Enhanced social connectivity in hybrid classrooms versus academic centrality in online settings

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Social learning, the ability to perceive, interpret, and assess the behavior of one's peers, is crucial for forming meaningful relationships and succeeding in various learning environments. Yet, the rise of online and hybrid settings poses new challenges to socialization. Here, we study the social interactions among 191 high school physics students in Chile, comparing online and hybrid classrooms that were assigned in the COVID-19 pandemic context. We found that students in hybrid settings were more connected and more likely to form casual relationships outside their immediate friend groups, which allowed them to gather new information from diverse sources. Along the same lines, in online classrooms, students who excelled in physics occupied more central positions in social networks. This trend was not evident in hybrid settings, suggesting that when social cues are limited, academic performance gains greater importance in establishing social hierarchies and potentially limiting access to diverse information. Our study highlights the importance of social interactions in educational contexts and raises questions about the impact of relational inaccessibility on virtual learning.

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I. INTRODUCTION

Understanding social learning—how students perceive, interpret, and engage with their peers—is crucial for both academic success and personal well being. However, the COVID-19 pandemic has shifted the socialization landscape in different contexts, including education, pushing many institutions to adopt online and hybrid teaching methods [1,2]. While online learning offers the benefit of accessibility, bypassing geographical and physical limitations [3], it also raises critical questions about the depth and quality of social interactions that students can achieve compared to traditional in-person classrooms.

In this context, our study focuses on high school physics classrooms in Chile, examining the social networks formed by 191 students in both online and hybrid learning environments. Online classrooms are entirely mediated by information communication technologies (ICTs), such as video calls, chats, and forums [4–7]. In contrast, hybrid classrooms offer a blend of online and face-to-face interactions, providing a more nuanced social experience. We aim to explore whether the ease of accessing resources online can make up for the loss of rich social cues and relationship-building opportunities that in-person interactions offer.

Previous research in physics education research (PER) has indicated that a student's academic reputation, particularly in subjects like physics, can significantly influence their social standing and network centrality [8–11]. On the other hand, some studies suggest that students often form cooperative ties based on who is available rather than who performs well academically [12]. Our study delves into these dynamics, investigating how they manifest differently in online and hybrid educational settings, where the strategies for forming collaborative ties could vary substantially.

Utilizing social network analysis, we map out three distinct types of student networks: collaboration networks, friendship circles, and peer-nominated academic reputation. We then compare these networks between online and hybrid classrooms to identify any emerging patterns or disparities. Based on the inherent limitations of ICT-mediated communication, we hypothesize that students in online settings may display fewer collaborative relationships and a more

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academic-centric social network compared to those in hybrid settings, which offer the added dimension of face-to-face interactions.

Our research aims to provide a comprehensive understanding of how the shift to online and hybrid learning environments affects both social learning and academic reputation in high school physics classrooms [4–7]. By elucidating the differences in social networks and collaborative ties between these two teaching modalities, we contribute to the broader literature in PER and educational psychology. Furthermore, our findings offer practical guidelines for educators and policymakers for designing more effective and socially enriching physics education in the digital age.

II. THEORETICAL FRAMEWORK

A. Social interactions in education

Understanding the benefits of student relationships in education can be done via an exploration of pertinent concepts such as social capital and communities of practice (COP). Social capital is the aggregate of resources, information, advice, and material goods that are accessible through social relationships by an individual or a community [13]. Conversely, COP refers to a system of interactions between individuals, materials, and activities within a set of norms, contributing collectively to a shared sense of identity [14,15]. While both concepts have garnered attention in PER, COP has been particularly noteworthy.

For example, a study in upper-level physics education showed that the development of a COP is plausible provided that students experience in-person sessions and long and complex experimental tasks, among other conditions [16]. First, face-to-face sessions are set to ease social interactions for sharing both problems and solutions and, particularly, for the use and manipulation of materials. Further, sharing a unique physical space (e.g., classroom) could be attributed to a sense of shared identity, as it is within this space that individuals enact collaborative learning and agency [17]. This evidence is consistent with recent findings on student participation in remote and in-person sessions [18]. In detail, engagement with instructors and classmates is considerably higher for those students attending in-person sessions, compared to their counterparts participating in online physics courses. Moreover, the effect of long and complex experimental activities on the development of COP might be attributed to the demands of collective decision making, communication, and the comprehension that the task outcome relies on a collective rather than on an individual effort [19].

These concepts provide frameworks for understanding how socialization facilitates the development of ideas, learning, and innovation, in addition to fostering a sense of belonging and identity. The benefits of such socialization can also be explicated through the lens of the zone of proximal development (ZPD), where individuals gain access to information and related ideas by collaborating with others possessing diverse or superior capabilities and understandings [20]. Additionally, social capital has been associated with COP in business and management studies [21], suggesting that individuals embedded within a COP are likely to have increased social capital.

In an educational context, students' learning communities in the classroom serve as their primary source of class-related information and materials, thus representing a form of social capital. Access to this capital, however, depends on the individual's structural position within the social network and their capacity to mobilize relationships to acquire resources [22,23]. While social capital has not been directly measured in PER literature, evidence indicates that well-connected individuals achieve higher grades [24,25] and exhibit increased persistence in physics courses [26], outcomes influenced by the accessibility to support and information, a form of capital that seems to enable success and development. Prior research in PER has found, for instance, that social ties enacted for problem solving, conceptual discussion, and nonphysics discussions are associated with academic success in future physics courses [27], evidence that highlights the social nature of the learning experience, and a critical component for human development. Conversely, individuals who struggle to form strong social bonds may find themselves excluded from accessing critical class resources. Because students' relationships are critical for both the development of COP and social capital, in the following section we discuss how teaching conditions, norms and broad structural characteristics of education model students' interactions utilizing evidence from social network studies in education.

