attractiveness' (Byrne, 1971; Verbrugge, 1977), and 'attractiveness' refers to the degree to which an individual's, for example, personality traits, behaviors, and appearance are perceived as appealing and desirable by others. What is more, friendships enable smoother interactions (Uzzi, 1997), serve as a motivator to put your best foot forward to achieve the best for your friend (Granovetter, 1985), foster social cohesion (Coleman, 1990), and lead to more beneficial exchanges (Homans, 1974). In the student context, friendships are shown to be a source of resources affecting academic performance (Brouwer et al., 2022; Brouwer, Flache, Jansen, Hofman, & Steglich, 2018; Stadtfeld, Vörös, Elmer, Boda, & Raabe, 2019).

The same reasons that lead individuals to find others attractive as friends can explain their choice of teammates. Previous work has shown that friends stick together in self-organized teams (Bailey & Skvoretz, 2017; Bercovitz & Feldman, 2011; Chen & Gong, 2018; Kaven et al., 2021; Tsoi & Aubrey, 2023). Based on previous arguments, collaborating with friends may be easier than working with students they are not affectively related to. Therefore, Hypothesis 1 states that *friends are more likely to be found in the same team.*

2. Familiarity: Teaming up with known others

Familiarity may influence the likelihood of students joining the same team. Here, familiarity means that prospective team members had prior interactions (potentially positive). A positive past interaction may particularly further the odds of repeating a collaboration. Familiar students are expected to be aware of prospective teammates' working approaches, and who they are, and could thus be better potential partners as they have already learned to work together (Bailey & Skvoretz, 2017). For familiar team members, the expenses and effort required to communicate and share information may be lower (Bercovitz & Feldman, 2011; Gulati, 1995). Previous interactions perceived as positive should be vital predictors of renewed collaborations (Bailey & Skvoretz, 2017). Studies have shown that positive prior collaborations are indeed a key determinant to continuing to work together in teams (Kaven et al., 2021; Lungeanu et al., 2014), as well as the formation of new teams (Bailey & Skvoretz, 2017; Bercovitz & Feldman, 2011; Huckman et al., 2009; Lungeanu et al., 2014; Maynard et al., 2019; Muskat et al., 2022; Putzeys et al., 2024).

Following our argumentation, we argue that the opportunities to get to know one another provided by the higher education context and educational program should foster the likelihood of students ending up in the same team. Hypothesis 2 states that *students who are familiar with each other due to previous experiences are more likely to be found in the same team.*

3. Similarity: Teaming up with similar peers

Students may form teams based on *similarity*. Homophily (i.e., the tendency of individuals to form connections with those with similar attributes or characteristics) is a pervasive finding (Lazarsfeld & Merton, 1954; McPherson et al., 2001). Individual attributes relevant for homophily in the context of student networks comprise gender (Brouwer et al., 2022; Stadtfeld et al., 2019), study major (Stadtfeld et al., 2019), age (Kossinets & Watts, 2009), and academic achievement (Brouwer et al., 2018).

We explore three attributes (i.e., individual characteristics) inducing homophily in teams: gender, academic achievement, and preference-for-collaboration (PFC) popularity (i.e., the number of students who would like to collaborate with a particular student). The phenomenon of homophily is well documented in the literature (e.g., McPherson et al., 2001). Even "invisible characteristics" of individuals, such as their attitudes and values, can significantly impact their likelihood of forming a connection (van Duijn et al., 2003) via observable signals or cues (e.g., language, clothing, cultural activities) to inform others about individual characteristics that are not readily observable.

There are multiple reasons why students have homophilous relations, and we highlight three that underlie the hypotheses we formulate later on. The first potential source is that individuals *want* to be related to similar individuals (McPherson et al., 2001). For gender, the attraction paradigm set forth by Byrne (1971) stresses that seeking similar others is appealing because others are "like me," following the first potential source of the homophily argument. Having similar grades or being equally popular as a collaborator can signal shared approaches to higher education. For example, a high grade may convey to others that one is hardworking and serious about succeeding in higher education. Similarly, being popular as a collaborator can signal similar study behaviors and reflect "who they are and how they work" as a student. Similar others can provide each other with resources – think of receiving social support, sharing social values, or feeling a 'sense of belonging' – which dissimilar actors cannot or are unwilling to give (as shown, for example, in theoretical work by Bianchi et al., 2020).

A potential second source of homophily – particularly applicable to academic achievement and PFC popularity – is that although lower-scoring students may want to form relationships with higher-scoring students, higher scorers reject such relationships and primarily interact with similar others. Lower-scoring students – students with low academic achievement – are left with the only option to interact with other lower-scoring students. For example, this tendency occurs in networks where actors must cooperate (Simpson & Willer, 2015). Cooperators reject ties to defectors, forcing defectors to form ties to similar others. They do this because it smoothens working together and protects cooperators from defectors who tend to reap the benefits of their cooperative efforts (this is, for example, theoretically explored by (de Matos Fernandes, Flache, Bakker, & Dijkstra, 2022a). Indeed, non-PFC popular students and those with lower academic achievement may aspire, propose, and join teams with their more successful peers to, for example, learn from them or reap the benefits of their success. Yet, they may be rejected by their 'higher' peers who prefer to interact with similar others.[1] Intuitively, academic achievement homophily (the same argument applies to PFC popularity homophily) may lead to lower-achieving students facing a double-edged sword: They may have less access to valuable information and qualities in networks and teams

[1] Status asymmetry – i.e., pursuing ties with higher-status others – may interfere with seeking similar others (Snijders & Lomi, 2019). Aspiration plays an important role in team formation. Such teams may be more popular in the sense that more students want to be part of such a team. Understanding the relationship between similarity and aspiration is crucial to understand the dynamics of PFC popularity and academic achievement. We control for this 'aspiration' effect, stating that students with higher academic achievement or PFC popularity might end up in larger groups.

if similarity preferences drive assortment in both the friendship network and team context.

A third potential source of homophily can be the byproduct of being similar in other dimensions than the variable of interest (Block & Grund, 2014; Hooijsma et al., 2020). For example, the similarity in academic achievement or PFC popularity may arise as a byproduct of more dominant features such as gender or status homophily. Building on the intuition that the tendency to connect to socio-demographically similar others preferentially may lead to similarity on other dimensions, teams may be more homophilous regarding academic achievement and PFC popularity.