B. Teaching conditions and students' social networks

As schools and classrooms evolve into highly social learning spaces, students are encouraged to partake in socialization and relationship building. Homophily—the tendency to form ties based on shared attributes such as race, age, religion, education, and social values—underpins our understanding of student relationships [12,28–30]. However, student interactions in an academic setting can also be shaped by performance expectations, classroom norms, and task nature [2,31] and the availability of others in the classroom [12]. Personal motivations and interests may influence whether individuals prioritize dense or sparse social group formation. For example, research suggests individuals seeking practical advice for advancement goals tend to form sparse, instrumental social networks, while those motivated by a sense of belonging tend to develop denser networks with strongly connected peers [32,33]. Moreover, motivations for social status and popularity can govern students' social networks [34–36]. Studies have revealed that academic popularity can be enacted through different social strategies, depending on whether classroom norms and expectations are oriented towards learning or performance goals. In learning-oriented classrooms, individuals tend to engage in complex patterns of collaborative interactions, whereas in grade-oriented classrooms, status is often achieved through competitive and instrumental behaviors [31]. Therefore, individuals' social strategies and the networks that emerge from them are influenced by a mix of contextual factors and personal inclinations. Recognizing these variables could better equip educators for lesson planning and navigating their unique roles within the classroom.

Moreover, social hierarchies such as academic and/or social popularity are important dimensions of human organization, because these serve as a cognitive shortcut for understanding the structure of the social system (e.g., who is popular and/or a source of information in the classroom) [37–39]. Research suggests that individuals are more likely to learn and remember hierarchical differences and status-related positions compared to more homogeneous social systems [40]. Social hierarchies can be perceived as salient attributes that characterize a social network, and recognizing social and/or academic status has value for a person's overall educational experience. For example, friendship, collaboration, or the identification of personality traits among classmates can greatly influence an individual's learning potential [8,41].

Nonetheless, a recent study in PER found evidence that differences in pedagogy and instruction might amplify and/or reward certain behaviors in the classroom [42]. For instance, answering questions in large physics lectures has been associated with a higher number of proficiency nominations, and the emergence of a proficiency network centralized in a reduced number of highly recognized peers. Differently, classroom dynamics grounded in small group activities such as physics labs, might offer a better scenario for students to showcase their unique set of relevant skills (e.g., leadership skills, artistic skills, communication, etc.) without the need to speak out in front of a large audience. In this learning scenario, the social network of proficiency nominations presents a less centralized topology, and with a more balanced distribution of nominations [42]. This evidence illustrates the contrasting nature of passive (i.e., lecture-based instruction) and more active learning classrooms (i.e., group-based instruction) in regards to the rewarded behaviors and their social recognition for possible network formation.

Despite the effect of the aforementioned contextual characteristics on students' social interactions, physical proximity might also emerge as a critical contributor in encouraging collaboration among students [12,43–45]. Accordingly, witnessing first-hand academic-related behaviors in the context of the classroom could fortify students' knowledge regarding the distribution of abilities among peers, the location of relevant class-related resources, and even adequate behaviors for affiliative goals (e.g., friendship). The latter affordability of in-person classrooms is presumably more limited in fully remote classrooms with ICTs' mediated communication, and therefore, students' social networks would evidence such limitations.

Students in face-to-face classrooms have shown tendencies to form working ties based on similar performance levels [46,47], and among those who display familiar behaviors [48]. Nonetheless, students might also resort to forming ties with those who are close to them or simply available and regardless of their perceived proficiency [12]. In-person education affords students almost instant access to others' behaviors, forms of communication, and nonverbal signals to form mental representations of the social system (i.e., who is friends and/or works with whom, social status, who is available, etc.) [49], which might better equip them to assess the potential value of specific interactions, either for affiliative or academic goals, or both. The exposition of such behaviors expands to students and between student and teachers, thus making it easier for learners to constantly gain information about the academic-related habits rewarded by teachers based on their personal biases [50]. Consequently, one could argue that the benefits of sharing a physical learning space with others allows individuals to recognize the conduct of those peers who are rewarded or punished in the classroom by succeeding or failing, particularly in active learning classrooms where students are required to collaborate and are constantly subjected to feedback from their peers and their teachers. Such social comprehension of social norms and hierarchies could encourage the exploration of new relationships [44], and with this, further access to new ideas and information beyond the student's cohesive group of friends. Finally, by covering the intricacies and affordability of in-person classrooms, one could understand the relational strategies enacted by students participating in the in-person component of hybrid teaching. In the following paragraph, we delve into the additional online component to establish a contrast with the in-person learning experience.

In remote classrooms, communication is mediated by information communication technologies, through video calls, for instance, or often times conceptualized as engagement with online material such as forums and chats [5]. Interacting with online content is often used as a proxy of centrality in the participation network, and is associated with a higher sense of belonging [51]. Similar to face-to-face classrooms, both low- and high-performing students are more likely to form ties with others who display the same levels of academic achievement [52]. From the perspective of individual attributes and motivations, students with a higher willingness to communicate, that is, the tendency to begin conversations with people [53] are more likely to navigate the network in the pursuit of new social ties, a phenomenon even observed among those initially in the periphery of the system. Conversely, students with low willingness to communicate turn to small and trustworthy social networks [54]. It is also observed that students resort to preexisting friendship networks, perceived as safe and secure pathways for collaboration in online learning contexts [55,56]. The situation is different for those with weaker initial friendship ties, as they might explore new relationships more freely and across various social groups with the benefit of information diversity [54].

Because of the nature of social capital and the critical assumption that social ties ease the flow and diffusion of information and materials, among other things [45], in the next section we address current theories utilized in social network analysis to explore learning and the adoption of new ideas.

C. Information and learning through social ties

As mentioned, individuals access various forms of resources through their social relationships. One of these resources, and a rather critical one in education, is information (e.g., physics ideas, strategies for problem solving, etc.). Additionally, the social network tradition has conciliated the potentials and limitations of having either sparse or cohesive social networks for information access and further development of ideas [57,58]. To understand the process of diffusion and learning under cohesive and sparse social structures, first it is important to point out that social relationships are likely to vary in strength. Accordingly, social ties might be rooted in intense emotional affection, shared experience, and reciprocity, while other relationships could have a more fragile existence with no personal nor emotional investment [59,60]. The last case portraits a weak tie among acquainted peers, for instance, whereas the former scenario might resemble the features of a friendship relationship (i.e., strong tie).