3.1. Gender

Gender homophily has been observed in many contexts and is a fundamental organizing principle in students' friendship networks (Brouwer et al., 2022; Kossinets & Watts, 2009; Stadtfeld et al., 2019. Previous research shows, furthermore, that pursuing same-gender others in the team context is a prevalent mechanism (Bailey & Skvoretz, 2017; Kaven et al., 2021). We study whether this is the case for students and state the following in Hypothesis 3a: *Students of the same gender are more likely to be found in the same team.*

3.2. Academic achievement

Academic achievement is an important feature in the formation of students' friendships (Brouwer et al., 2022) and teams (Bailey & Skvoretz, 2017; Kaven et al., 2021) formation. Students with similar academic achievements are more likely to be (or become) friends. If friendship networks often exhibit academic achievement homophily, the question is whether we find the same in teams. Therefore, we hypothesize that preferences for similarity in academic achievement found in friendship networks should also exist in the context of our project teams. Hypothesis 3b thus states that *students similar in academic achievement are more likely to be found in the same team.*

3.3. PFC popularity

The third attribute that can elicit homophily is PFC popularity. The core feature of this attribute is whether students are willing to pay a cost (e.g., time or effort) for the team to receive a benefit. Empirical network research shows that connected individuals tend to be similar in cooperativeness (Apicella,. Marlowe, Fowler, & Christakis, 2012; Brouwer & de Matos Fernandes, 2023). Diverging from network research, theoretical literature studying the consequences of hypothesized team formation mechanisms shows that similar cooperative others tend to stick together in groups (Guido et al., 2019). Whether the theoretical work on network formation also holds for an empirical case in which students must form teams is yet unknown. Some work shows that self-organized teams cooperate better than teams formed at random (Fischer, Rilke, & Yurtoglu, 2023). This could suggest that similar cooperative others seek each other out in teams or that self-organized teams work better together because students are matched with others they like. Based on the literature on network homophily and theoretical literature on team formation, we expect that *students similar in PFC popularity are more likely to be found in the same team* (Hypothesis 3c).

4. Research gap

We need a better understanding of the factors influencing students' decisions to form particular types of teams. This knowledge would contribute to a deeper understanding of the social dynamics and individual preferences underlying team formation in educational and professional environments. The study of student team formation has practical implications for educators, who may design educational interventions that leverage these self-selection tendencies. For example, this knowledge can guide the development of strategies to facilitate diverse teams, create tailored learning environments, and create teams that align with the program's goals and students' preferences and strengths. Potential outcomes could be fostering engagement and preparing students for diverse professional environments.

One potential reason for the current gaps in this research is the lack of models that can be used to test the factors driving team formation and capture the complexity of such a process. Network models have been used to model the formation of relationships between individuals. These models have been extended to the case of bipartite networks, where relationships between individuals and groups (for example, teams). However, they are limited because they require teams to be defined in advance (for more information, see the Method section). In this paper, we complement previous approaches by proposing a new modeling framework that can be used to model the emergence of self-organized teams when the number and characteristics of teams are not known in advance.

5. The current study

We examine project teams in a cohort of first-year bachelor students. The data encompasses 70 students asked to form teams to carry out a semester project. This paper dives into three underlying antecedents of project team formation: friendships, familiarity with fellow team members due to previous teamwork and interactions, and similarity of team members regarding gender, academic achievement, and preference-for-collaboration popularity. To be clear, we always use the word "team" to refer to a group of students working together, because the term "group" applies to a wide range of social entities that are not formalized teams (for more information on the distinction between groups and teams, we refer to Armstead, Bierman, Bradshaw, Martin, and Wright (2016), and Vangrieken, Boon, Dochy, and Kyndt (2017). We reserve the term "group" to describe an abstract set of individuals (mostly when describing our modeling framework).

Because teams are a group-level relation and individuals are nested in teams, we use a model tailored for group-level data, which can be used to test these determinants together (familiarity, friendships, and similarity); that is, the Exponential Random Partition Model (ERPM; Hoffman, Block, & Snijders, 2023). Here, we define a partition as a set of teams within the one-year cohort. The units of analysis are the teams, whereas, in networks, the units of analysis are dyadic relations. ERPMs allow us to explicitly model the number of teams, their sizes, and what drives their final composition, considering that teams cannot overlap (meaning that a student cannot be part of multiple teams). Because students must belong to one and only one team, the composition of a team indirectly depends on what alternative teams could have been formed. The ERPM framework thus fits our data better than other methodologies. To our knowledge, this study is the first to employ this novel framework to study team formation in higher education, which makes it explorative in the sense that it is the first one to examine how friendship, familiarity, and similarity – and their interrelatedness – affect team compositions.

6. Method

6.1. Data collection

We analyze data obtained from $N = 70$ first-year bachelor students from a Dutch university. Participation in the data collection process was voluntary. Students answered a 30-min computer-based questionnaire at the end of the first semester. Ethical approval was obtained from the ethics committee of the Department of Social Sciences of the university where the study was conducted.

6.2. Instruments

6.2.1. Project team

In the last weeks of semester 1, students were asked to choose a project team via an online platform. The course for which the students themselves form teams ran in semester 2. The goal of the project course was to follow a complete research cycle, from reviewing the literature to collecting data, analyzing the data, and writing a report on the topic and data analyzed. Students were not rewarded for specific tasks. Each task in the project course is related to a step in the research cycle. All students were required to partake in each step. A single group grade was awarded to the whole team. The group grade was based on the final research report. Successfully finishing the course resulted in 10 credit points (ECTS) which were a significant portion of the 60 credits required for the whole academic year.

The students formed 12 teams, each focusing on one topic related to active citizenship in a local municipality (e.g., trust, norms, solidarity, social values). Each student selected their team on an online platform where they could see the choices of other students. All students had the same opportunities to enroll in a team after the registration opened. The team selection had to be made individually on the platform, but students could discuss the current composition of teams before the online registration and after the registration opened. The number of teams was not fixed, but the size of a team had to remain below 7. The final distribution was two teams with four students, one with five students, six with six students, and three with seven students. Each project team was assigned a tutor (teacher) who guided the students through the research process, but the students were responsible for the quality of the report. We extracted the compositions of the second-semester project teams from the online registration system.

6.2.2. Friendships

Friendships were collected via online questionnaires in which students rated their fellow students on a scale from 1 ('best friends') to 6 ('I don't know who this is'). To measure a friendship relationship, we dichotomized the variable: 1 ('best friends'), 2 ('friend'), and 3 ('friendly relationships') were coded as 1 ('a friendship'), whereas 4 ('neutral'), 5 ('only known from face or name') and 6 ('I don't know who this is') were coded as 0 ('no friendship') (following the approach recommended by van de Bunt et al., 1999). A friendship is thus either absent or present. The density of the network is 0.09. The density statistic is based on the total number of nominations (418) divided by all nominations (70*69 = 4830). Students reported, on average, approximately six friendship nominations (418/70 = 5.97). Of 418 nominations, 254 are reciprocated relations, resulting in a reciprocity index of 0.61.

6.2.3. Familiarity

We collected two variables to make a familiarity variable: the composition of learning communities and project teams in the first semester. Both learning communities and project teams were defined by random assignment rather than self-organization, based on the time students enrolled in the study program. Students were then provided intensive guidance by staff to succeed in their projects. Therefore, we expect prior encounters in both settings to be mainly neutral to positive.