With this in mind, one of the critical processes for knowledge acquisition and development documented in the social network literature refers to whether actors are capable of accessing novel ideas through social ties beyond their cohesive groups. Here, it is assumed that a cohesive cluster is formed by strongly connected peers (e.g., a group of friends) who manage information that could fall into redundancy after some time. Therefore, the development of new and innovative solutions to problems would require an inflow of new ideas and perspectives accessible through boundary spanning ties, that is, relationships with actors located in different portions of the social system [57,61]. Nonetheless, the level of complexity of these new ideas would depend on the strength of the relationship through which such information is accessible, as suggested by the theory of weak ties [59,60]. Here, weak ties, or relationships between acquainted peers who likely belong to different parts of the social network are better to diffuse simple and tacit knowledge [62]. Conversely, strong ties are more suitable for the transfer and collective learning of more complex ideas [62], because these relationships are rooted in a common language, interests, and a rather high commitment to helping each other [8]. Resources rooted in a cohesive network are less resistant to flow between actors due to the strength of their social relationships, thus easing transaction costs and encouraging collaboration [63]. Conversely, the social investment required to transfer complex knowledge (e.g., time, energy and resources), makes it unlikely for this type of information to flow through weak ties.

Moreover, when it comes to accessing and learning new information through social networks, one could argue that computed-mediated communication could ease the process of social exploration, that is, navigating through new social ties in the pursuit of new information, for instance. In the context of online learning, this social exploration might be perceived as less costly than in a face-to-face classroom, particularly if such exploration occurs in chats or forums, where students can post questions and comments. Yet, social exploration through in-person interactions might bring actors a more complex set of personality traits (e.g., extroversion), along with verbal skills and willingness to communicate with others [53]. Taking these contrasting scenarios, one could argue that computer-mediated communication might also diminish the chances of forming new strong bonds among students, particularly when social exploration takes place in written formats through chats and forums. This limitation might stimulate online participants to find support and collaboration within their previously existing cohesive groups, as suggested by prior research [55,56].

Finally, as social exploration yields access to new ideas, it is quite important also to be part of a cohesive social network for the learning and further development of new ideas and solutions, a process associated with knowledge exploitation. As sparse networks ease the exploration of new ideas through weak ties, cohesive networks are preferred for in-depth questioning and understanding of new information [57,58]. Here, online and hybrid classroom attendees might experience similar levels of knowledge exploitation, as this process depends on being strongly connected to others, a condition that is likely to be met by individuals attending remote and hybrid education.

It is worth mentioning that in this research we do not attempt to directly test whether online or hybrid attendees are more likely to experience knowledge exploration or exploitation. However, we draw from these processes and their associations with the strength of the ties as a theoretical and methodological orientation to comprehend the implications of our findings, and discuss the relative affordances of online and hybrid classrooms for accessing information, learning and overall student development.

III. METHODS

A. Research context

The study was conducted between the second semester of 2020 and the first semester of 2021. The sample consisted of secondary students from 8 physics classes from two high schools in Chile (Sch-1 and Sch-2).

TABLE I. Summary of sample population and teaching conditions.

Year	School	Grade	Classes (no. students)	Age range	Teaching modality
2020	School 1	11th grade (secondary)	A (29) and B (26)	16–17 years old	Online
2020	School 2	11th grade (secondary)	A (23) and B (23)	16–17 years old	Online
2021	School 2	10th grade (secondary)	A (24) and B (24)	15–16 years old	Hybrid (online + in-person)
2021	School 2	9th grade (secondary)	C (22) and D (20)	14–15 years old	Hybrid (online + in-person)

Participants were 101 students in 11th grade participating in online classes (2020), and 48 and 42 hybrid attendees from 9th and 10th grades, respectively, in the year 2021. In 2020, due to sanitary restrictions due to COVID-19, schools had to transition from face-to-face education to an online teaching modality supported by various ICTs. Later, in the first semester of 2021 and followed by a decrease in COVID-19 cases in the country, schools facilitated students the alternative of a hybrid teaching modality. In hybrid classrooms, a portion of the students participate face-to-face, while the rest of the group works remotely on the class activities. Here, students had to physically attend the school and classroom every other week to follow sanitary regulations, while the remaining days they participated online. Table I summarizes the relevant data for the study. Furthermore, the study design is depicted in Fig. 1, where readers can notice the different schools, classes, and times where data were collected.

For practical context, students in the Chilean school system are organized in cohorts based on age. For every cohort, and depending on the number of students per cohort, individuals might be divided and assigned to classes (e.g., class A and B in 9th grade). Each class is perceived as a stable social system in the sense that students in this group will share the same classroom for almost every subject in the school curriculum, with a few exceptions in 11th and 12th grade where school electives are introduced. Under this set of structural conditions, a student could very well be a member of the same class from 1st grade to their high school graduation. Consequently, the social experience in the Chilean school system might be understood as relatively stable.

B. Data collection and network measures

To map social relationships, we administered an online survey designed to map students' collaboration networks, friendships, and perceptions of academic reputation in physics. The data was collected at the end of the second semester in 2020 (online teaching), and the end of the first semester (hybrid teaching) in 2021. In addition, teachers and the school provided students' grades and gender, to be later used as control variables in our analysis. The survey instruments were designed for students to answer the following social network questions:

1. From the students in the classroom roster, indicate those who are your friends.
2. From the students in the classroom roster, indicate those who you consider are high achieving students in physics.
3. From the students in the classroom roster, indicate those you collaborated with during the classroom activities.

The survey was administered in Spanish, during the Physics class time in the final 20 min. Students attended the computer lab (room in the educational center) to answer the survey. If a student was not present during data collection, they were offered the opportunity to answer the survey at a different time or as soon as they returned to class, being accompanied by the same Physics teacher to the

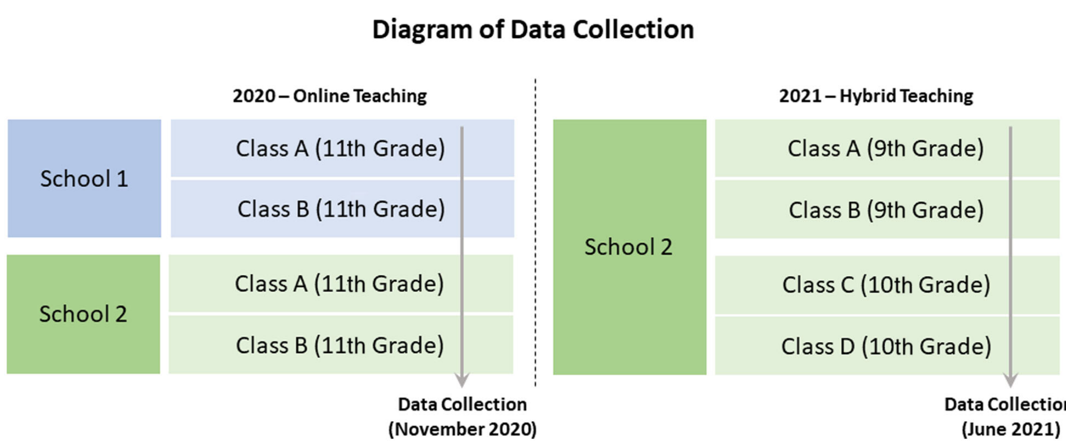

FIG. 1. Timeline for data collection in schools 1 (blue) and 2 (green) during online and hybrid education modes. We note that the data collection took place in a single time in each teaching modality, November 2020 for online classes and June 2021 for hybrid classes.

TABLE II. Network metrics and their definitions. a_{ij} is the number of links between students i and j, and N is the total number of students.

Notation	Definition
$k_i^{\text{in}} = \sum_{j \neq i} a_{ji}$	Indegree is the number of incoming connections that a student i receives from their peers in the classroom [26].
$k_i^{\text{out}} = \sum_{j \neq i} a_{ij}$	Outdegree is the number of outgoing connections that a student i sent out to their peers in the classroom [26].
$k_i = k_i^{\text{in}} + k_i^{\text{out}}$	Degree centrality quantifies the total number of connections that a student i has in their classroom. Corresponds to the sum of indegree and outdegree centralities [26].
$b_i = \sum_{jk} \frac{n^i_{j,k}}{n_{j,k}}$	Betweenness centrality represents the proportion of all shortest paths (geodesics) between vertices j and k that pass through a given vertex i divided by the number of total geodesics [65].
$k_i^{\text{strong}} = \sum_{j \neq i}(F_{ji} C_{ji})$	Strong ties represent the number of times node i connects to a friend j in the collaboration network. F_{ji} and C_{ji}, denote the number of links between students i and j in the friendship and collaboration networks, respectively [8].
$k_i^{\text{weak}} = \sum_{j \neq i}(C_{ji} - F_{ji} C_{ji})$	Weak ties represent the number of times node i connects with a nonfriend (i.e., acquainted) j in the collaboration network [8].

computer lab. Students attending the online class received email messages and personal chat from the professor, and in all cases responded positively to the survey. Every student who participated in the study responded to the survey. To ease students' responses, the survey questions were close ended, and included the roster of students attending their class so participants could select the names of their friends, nominate high-achieving peers, and those they collaborated with. A Spanish verion of the network survey items and structure is available in Fig. 5. This survey structure has been utilized in previous studies [8,27]. These procedures yielded three unweighted directed networks (existing tie: 1; nonexisting tie: 0) [64]: Friendship network, academic reputation network, and collaboration network. Directed networks inform the directionality of the ties, adding a hierarchical dimension to the analysis through simple metrics like outdegree or indegree. For instance, higher indegree (i.e., nominations) in the reputation network suggests a top position in the academic hierarchy, compared with a student with zero nominations [42].

We define an adjacency matrix for the directed network for each classroom: a_{ij}, which takes a value of one if there is a link from student i to j, and zero otherwise. To quantify individual centrality in student classrooms, we used different network measures: degree; outdegree; indegree; betweenness centrality; strong ties; and weak ties. Table II provides a mathematical and descriptive definition for each of these network measures. In order to explore further the nature of these social networks, additionally, we determine students' degree of strong and weak collaboration ties by following the procedure presented in [8]. Here, a strong tie is observed when a student collaborates with a friend, whereas a weak tie regards to a student working with a nonfriend peer (i.e., no friendship tie between them).

C. Data analysis

In the preceding section we describe the centrality measures utilized in this study. These measures, which quantitatively depict the importance or influence of nodes within a network, were derived from the collaboration network. The analysis focuses on the collaboration network, because high centrality is conceived as a sign of social embeddedness in the classroom community, whereas lack of centrality is attributed to limited engagement in the social system that is the classroom and its associated learning assignments. We subsequently utilized these measures as dependent variables in multiple linear regression models. However, it is important to note that we applied a logarithmic transformation to these network measures before using them as dependent variables.

The rationale behind this transformation lies in addressing issues related to network data distribution. Network centrality measures are often skewed, violating the normality assumption in regression models (see Fig. 6 in the Appendix for variable distribution and correlations). This skewness can lead to potential biases and inaccuracies in the results. By applying a logarithmic transformation, we aimed to normalize the distribution of these measures, making them more suitable for linear regression modeling [66]. Figure 7 in the Appendix depicts the distribution and correlation among the log-transformed variables used in this study. Table V in the Appendix shows the normality test conducted on the log, median, and mean of the variables utilized in the analysis. Even though the transformed variables are not normally distributed, these are less skewed than the nontransformed variables. In addition, we fitted multilevel models using nontransformed variables to observe similar coefficients and significance to the ones reported in the main body of the manuscript (see Table VI in the Appendix). Finally, and because this transformation mitigates the impact of extreme values or "outliers," leading to more reliable and robust model estimates [67], we report and describe the models fitted on log-transformed variables.