Learning communities. At the beginning of the year (five months before the project course we are examining), students were divided into small learning communities that meet weekly or bi-weekly for approximately 45 min. Learning communities allow students to meet other students more regularly and to get to know one another (Brouwer et al., 2018; Smith, MacGregor, Matthews, & Gabelnick, 2004; Zhao & Kuh, 2004). The project course we study starts when learning communities' influence on team formation decreases. There were, in total, eight learning communities, with only two students not being part of any learning community. The size of learning communities ranged from 6 to 11 students.

Prior project team. Project teams were formed for a course in the first semester, unrelated to the second-semester project course studied here. The prior project course ran simultaneously with the learning community meetings. Prior project teams were based on the composition of learning communities, albeit in teams of a maximum of three students.

Familiarity variable. We created a binary matrix to indicate whether two students were in the same project team and/or learning community. This familiarity matrix is symmetric, meaning that ties in the associated network are undirected. The density of the familiarity matrix is 0.11. The density statistic is based on the total number of undirected relations (273) divided by all possible undirected relationships ([70*69]/2 = 2415). Students are, on average, familiar with almost 4 other students (273/70 = 3.90). Of 273 familiarity ties, 97 (36%) overlap with friendships. In total, 23% of friendship ties were also familiarity ties (97/418).

6.2.4. Similarity attributes

Gender. The sample contains 32% males ($N = 22$) and 68% females ($N = 46$).

Academic achievement. We collected all the grades received by the students in their first semester and computed their averages. The grades were extracted from the university's internal system after receiving informed consent from the students. Each student's grade was weighed by the number of credits obtained for this course, divided by the maximum possible credit points. This resulted in a minimal achievement of 4, an academic achievement of 9, and an average academic achievement of 6.93 ($SD = 1.08$). In the Dutch grading system, 1 is the lowest grade possible, while 10 is the highest.

PFC popularity. Cooperation can be measured in different ways, for example, by using economic games (Apicella et al., 2012; Fischbacher et al., 2001), direct observations (Ferguson, 2022), self-reports (de Matos Fernandes, Bakker, & Dijkstra, 2022b), or perceptions of others (Rossetti et al., 2022). Here, we rely on the perceptions of others – PFC popularity – to infer how well others around them view a student. Specifically, PFC popularity was measured by asking students whom they would prefer to collaborate with. Students rated the statement 'I would like to collaborate with [name]' on a 5-point Likert scale, ranging from 1 ('strongly disagree') to 5 ('strongly agree'), with the option of 6 ('I do not know'). Categories 1, 2, 3, and 6 were re-coded as not popular to collaborate with (a score of 0), and 4 and 5 as popular to collaborate with (a score of 1). The dichotomization allows the measure of popularity via measuring in-degree scores, as commonly done in network research. The PFC popularity is calculated as the number of students indicating that they would like to collaborate with a particular student. We assume that a student perceived as a popular collaborator is a student who can work well with others. As such, we assume that the PFC popularity measure builds on tell-tale signs of collaboration behavior. This variable ranges from 0 to 16, with an average of 6.93 ($SD = 3.31$).

6.3. Statistical analysis

6.3.1. Relation between ERPMs and network models

Exponential Random Partition Models (ERPM; Hoffman et al., 2023) are related to the most commonly used network models, such as the Stochastic Actor-Oriented Model (SAOM; Snijders, van de Bunt, & Steglich, 2010) or the Exponential Random Graph Model (ERGM; Lusher, Koskinen, & Robins, 2013; Wang et al., 2009), but there are also key differences that warrant the need for ERPMs when studying team formation. Because current literature mostly uses network models (Kaven et al., 2021; Zhu et al., 2013), we first briefly describe ERGMs and SAOMs before explaining how ERPMs can improve our understanding of team formation compared to network models.

Network models express the probability of a tie between two nodes being present or absent. SAOMs and ERGMs can be used to explain dyadic relationships (e.g., friendship) by specifying network formation mechanisms (e.g., reciprocity, transitivity, homophily). SAOMs and

ERGMs can be used to model group relationships in the form of two-mode (or bipartite) networks, in which individuals (i.e., nodes of the first mode) can form ties to groups (i.e., nodes of the second mode). A limitation of this procedure is that in bipartite SAOMs and ERGMs, group nodes need to be defined in advance, and individuals can belong to none, one, or several groups simultaneously. These assumptions are problematic for our study, where groups are not defined in advance and individuals can only be part of one group at a time.

In contrast, the ERPM is tailored for data where groups (or teams) are not defined in advance, and individuals can be part of only one group (or team). The ERPM's logic thus departs from network models for one-mode or two-mode networks and corresponds much better to the data at hand. The ERPM considers the number of groups and their compositions as fully emergent rather than exogenously imposed. Contrary to SAOMs and ERGMs, the ERPM explains group relationships (e.g., teams) by specifying group formation mechanisms. This focus on group relations allows us to go beyond simple dyadic mechanisms (e.g., "I prefer someone similar to me") and model group-level mechanisms (e.g., "I prefer to be in a homogeneous team"). A full comparison between ERPMs and other models is provided by Hoffman et al. (2023), and Hoffman and Chabot (2023) present a study implementing SAOMs and ERPMs separately.

6.4. Model definition

We use an ERPM to model the partition of students into teams and uncover the processes driving the formation of these teams. The framework allows us to explicitly model the number of groups (here, self-organized teams), their sizes, and their composition, considering that groups cannot overlap.

The model defines a random partition P (i.e., a set of non-overlapping teams) over a set of actors $\{1,\ldots,N\}$. In our case, we have $N = 70$ actors (students). The probability distribution of P is given as an exponential family distribution over the whole set of possible partitions $\wp$. Because team size was restricted (from 4 to 7 members), we restricted the set $\wp$ of possible partitions to partitions that contained teams within this range. Due to the design of the course and available tutors, we restricted the number of teams to a maximum of 12. The probability of observing a partition p_{obs} is then expressed as:

$$Pr(P = p_{observed} \mid \alpha) = \frac{\exp\left(\sum_k \alpha_k s_k(p_{obs})\right)}{\sum_{\tilde{P}\in\wp} e^{\exp\left(\sum_k \alpha_k s_k(\tilde{P})\right)}} \quad (1)$$

with $s = (s_k)$ a vector of k statistics and $\alpha = (\alpha_k)$ the parameter vector for the distribution. The statistics s_k can describe any characteristic of the partition, but we specifically use here sums of team-level statistics to make the interpretation of the model easier. These statistics aim to reproduce important features of the partition and thus capture team formation processes. The maximum likelihood estimates of α can be obtained via stochastic approximation (see section 4.3). Because maximum likelihood estimation and the method of moments are equivalent for exponential families, we are essentially looking for the parameter values for which the distribution of the statistics $s(P)$ predicted by the model are centered around the observed statistics $s_{obs}(P)$.