Our main multilevel model for network centrality measures with respect to schools, classrooms, and students can be specified as follows:

$$\begin{aligned}\mathrm{NCM}_{ijk} = {} & \gamma_{000} + \gamma_{100} \times (\mathrm{TM}_{ijk}) + \gamma_{010} \times (\mathrm{AR}_{ijk}) \\ & + \gamma_{001} \times (\mathrm{FD}_{ijk}) + \gamma_{002} \times (\mathrm{Gender}_{ijk}) \\ & + \gamma_{003} \times (\mathrm{Grade}_{ijk}) + \gamma_{110} \times (\mathrm{TM}_{ijk} \times \mathrm{AR}_{ijk}) \\ & + u_{0jk} + u_{1jk} \times (\mathrm{AR}_{ijk}) + v_{00k} + e_{ijk},\end{aligned}$$

where

- i indexes students, j indexes classrooms, and k indexes schools.
- NCM represents a network centrality measure in the collaboration network.
- TM represents teaching modality. This measure was treated as a binary categorical variable, segmented into "online" and "hybrid" classes. The online category was used as the baseline, against which the hybrid category was compared.
- AR represents academic reputation defined as the nominations within the academic reputation network in physics. It represents the number of nominations received by an individual from their peers, signifying their academic reputation within the discipline of physics. It was treated as a continuous variable.
- FD represents the number of connections within the friendship network. This variable is also treated as continuous.
- Gender: We used school records for "male" and "female," with male as the baseline comparison category.
- Grade: The class level of each student. We have data from 9th, 10th, and 11th grade.
- γ_{000} is the grand mean of network centrality measures across all schools, classrooms, and students.
- γ_{100}, γ_{010}, γ_{001}, γ_{002}, γ_{003}, γ_{110} are the fixed effects coefficients.
- u_{0jk} and u_{1jk} are the random intercepts for classrooms and the random slope for academic reputation within classrooms, respectively.
- v_{00k} is the random intercept for schools.
- e_{ijk} is the residual error term.

The random effects are assumed to be normally distributed:

$$\begin{aligned} u_{0jk}, u_{1jk} &\sim N(0, \sigma_u^2), \\ v_{00k} &\sim N(0, \sigma_v^2), \\ e_{ijk} &\sim N(0, \sigma_e^2). \end{aligned}$$

The goal of fitting multilevel linear regression models was twofold. First, we aimed to discern potential differences in collaborative interactions between students engaged in online versus hybrid teaching modalities. This was assessed while controlling for potential confounding factors, including school-based effects, gender differences, social popularity (as indicated by the degree of connectivity within the friendship network), academic popularity (as indicated by received nominations within the academic reputation network), and grade level.

Second, we aimed to investigate the influence of information communication technologies on communication patterns within online classrooms, with a particular focus on its effect on collaborative interactions. Specifically, we assessed whether ICT-mediated communication was more likely to occur between students with high academic reputations. This investigation was guided by the premise that collaboration with academically reputable peers is a strategic approach to optimizing access to information and resources. We introduced an interaction term between teaching modality and academic reputation into our regression models to explore this relationship. Finally, following the guidelines proposed by Dou and Zwolak [68], we employed bootstrapping to produce multiple regression models. The coefficients derived from this bootstrapping process are consistent with the multilevel linear regression models showcased in this paper. Detailed bootstrapping outcomes for each model can be found in Tables VII–XV in the Appendix. Furthermore, our models showed no signs of multicollinearity, as evidenced in Table XVI within the Appendix. This analysis was conducted on UCINET 6 software for social network analysis, employed to calculate the network centrality measures [69]; and subsequent data processing and analysis were undertaken using standard R libraries [70].

IV. RESULTS

In this section we introduce the results from the analysis conducted to test differences in the collaboration networks measured in two schools, and during online and hybrid school sessions held in the years 2020 and 2021, respectively. Table III shows the means and standard deviations of the social network variables utilized in the study. Here, it is noticeable the difference in the means of the dependent variables (indegree, outdegree, weak ties, strong ties, and

TABLE III. Mean and standard deviation of the dependent social network variables derived from the collaboration network (indegree, outdegree, weak ties, strong ties, and betweenness centrality), and the continuous independent variables (academic prestige, and friendship degree) by online and hybrid teaching conditions. All variables are transformed using natural log.

	ln(indegree)	ln(outdegree)	ln(weak ties)	ln(strong ties)	ln(betweenness)	ln(acad. reputation)	ln(friendship)
	M(SD)	M(SD)	M(SD)	M(SD)	M(SD)	M(SD)	M(SD)
Online	0.85 (0.70)	0.85 (0.70)	0.46 (0.56)	1.16 (0.73)	1.20 (1.58)	1.08 (1.01)	1.34 (1.01)
Hybrid	1.60 (0.31)	1.58 (0.38)	1.32 (0.68)	1.51 (0.61)	2.48 (1.28)	1.67 (0.64)	2.07 (0.49)

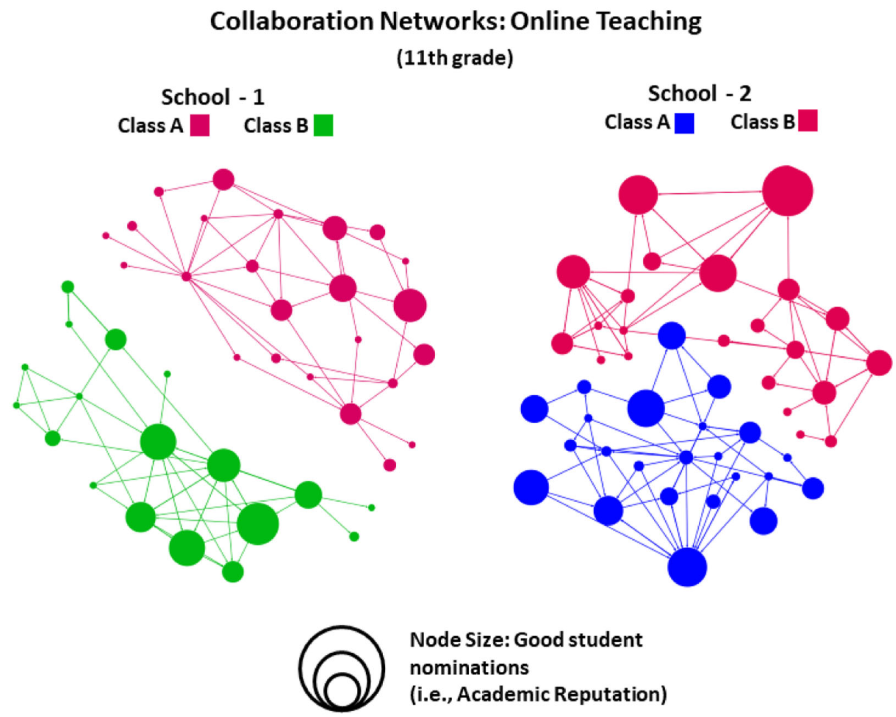

FIG. 2. Collaboration networks from classes in Schools 1 and 2 during online teaching. The size of the nodes indicates levels of academic reputation (i.e., larger nodes receive more nominations).

betweenness centrality) measured from the collaboration network, between online and hybrid classrooms. Further, Figs. 2 and 3 depict the collaboration networks mapped during the study, during online and hybrid classrooms, respectively. Table IV shows the multilevel regression models fitted for the network dependent variables: indegree centrality (1 and 2); outdegree (3); weak ties (4 and 5); strong ties (6 and 7); and betweenness centrality (8 and 9).

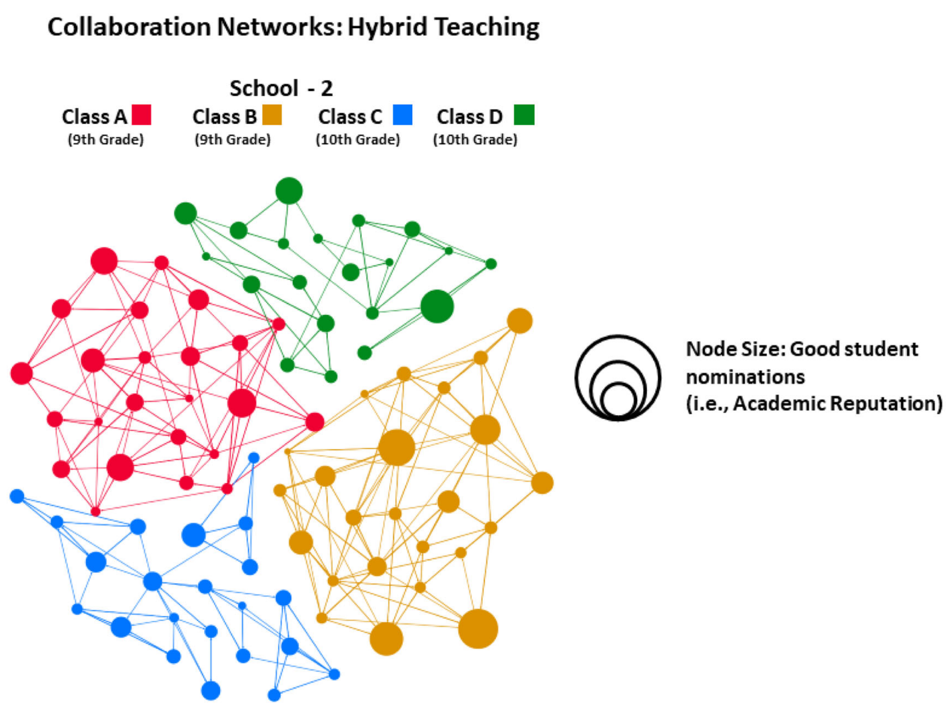

FIG. 3. Collaboration networks from classes in School 2 during hybrid teaching. The size of the nodes indicates levels of academic reputation (i.e., larger nodes receive more nominations).

TABLE IV. Multilevel models illustrate the regression of social network variables on teaching modality (online and hybrid) and control variables: academic reputation nominations, friendship degree, and gender (female). The models incorporate an interaction term between teaching modality and academic reputation nominations. Notably, the models allow for varying slopes and intercepts for each group as defined by school and classrooms. The observed effects withstand random intercept effects at both school and classroom levels, in addition to the random effects attributed to the variable academic reputation (Ac. Reputation).

	Dependent variable:								
	ln(indegree)		ln(outdegree)	ln(weak ties)		ln(strong ties)		ln(betweenness)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Teaching (hybrid)	0.57**	1.34**	0.31*	1.33**	1.41**	0.23	0.36	2.01**	2.52**
	(0.08)	(0.15)	(0.15)	(0.18)	(0.22)	(0.17)	(0.22)	(0.35)	(0.41)
Acad. reputation (physics)	0.34**	0.57**	0.17	0.16	0.22*	0.41**	0.45**	0.71**	1.02**
	(0.09)	(0.04)	(0.11)	(0.17)	(0.11)	(0.14)	(0.12)	(0.19)	(0.32)
Friendship degree	0.05	0.06	0.21**					0.19	0.25*
	(0.04)	(0.04)	(0.07)					(0.12)	(0.12)
Gender (female)	0.11*	0.09†	0.01	0.10	0.09	0.01	0.01	−0.07	−0.08
	(0.08)	(0.08)	(0.11)	(0.22)	(0.26)	(0.20)	(0.20)	(0.46)	(0.38)
Grade (10th)	−0.39**	−0.39**	−0.41**	−0.45*	−0.44†	−0.35†	−0.34†	−1.43**	−1.32**
	(0.08)	(0.08)	(0.11)	(0.22)	(0.26)	(0.20)	(0.20)	(0.46)	(0.38)
Hybrid*acad. rep.		−0.47**			−0.24†		−0.14		−0.99**
		(0.08)			(0.14)		(0.14)		(0.29)
Constant	0.48**	0.11	0.44	0.22*	0.20*	0.74**	0.71**	−0.05	−0.26
	(0.17)	(0.10)	(0.47)	(0.09)	(0.10)	(0.28)	(0.26)	(0.25)	(0.27)
SD random effects (class-school)	0.42	0.13	0.03	0.11	0.11	0.06	0.16	0.13	0.00
SD random effects (class-school/ac. rep.)	0.25	0.06	0.02	0.08	0.08	0.12	0.03	0.44	0.21
SD random effects (school)	0.00	0.00	0.65	0.47	0.47	0.99	1.00	0.00	0.12
SD random effects (school/ac. rep.)	0.00	0.00	0.14	0.23	0.19	0.17	0.07	0.00	0.39
Observations	191	191	191	191	191	191	191	191	191
R^2 marg.	0.65	0.75	0.29	0.44	0.73	0.57	0.59	0.56	0.46
Log likelihood	−80.52	−74.74	−149.42	−149.53	−150.24	−138.41	−137.53	−298.79	−296.02
Akaike inf. crit.	187.04	177.48	324.84	325.05	328.48	302.82	303.05	623.58	620.05
Bayesian inf. crit.	229.32	223.01	367.12	367.33	374.01	345.10	348.58	665.85	665.58
RMSE	0.32	0.32	0.49	0.48	0.48	0.44	0.44	1.06	1.06

$^{\dagger}p < 0.1$.
$^{*}p < 0.05$.
$^{**}p < 0.01$.