One can note that Equation (1) mirrors the joint form of an ERGM (Lusher et al., 2013) with the support of the distribution being a set of partitions rather than a set of networks. While the intuition behind both models remains similar, there are some notable differences. Both models are used similarly to a logistic regression to predict ties or teams, considering different dependencies. The ERGM expresses the probability of a tie between two nodes being present or absent, depending on the characteristics of these nodes and the presence of other ties in the network. On the other hand, the ERPM expresses the probability of a team to be formed, depending on the characteristics of its members and potentially the composition of other teams. Because individuals must belong to one and only one team, the probability of a team indirectly depends on what alternative teams could have been formed. Moreover, the sufficient statistics used in the ERPM differ from those used in ERGMs. Statistics in ERGMs usually measure (dyadic) tie configurations (e.g., the number of ties). In contrast, ERPM statistics measure team configurations (e.g., the number of teams). To be clear, the unit of analysis in ERPMs comprises the team, whereas the unit of analysis in network models (SAOMs or ERGMs) is the dyad.

6.4.1. Model specification[2]

Statistics in the model should represent the factors explaining the final composition of the observed partition (mirroring, for example, the use of independent variables in classic regression frameworks). The factors of interest for our hypotheses are friendship, familiarity with one another, and similarity in three individual attributes (gender, academic achievement, and PFC popularity). In what follows, we list all the statistics included in the model and highlight per statistic: (1) what the statistic represents, (2) how the statistic is defined, and (3) how the parameter associated with the statistic can be interpreted. We first describe the statistics specifically related to our hypotheses and then define additional statistics used as controls.

The effect of friendship and familiarity are included in the ERPM with the network tie statistic, which counts the sum of relations (friendship or familiarity) present within teams in the partition. This statistic captures students' tendency to form teams with friends and familiar partners. If we define $Z_{i,j}$ as a dyadic binary covariate indicating, for example, whether students are friends or familiar with each other, this statistic is defined as:

$$s_{\text{network tie}}(P) = \sum_{G\in P}\sum_{i,j\in G} Z_{i,j}$$

A positive parameter for this statistic indicates a tendency for individuals to form teams with peers they have a relationship with, in other words, a tendency to find many network ties within rather than between teams. We, therefore, test *Hypothesis 1* using this statistic with Z defined as the friendship network and *Hypothesis 2* with Z defined as the familiarity network.

We then indicate the effect of similarity in gender, academic achievement, or PFC popularity with two types of statistics to represent the tendency to form homogenous teams regarding these attributes. We first use dyadic similarity statistics to capture the tendency for pairs of similar individuals to join the same team. For a categorical attribute, we define for each pair of actors i and j the variable $\text{same}_{i,j}(a)$ as a variable taking a value of 1 if the two actors have the same value of the attribute a, and 0 otherwise. We use this notation for gender. For continuous attributes, we define $\text{diff}_{i,j}(a)$ as the absolute difference between the attribute values of actors i and j. Higher values of $-\text{diff}_{i,j}(a)$ point to students being more similar (here, a can be either the academic achievement or the PFC popularity attribute). The dyadic similarity statistic is then defined as a sum of either the same attribute pairs or absolute differences within groups:

$$s_{\text{dyadic similarity}}(P) = \sum_{G\in P}\sum_{i,j\in G}\text{same}_{i,j}(a) \;\; or \;\; \sum_{G\in P}\sum_{i,j\in G} -\text{diff}_{i,j}(a)$$

In the case of a categorical attribute (here, gender), a positive parameter predicts that more pairs with the same gender are found in the same teams. In the case of academic achievement and PFC popularity, a positive parameter would indicate a tendency to find, within teams, pairs of individuals with low differences (i.e., similar values).

[2] The developers of ERPM provided us with an example R-script and ERPM-manual, both freely available on GitHub (https://github.com/stocnet/ERPM). The example R-script and manual were used for this study.

Second, we define team similarity statistics to represent the tendency for individuals to form homogenous teams. For a categorical variable (i.e., gender), the variable same_G takes the value 1 when all individuals in the team G are from the same category and 0 if they do not. For continuous variables (i.e., academic achievement and PFC popularity), we define range_G as the difference between the highest and the lowest value in the group G. Values of $-\text{range}_G$ indicate homogeneity in the team. The team similarity statistic is defined as the number of teams with only members of the same category or the additive inverse of the sum of attribute ranges in all teams. Formally, we write:

$$s_{\text{team similarity}}(P) = \sum_{G \in P} \text{same}_G \quad or \quad \sum_{G \in P} - \text{range}_G$$

For gender, a positive parameter associated with this statistic indicates a tendency to form non-mixed teams. The interpretation of the individual level would be that students tend to form teams where everyone is from the same gender as them, in other words, where no one is different from them. A positive parameter for academic achievement and PFC popularity corresponds to a tendency to form teams where the difference between the two most different individuals is low. At the individual level, a student would then tend to have a low difference from the students most different from themselves in the team.

We use dyadic and team similarity statistics for gender, academic achievement, and PFC popularity as two alternative tests of *Hypotheses 3a, 3b,* and *3c*, respectively. The distinction between both types of statistics is important. Dyadic similarity expresses that students select similar teammates, potentially tolerating some dissimilar ones, while team similarity expresses that students optimize similarity among *all* teammates. Without any clear expectation as to why one would be a better specification than the other, we define models with either specification and compare them to understand which one better represents similarity selection in our context.

One should note that dyadic and team similarity are closely related and that both types of statistic might lead to similar attribute distributions in the partition. To understand this, one can consider the case of a student leaving team A with dissimilar others to join team B with more similar others: with this change, team A and team B can become more homogeneous. Eventually, teams might become completely homogenous simply because individuals try to optimize similarity at a dyadic level. A similar effect is well-known in residential segregation models (Flache & de Matos Fernandes, 2021; Schelling, 1971), where dyadic similarity preferences can lead to segregated neighborhoods due to relocation cascades.

In addition, other statistics are included in the model. The first control statistic, specific to the partition context, is a count of the number of teams. If the parameter is negative, the model predicts fewer but larger teams than in a random partition. Conversely, a positive parameter expresses a tendency to form many small teams. This statistic thus controls the distribution of team sizes.

Other control statistics account for the popularity of students with higher academic achievement or PFC popularity. Because popularity mechanisms may be confounded with similarity preference mechanisms (see section 2.3), we control for popularity specifically by considering that more attractive students may attract more peers in their teams and thus be found in larger teams. We thus include as a statistic the sum of each student's attribute multiplied by the size of their teams. The statistic is equivalent (up to a multiplicative factor) to summing over teams the product of team size and the average value of the attribute in the team. If we define a_i as the attribute of individual i (their academic achievement or PFC popularity) and $|G|$ as the size of the team G, the popularity statistic is defined as:

$$s_{\text{popularity}}(P) = \sum_{G \in P} \sum_{i \in G} |G| a_i$$

Positive parameters for popularity statistics thus express the tendency of individuals scoring high on a given attribute to be found in larger teams. This statistic also has an important influence on the group size distribution.