In this set of models, and as mentioned earlier, the main predictors are the teaching condition (online or hybrid) and academic reputation, or the number of good physics student nominations.

Because online is the baseline category in the predictor teaching modality, a positive or negative coefficient observed in Table IV suggests a difference between hybrid and online in favor or against the hybrid condition. A similar interpretation holds for the control variable gender, with males as the baseline category, and the factor grade (10th) with 9th grade as baseline. Model 1 for indegree centrality showed statistical differences in the number of incoming collaborative ties between students in online and hybrid learning contexts. What stands out here is the significant differences between teaching modalities in favor of hybrid attendees ($b = 0.568$, $p < 0.01$), along with the positive effect of academic reputation ($b = 0.342$, $p < 0.01$) and females ($b = 0.106$, $p < 0.05$). The significant difference in the main predictor means that when all other variables remain constant, students in hybrid classrooms receive 76% more incoming ties [$\exp(0.568) = 1.764$], compared to those in online classrooms. For academic prestige, an increase of 1% on these variables implies a 40% increase in indegree [$\exp(0.342) = 1.40$], while female students have an 11% difference in indegree [$\exp(0.106) = 1.11$], provided all other variables remain constant.

Furthermore, after including the interaction between the teaching modality and academic reputation (model 2), we now observe an even larger difference in the main predictor hybrid teaching ($b = 1.343$, $p < 0.01$), and

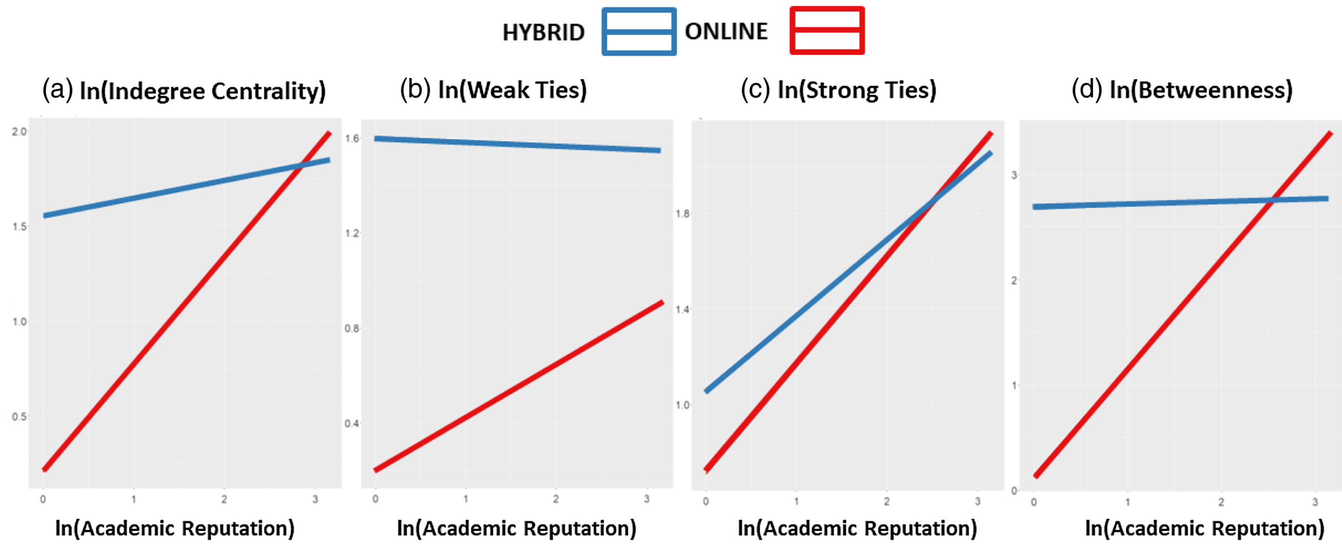

FIG. 4. Interaction effect between the main predictor (hybrid) and academic physics reputation nominations for predicting (a) indegree centrality, (b) weak ties, (c) strong ties, and (d) betweenness centrality.

almost 10% more of the explained variance than model 1. Additionally, the academic reputation remains positive, while the interaction term yields a negative coefficient ($b = -0.47$, $p < 0.01$). As depicted in Fig. 4(a), in both conditions the variable academic reputation shows positive slopes. The negative interaction coefficient, however, indicates that this effect is larger in online classrooms, while in hybrid learning the association of good student nominations and indegree for collaboration is attenuated.

For outdegree centrality, that is, outgoing collaborative ties and with 29% of explained variance, we observed differences in favor of hybrid teaching, ($b = 0.310$, $p < 0.05$), meaning that hybrid attendees have 36% more outgoing ties for collaboration when all other predictors remain constant [$\exp(0.310) = 1.363$]. For this network dependent variable, we found no effect from the variable academic reputation, while friendship degree yields a positive coefficient. It is worth mentioning that an alternative model for outdegree centralilty with the interaction between teaching modality and academic reputation did not show differences across the teaching conditions nor changes in the effects observed in model 3, and explained a similar variance.

Models 4 and 5 were fit to predict the degree of weak ties, that is, the number of collaborative relationships between acquainted peers. As shown in Table IV, both models yield significant differences in favor of the hybrid classrooms in the number of weak ties, and this effect holds even after introducing the interaction term between teaching modality and academic reputation in physics. Importantly, the R squared increases almost 30% with the interaction term. The variable academic reputation is associated with weak ties in model 5 ($b = 0.223$, $p < 0.05$, 25% more weak ties per percentage in academic reputation). Further, the interaction term results in a negative coefficient at 10% of significance ($b = -0.241$, $p < 0.1$), thus suggesting a difference in the relationship between academic reputation and weak ties in hybrid and online classrooms. Figure 4(b) depicts such differences between teaching conditions, and where we noticed a small but negative slope in the hybrid condition (blue line), and a positive relationship for online attendees (red line). In simpler terms, the effect of academic status in fostering collaborative relationships with nonfriends is positive among online students, whereas in hybrid classrooms such social hierarchy is rather irrelevant.