6.4.2. *Missing data*

We imputed missing attribute data using the Multivariate Imputation by Chained Equations (MICE) package in R (van Buuren & Groothuis-Oudshoorn, 2011) to be able to specify the variables used in our models—missing data comprised two gender values and two academic achievement values. The imputed values were generated using predictive mean matching, estimating missing values by matching missing cases to the observed data. The ERPM uses the result of the imputations as the input dataset for the model (and not the set of various imputations as input for the model).

6.5. *Analytical strategy*

The estimation of the ERPM is implemented in R (R Core Team, 2022), using the R package *ERPM*.[3] The maximum likelihood estimation of the model parameters builds upon the Robbins-Monro algorithm (Robbins & Monro, 1951) initially proposed for ERGMs (Snijders, 2002) using a Markov Chain Monte Carlo (MCMC) scheme to sample from the distribution (as the calculation of Equation (1) is intractable). The statistical significance of the parameters is assessed via a Wald test using the standard error of the estimator. All details on the algorithm are provided by Hoffman and colleagues (2023).

We estimate two models to test our hypotheses. Model 1 uses similarity statistics defined at the level of dyads, while Model 2 includes an alternative statistic for similarity at the team level (see above). Table 1 provides an overview of the hypotheses linked to the expected sign of the statistic and an actor-oriented explanation of the expected results. The major difference in the actor-oriented explanation can be found via the description of dyadic and team similarity (*Hypotheses 3a, 3b,* and *3c*). Finally, we examine the goodness of fit of both models in to assess whether data simulated from the model reproduces the observed data well.

7. Results

7.1. *Descriptive results*

Table 2 provides for each team summary statistics related to gender, academic achievement, PFC popularity reputations, friendship nominations, familiarity ties, and team size. Table 2 shows that the range of academic achievement and PFC popularity differs across teams. The differences in within-team variance for PFC popularity and academic achievement show that some teams comprise students with similar academic achievement (e.g., teams 11 and 12) and PFC popularity (e.g., teams 5 and 11). In contrast, others contain students with widely different scores on PFC popularity (e.g., teams 2 and 9) and academic achievement (e.g., teams 5 and 9). Most students have at least one friend in their team. Eighty-eight (21%) friendship nominations are distributed within the same team, and 330 (79%) are among students in different teams. Twenty-six students have no friends in their team. Table 2 and Fig. 1 show that some teams comprise many friendship ties, represented as red links between nodes.

We find a correlation of 0.433 ($p < 0.001$) between PFC popularity and academic achievement, indicating that students with higher academic achievement are also more likely desired as collaborators. Two ANOVAs also show that PFC popularity ($F_{1,68} = 0.070$, $p = 0.792$) and

[3] The R-package can be found at https://github.com/stocnet/ERPM. The R-script used for this study is shared via the Open Science Framework (OSF) and accessible via https://doi.org/10.17605/OSF.IO/3GDBX. The data is from a relatively small subset of students from one academic year, not long ago. We did not receive approval from the students to share the data publicly.

Table 1
A summary of the hypotheses, expected outcomes of the ERPM statistics, and actor-oriented explanation of the expected results.

Description of the hypothesis	Expected sign of parameter	Actor-oriented explanation of expected result
H1: Friends are more likely to be found in the same team.	+	A student is more likely to join a team with many friends.
H2: Students who are familiar with each other due to previous experiences are more likely to be found in the same team.	+	A student is more likely to join a team with many familiar others.
H3a: Students of the same gender are more likely to be found in the same team.	+	*Dyadic similarity*: A student is more likely to join a team with individuals of the same gender. *Team similarity*: A student is more likely to join teams in which the team is entirely of the same gender.
H3b: Students similar in academic achievement are more likely to be found in the same team.	+	*Dyadic similarity*: A student is more likely to join a team with others with low differences in academic achievement. *Team similarity*: A student is more likely to join a team with the lowest academic achievement difference.
H3c: Students similar in PFC popularity are more likely to be found in the same team.	+	*Dyadic similarity*: A student is more likely to join a team with others with low differences in PFC popularity. *Team similarity*: A student is more likely to join a team with the lowest difference in PFC popularity.

academic achievement ($F_{1,68} = 0.013$, $p = 0.910$) do not differ significantly per gender.

7.2. Hypotheses

We investigate whether friendships, familiarity, and similarity in gender, academic achievement, and PFC popularity affect project team compositions among first-year higher-education students. In what follows, we first discuss per hypothesis preliminary results in the form of the average of friendship nominations and familiarity ties within and across teams, intra-class correlation coefficients (ICC), and Blau indices. The statistics do not control for the other features or team dependencies but give descriptive information on whether teams align with the variable of interest. The ICC captures intra-team consistency in academic achievement and PFC popularity. The Blau index (also known as the Gini-Simpson index) indicates to what degree teams are diverse regarding gender. After these descriptive results, we investigate with ERPMs the tendency of students to optimize their team composition based on friendships, familiarity, and similarity, controlling for all team formation processes at once. The ERPM results are presented in Table 3.

Hypothesis 1 states that friends were more likely to be in the same team. Each student nominated, on average, 1.26 others as friends within teams and 4.71 between teams. The question of whether friendships are distributed equally between teams or that some teams have more-than-expected friends within the team is answered using the ERPM. We report the results of Model 1, given that both models report a similarly significant and directional effect. The significant estimate of 1.13 (*SE* = 0.17) for the effect of friendship denotes that students tend to be part of project teams with friends. A partition in which two friends are in the same team is 3.10 ($e^{1.13}$) times more likely than a partition where they are not, everything else being constant. The presence of friends appears to be a key feature of team formation. Our results support *Hypothesis 1*.

Hypothesis 2 proposes that students familiar with each other due to previous experiences were more likely to be found in the same team. At first glance, students have, on average, 0.37 familiarity relations with others in their team and 3.53 of such relations across teams. Most teams comprise students who do not share familiarity ties. We analyze the role of this feature on final team compositions using the ERPMs, controlling for other co-occurring processes. In both models, students do not end up in teams with those with whom they shared a learning community or prior project team in the past. For instance, the results in Model 1 suggest that a partition in which two students who are familiar with each other are in the same team is 0.57 ($e^{-0.57}$) less likely than a partition where they are not, ceteris paribus. Based on the results, we, therefore, reject Hypothesis 2.

We hypothesize that students similar in gender (*Hypothesis 3a*), academic achievement (*Hypothesis 3b*), or PFC popularity (*Hypothesis 3c*) were more likely to be in the same team. We find an ICC score of 0.310 and 0.262 for academic achievement and PFC popularity, respectively. ICC scores below 0.5 indicate poor intra-team alignment. This suggests that teams are diverse in terms of academic achievement or PFC popularity, at least descriptively. Furthermore, the high Blau index of 0.915 for gender indicates that teams tend to be homogenous. The Blau index result suggests that males and females tend to be with similar others in

Table 2
Descriptive information per team numbered from 1 to 12.

Team	Size	Gender	Academic Achievement		PFC popularity	Friends	Familiarity ties	
#	Count	Female (%)	M (SD)	Range	M (SD)		Count	Range
1	7	7 (100%)	7.29 (1.11)	3	10.58 (2.82)	8	24	7
2	4	3 (75%)	7.00 (0.82)	2	7.00 (6.22)	14	4	1
3	6	6 (100%)	6.50 (0.84)	2	4.50 (1.64)	4	8	2
4	6	5 (83%)	7.67 (0.52)	1	8.00 (3.29)	9	8	2
5	6	6 (100%)	6.67 (1.37)	4	5.67 (1.51)	4	2	2
6	6	2 (33%)	6.17 (0.98)	2	6.33 (2.66)	6	10	2
7	5	2 (40%)	5.60 (0.89)	2	4.20 (1.48)	4	1	2
8	6	6 (100%)	7.17 (0.75)	2	7.83 (3.37)	8	8	1
9	7	3 (42%)	6.57 (1.51)	4	6.86 (4.53)	13	12	3
10	7	4 (57%)	7.14 (1.07)	3	8.71 (2.68)	8	3	1
11	6	5 (83%)	8.00 (0.00)	0	5.67 (1.21)	3	6	2
12	4	1 (25%)	6.50 (0.58)	1	6.25 (2.22)	5	2	1

Note. # = number; *M* = mean; *SD* = standard deviation; Range = calculating the same team's max minus the min score.

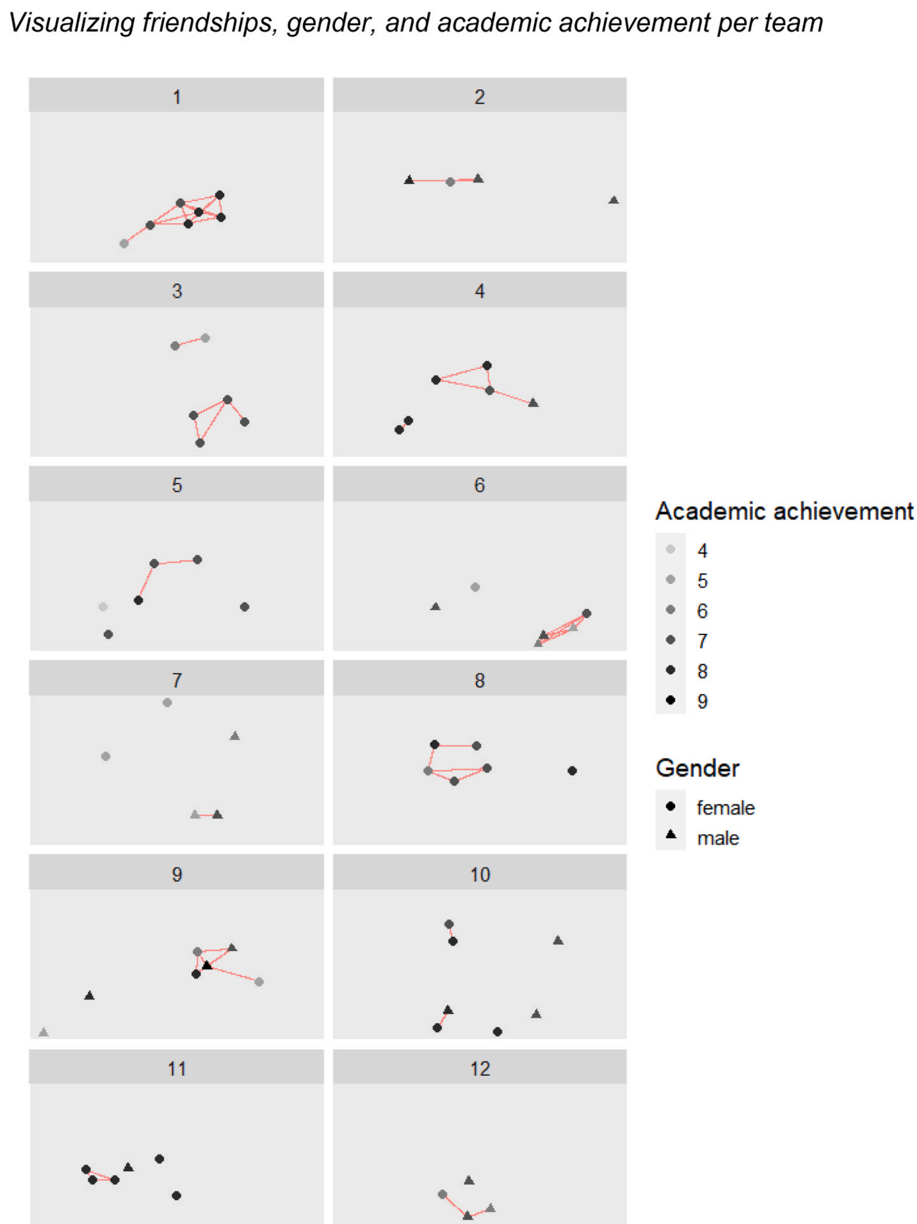

Fig. 1. *Visualizing friendships, gender, and academic achievement* per *team*
Note. A light-red line between nodes refers to a present friendship nomination. Females are visualized in circles, and males in triangles. A darker color refers to a higher academic achievement of the student. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

teams. We use the ERPMs to test our similarity hypotheses. Model 1 considers a dyadic similarity measure, and Model 2 includes a team similarity statistic for gender, academic achievement, and PFC popularity.

Model 1 provides evidence for an effect of gender similarity (est. = 0.25, *SE* = 0.12). A partition with one more pair of students from the same gender in the same team than another partition is 1.28 ($e^{0.25}$) times more likely, other things remaining equal. Students thus tend to end up in teams with students from the same gender. The positive academic achievement difference statistic suggests that students tend to have similar academic achievement in teams (est. = 0.17, *SE* = 0.06). We find that an increase of 1 in the sum of dyadic similarities between teammates (this would correspond to two grades getting closer to one point out of 10) makes a partition 1.19 ($e^{0.17}$) times more likely, other things being equal. Our results in Model 1 thus support *Hypotheses 3a* and *3b*. The effect of PFC popularity (est. = 0.03, *SE* = 0.03) is not significant. We do not find evidence for *Hypothesis 3c*.

Model 2 investigates whether there is a tendency for team-level homogeneity regarding gender, academic achievement, and PFC popularity. The lower log-likelihood of Model 2 indicates that the specification using team similarity statistics fits the data slightly worse than the one using dyadic similarity statistics.[4] For gender, there is a

[4] We studied variations of the team and dyadic similarity statistics to inspect whether the fit of the ERPM improved comparison to Models 1 and 2 in Table 3. We first included dyadic similarity for academic achievement and PFC popularity and team similarity for gender. This resulted in a slightly worsened log-likelihood of −138.41. The second variation was to include the dyadic similarity statistic of gender and the team similarity statistics of academic achievement and PFC popularity. The fit of the model worsened to a log-likelihood of −139.79 compared to Models 1 and 2.

Table 3
Estimated parameters for the ERPMs studying project team compositions.

	Model 1			Model 2		
	Estimate	*SE*	OR	Estimate	*SE*	OR
Number of teams	−15.82	10.51	<0.01	−14.88	10.85	<0.01
Popularity						
Academic achievement	−0.10	0.08	0.90	−0.10	0.07	0.90
PFC popularity	0.04	0.05	1.04	0.04	0.04	1.04
Friendships						
Friendship nomination	1.13**	0.17	3.10	1.15**	0.20	3.16
Familiarity						
Familiarity tie	−0.57	0.54	0.57	−0.57	0.56	0.57
Dyadic similarity						
Gender	0.25*	0.12	1.28			
Academic achievement	0.17**	0.06	1.18			
PFC popularity	0.02	0.03	1.02			
Team similarity						
Gender				1.56	0.92	4.76
Academic achievement				1.12*	0.48	3.06
PFC popularity				0.11	0.19	0.90
Log-likelihood	−134.24			−135.44		

Note. Estimate = log-odds; *SE* = standard error; OR = odds-ratio; The OR compares one partition to another where the statistic of interest is higher by one unit, ceteris paribus; Convergence ratios for all estimates are ≤0.30; *$p < 0.05$; **$p < 0.01$.

tendency to form homogenous teams, but it is not significant (est. = 1.56; *SE* = 0.92). This may be because we only observed 4 perfectly homogenous teams regarding gender, and we did not have enough statistical power to detect this effect. Yet, we observe a lot of homophilous ties, i.e., with similar others, because of these perfectly homogenous teams, and in many teams, at least two-thirds are from the same gender. This may explain why we did find a significant gender dyadic similarity effect in Model 1. The positive estimate for team similarity in academic achievement (est. = 1.12; *SE* = 0.48) indicates that the range of academic achievement in teams tends to be low, indicating a tendency for team similarity. The PFC popularity is insignificant as in Model 1 (est. = 0.11; *SE* = 0.19).

7.3. *Other ERPM statistics*

We can infer from the negative parameter for the number of teams in Models 1 and 2 that there is a tendency to form fewer teams than expected at random. This means that teams tend to comprise many students. For example, a team comprising six students is more likely to remain than splitting into two teams comprising three students each. The results in Table 3 also show that popularity – meaning pursuing teams with constituents who have higher academic achievement and PFC popularity – is not a determining mechanism for the final team compositions in both models.

7.4. *Goodness of fit of the ERPM*

Appendix B includes an assessment of the goodness of fit (GOF) for both models. We use several auxiliary statistics to evaluate the resemblance of simulated partitions sampled from the model with the observed data. Simulations for both models are based on 500 simulation runs. Figures B1 and B2 in the Appendix demonstrate that Models 1 and 2 capture the distributions of team sizes and attributes well in the teams. For example, Figure B1 shows the count of teams with 4, 5, 6, or 7 students in the simulations being well-fitted with the observed data. Even though the simulations slightly over- and underestimate teams with 5 and 6 students, respectively. In Figure B2, we assess auxiliary statistics related to similarity that are not included in the model. The model with dyadic academic achievement similarity reproduces well the homogeneity observed in the teams. The opposite holds as well: The GOF of the model with team similarity provides a satisfactory fit with a dyadic similarity index. Moreover, Figure B4 shows that the simulations satisfactorily capture the observed academic achievement differences. For example, most students have a 7 as academic achievement, and there are thus more connections to similar 7-achievers within teams. The simulations capture this tendency well. The ERPMs also effectively model the observed gender combinations, as illustrated in Figure B5. Gender combinations comprise female-female, male-male, and male-female relations. Next, Figures B.6 and B.7 show that both models fit the observed data regarding the average number of friends and familiar students within teams. Both models provide a satisfactory fit to the observed data, as evidenced by similar log-likelihoods.

8. Discussion and conclusion

Teams allow individuals to pool their skills, knowledge, and resources to achieve common goals and objectives (Bell, 2007; Guzzo & Dickson, 1996; Salas et al., 2018). We hypothesized that friendships, familiarity through prior teamwork, and the tendency to form teams with similar others play an important role when forming teams. Akin to earlier findings in which the role of friendships next to other types of networks is investigated (Brouwer et al., 2022), we find that friendships spill over to the team context (Hypothesis 1 supported), which aligns with findings in team formation (e.g., Kaven et al., 2021). Familiarity plays no decisive role in this context for the final team composition (Hypothesis 2 was not supported). This contradicts the literature stating that prior experiences are key to team formation (e.g., Bailey & Skvoretz, 2017). For instance, recent qualitative work explicates that a major reason to join a team is prior experiences and, thus, familiarity (Putzeys et al., 2024). A potential reason why we do not find evidence for a familiarity effect is that students possibly did not like the prior configuration based on the enrollment date, or that the effect of familiarity was too small to be detected.

Furthermore, gender and academic achievement similarity are important for establishing teams: Students with the same gender and similar grades are more likely to end up in the same team (Hypothesis 3a and 3b supported). Both dimensions are described in the literature as salient factors for joining teams (Bailey & Skvoretz, 2017; Kaven et al., 2021), and our results align with the literature. The result concerning gender and academic achievement similarity is relevant because the ERPM accounts for the original gender and academic achievement distribution. This effect thus states that given the number of males and females and the distribution of grades within teams – controlling for the team sizes and other parameters – the number of same-gender pairs is high, and there are low academic achievement differences within the teams. Yet, regarding Hypothesis 3c, we found that similarities in PFC popularity are not major antecedents of team formation. This contrasts theoretical work showing that similar cooperative others tend to stick together in groups (e.g., Guido et al., 2019). Potential reasons could be using peer perceptions to measure PFC popularity. Nevertheless, our results align with other work pointing to the importance of friendship rather than skills (Chen & Gong, 2018), such as cooperativeness. To summarize, this study considers non-academic (friendships and gender) and academic factors (academic achievement) as the most important antecedents of final team compositions.

8.1. *Practical relevance*

This research has practical consequences as individuals not only form friendships but also need to work together in more formal teams, often simultaneously. Our study suggests that students want friends around, possibly indicating that students also "want to have a good time" and potentially find it "safe" to form a team with friends and same-gender others. This follows the extensive literature on the tendency to form homophilous ties to others (Byrne, 1971; McPherson et al., 2001). Also, we find that similarity in academic achievement fosters joining the same team. A potential implication is that lower achievers cannot learn from their high-achieving peers in the team context. It appears that social learning cannot occur for some students, given that the best students – reflected in their academic achievement – tend to team up, leaving others aside.

Our study informs educators about the mechanisms that drive self-organized teams. In practice, our study may provide input depending on what goal educators strive to achieve with team projects. If educators want teams to be diverse and their constituency a mixture of friends and non-friends, then we show that self-organization may not be the best way to organize team projects. For a study director, it may be helpful to encourage students to form teams with peers outside of their immediate friend group to form more diverse teams in terms of gender. Also, if educators strive to have teams with a mixture of lower and higher achievers, self-organization may not be the best option to form teams. Random assignment or institutional control may be better ways to form teams.

Organizations outside academia can use these findings to better understand team formation and account for factors like friendships and gender homophily when individuals themselves form teams. Work in organizational contexts already hints at the importance of dyadic relationships in forming teams (Curseu et al., 2009). Relatedly, teams comprising friends can be beneficial for the team. Bercovitz and Feldman (2011) show that such teams may succeed more in terms of commercialization than teams with fewer friends.

For research, this study is a testament to the importance of networks. Network research is essential for analyzing and addressing various social, economic, and political issues, ranging from segregation dynamics to disseminating misinformation. For example, networks profoundly affect academic success (Brouwer et al., 2018; Stadtfeld et al., 2019). We show that network relations also affect team compositions. Collecting network and team data and analyzing the data with appropriate analytical tools helps us better understand how information, resources, and influence flow via the network into other domains, such as teams.

Although we do not find evidence for familiarity in this paper, most research points to the importance of familiarity in forming teams (e.g., Bailey & Skvoretz, 2017). The studied context of first-year students could have played a role. If we align our non-finding to the existing literature, a practical consequence can be that familiarity – in terms of prior co-working experiences – is not yet important for forming teams, whereas friendships – another type of familiarity – are. It could be that prior positive experiences are more important later in their studies than at the start of their studies. Students must adjust to a new social and academic environment in the first year. Students in the second or third year may have enough co-working experiences with others to judge their value as potential teammates more aptly. The importance of familiarity may express itself later in their studies, suggesting a potential timing effect.

8.2. Limitations

We consider several limitations in this study. First, the PFC popularity measure is a relatively innovative measure of collaboration intentions. Although the experimental and model-based literature on cooperation emphasizes the importance of cooperation as individual assets for network and team formation (Simpson & Willer, 2015), we do not find this in our empirical case. This discrepancy could be due to several reasons, such as using a measure relying on peer perceptions, the lack of clarity in determining whether the measure reflects tell-tale behavior, and the confounding effect of a high correlation with academic achievement. PFC popularity can also reflect non-cooperation features that make one more attractive as a team partner. One can think of preferring to cooperate with someone because they are knowledgeable, intelligent, conscientious, or generally motivated to work hard in teams. There are thus other reasons why students can prefer to cooperate. We suggest that future studies should rely on or compare this measure with more in-depth individual information. For example, one could rely on measures explicitly designed to indicate how cooperative one is (de Matos Fernandes et al., 2022b; Ehlert, Kindschi, Algesheimer, & Rauhut, 2020).

Second, the study did not inspect the consequences of team formation, and in particular, the consequences of friends teaming up. The data were collected during a crucial period of transitioning from secondary to higher education, during which students needed to adjust quickly to their new environment. Making friends was thus essential for these students. Friendships are among the most important sources of support, help, or peer feedback to achieve academic success (Stadtfeld et al., 2019). Perhaps that is also why friendships are vital in forming project teams in the first year, whereas skills and abilities become more important later on. Yet, there may be downsides to working with friends who shield each other from social repercussions (Flache & Macy, 1996). Friends may stand by or not correct one another if an error is made instead of pursuing the team's best interests. Having friends in a project team may thus have unintended negative consequences for its success along the way. However, the current study did not inspect the consequences of team formation for group performance.

Third, the data was gathered among students in one study program and one study year, limiting generalizability to all other possible study and work contexts. For example, teams outside academia may be goal-oriented and more diverse in terms of skills. We suggest remedying this situation by implementing a similar approach in diverse (non) academic contexts to inspect whether the findings are generalizable.

Fourth, the project course was compulsory for students. Therefore, they needed to choose a team related to a topic on active citizenship. This study is unaware of tendencies to opt-out from teams or avoid joining a team altogether. Thus, an open question remains whether we would find similar tendencies in self-organized teams in optional courses. Also, each team focused on one topic related to active citizenship in a local municipality (e.g., trust, norms, solidarity, social values). Hence, choosing to join a team may not solely be affected by potential teammates but also by the topic of the team. Even so, the main goal of the course was to get students acquainted with how to do research (writing a report, doing statistical analysis, and presenting the results), and the role of the topic was relatively small. Future research could investigate team formation among students in project courses where they could not choose a topic, but all the teams have the same topic.

8.3. Future work

Some potential avenues for future studies comprise examining the role of diversity and inclusion in team formation and academic performance, studying the role of individual characteristics and personalities in team formation, and exploring ways to optimize the formation of teams. Some work stresses that diverse teams – in terms of gender, ethnicity, creativity, and ability – are better equipped to accommodate contemporary challenges (King et al., 2009; van Knippenberg & Schippers, 2007), whereas others are largely inconclusive on whether diversity in teams fosters or hampers collective success (Bercovitz & Feldman, 2011; Campbell et al., 2013; Ilgen et al., 2005; Jackson et al., 2003; Yang et al., 2022). This line of literature particularly zooms in on the organizational and work context in which productivity and creativity are the main focus. Also, the diversity-similarity line of research zooms in on whether teams are more able to produce valuable outcomes. Here, we took a step back and studied what features affected the final team composition, whereas future research can inspect whether more or less diversity affects the performance of self-organized groups.

Moreover, an extension can be to inspect whether and, if so, to what degree friendship network effects (e.g., the relationship between friendships and gender, academic achievement, and PFC popularity) affect team formation and vice versa. There is literature on multidimensional homophily in networks (Block & Grund, 2014; Hooijsma et al., 2020), stating that similarity in one attribute may arise as a byproduct of more dominant features, such as gender homophily. To our knowledge, there is little to no empirical evidence for multidimensional homophily in teams. Intuitively, if tied individuals are more similar on multiple dimensions in a social network, it may be that multidimensional network similarity spills over (or fuels) similarity in teams. For example, one can question whether academic achievement (or gender) homophily in networks (e.g., Brouwer et al., 2018) is why we find a similar tendency in teams.

In summary, this paper examines the possible antecedents of student teams in higher education using the novel framework of exponential random partitions modeling (ERPM). This type of framework allows researchers and practitioners to understand team formations' complex and dynamic nature in various settings. We disentangled whether students formed teams based on friendships, familiarity, and similarity in individual attributes, arguing that joining a team based on its ability to realize a productive outcome may, at times, be inferior to joining a team based on non-productivity reasons (e.g., many friends in the team). Thus, educators must consider both academic and non-academic factors when forming teams.

CRediT authorship contribution statement

Carlos A. de Matos Fernandes: Writing – review & editing, Writing – original draft, Visualization, Methodology, Investigation, Formal analysis, Conceptualization. **Marion Hoffman:** Writing – review & editing, Writing – original draft, Supervision, Software, Methodology, Investigation, Conceptualization. **Jasperina Brouwer:** Writing – review & editing, Writing – original draft, Supervision, Resources, Investigation, Data curation, Conceptualization.

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Appendices. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.learninstruc.2024.101931.

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