The next set of models (6 and 7) for strong ties (i.e., collaborative ties between friends) show no differences across teaching conditions. Here, the academic reputation yields positive effects even after the introduction of the interaction term. The lack of significance in the interaction is better observed in Fig. 4(c), we one can notice a rather similar relationship between online and hybrid students in the effect of academic status and strong ties. Interestingly, the interaction term does improve the explained variance by 18%. Finally, models for betweenness centrality (8 and 9) exhibit positive differences in favor of hybrid classroom attendees in both models. Again, academic reputation yields a positive effect over the dependent network variable, while the interaction between the teaching condition and academic status reveals a statistical difference between teaching conditions ($b = -0.987$, $p < 0.01$). As depicted in Fig. 4(d), the variable academic reputation in physics has a stronger positive relationship among online students (red line) for betweenness centrality, compared to those attending hybrid education (blue line). Furthermore, readers can see in more detail the relationships between the network dependent variables with academic reputation by school and class in Figs. 8 (indegree centrality), 9 (outdegree centrality), 10 (weak ties), 11 (strong ties), and 12 (betweenness centrality) in the Appendix.

Finally, and besides model 1 for indegree centrality where female students receive significantly more collaborative ties, we do not observe gender differences in the other dependent network variables. Following, and because online students are all in 11th grade, for redundancy the regression model does not account for such grade, and thus the control variable grade includes 10th and 9th grades. As noticed across all models, the grade coefficients show that 10th graders are less likely to interact with one another, compared to those in grade 9.

V. DISCUSSION

The regression models show differences in the network centrality measurements between students attending online and hybrid classrooms. According to the evidence, hybrid classroom attendees achieved higher indegree centrality, degree of weak ties (i.e., working ties among acquainted students) and betweenness centrality than those participating in online sessions. These results indicate that students who experienced hybrid classrooms, that is, in-person sessions along with remote participation, display a more diverse set of working interactions than those in online physics education. These results might translate into a higher number of opportunities for asking and sharing physics-related ideas during the various learning activities conducted in hybrid educational modalities, and likely a richer learning community. As found in previous studies, physical proximity has effects on different social network phenomena, such as diffusion [45], or the likelihood of nodes to connect as a function of their distance [12,44], and even social engagement in undergraduate physics [18]. More so, and as suggested by the literature, compared to ICT-mediated communication in online classrooms, in-person learning experience eases social engagement and the development of social knowledge for the development of a community of practice [16].

In our experience, the argument of physical proximity becomes relevant given the contrasting nature of the learning spaces, digital and physical, occupied by students during the analyzed semesters. Online participants, for instance, are limited to interact with their peers via ICTs, either through phone and/or video calls that require a certain degree of previous coordination, or via text apps and/or discussion forums, mechanisms that do not necessarily rely on prior agreement as information could remain visible and accessible for days. The coordination required for engaging in phone and/or video-mediate communication is a plausible explanation for why online students are less drawn to interact with peers outside their friendship clusters, as this coordination might be easier for those students who share a cohesive bond, rather than a weak tie. This evidence holds even when online attendees might explore new social ties through chats and forums, which are arguably less costly activities than phone or video calls, and even compared to engaging in new in-person communication. This result is consistent with prior research [55,56], where students' willingness to communicate leads them to either explore new social ties (i.e., high willingness to communicate), or to remain in cohesive groups (i.e., low willingness to communicate. Even though it is impossible to suggest whether individual participants in online or hybrid teaching display higher or lower levels of willingness to communicate based on the data and evidence, we could argue that the structural teaching conditions could encourage or discourage students' willingness to connect with unknown peers, and thus engage in social exploration. In detail, the physical space used by students attending face-to-face sessions during hybrid education might encourage willingness to communicate, as participants can simply approach others located in different places of the classroom, or during recess, and ask for help, advice, or materials. These sets of actions might require less effort than when classmates are only accessible through ICTs (e.g., zoom meetings, chats, or forums). Furthermore, the physical proximity may even facilitate the required coordination for later communication through ICTs, thus reducing its cost and increasing the effectiveness of collaboration during students' remote participation in this hybrid teaching modality.

In line with the benefits of physical proximity, the affordability of face-to-face interactions in hybrid classrooms include higher accessibility to others' conduct, questioning skills, academic engagement, motivation and problem solving skills. This accessibility to others' conduct and attitudes in the classroom could have favored work-related interactions. The fact that hybrid attendees do not exclusively resort to their friends for work could be explained by this unique attribute, with physical classrooms providing greater opportunities to witness, interpret and assess social conduct in the pursuit of academically and/or socially effective interactions. Again, in the context of online education, such behavioral signalling and assessments are rather limited to cases where students used video for communication, a form of interaction most likely observed among friends rather than acquainted peers, as previously suggested. This phenomenon provides students with access to the redundant behaviors of their close friends, and therefore, hinders their chances of observing and assessing new conduct and diversifying their social ties. From a teacher's perspective, having students physically present in the classroom also facilitates the enactment and management of different learning activities, individual or group work, its coordination, and instant student-student and teacher-student communication and feedback.

The fact that hybrid classrooms yielded higher levels of betweenness centrality implies that more students are located in the pathways connecting two of their peers, a characteristic associated with possible control over the information that flows through the focal node [71]. This structural position is significantly occupied by those students who enjoy high levels of academic reputation in their classrooms. The differences between online and hybrid regarding betweenness centrality might be attributed to the levels of social integration observed in both groups. Here, it is reasonable to think that hybrid students would be more likely to connect a pair of untied peers given their higher indegree centrality, and presumably their engagement in social exploration through weak ties. Conversely, with online students resorting to their existing friendship groups, arguably clusters of well-connected individuals, it might be less likely for them to be uniquely located in the pathway between two disconnected peers. This explanation is plausible given the evidence that online students are more drawn to work with their friends (i.e., strong ties) in cohesive groups rather than exploring new social ties with acquainted peers (i.e., weak ties) [8,55,56]. Therefore, in an online collaboration network there might be small chances for a student to bridge ties between two disconnected peers, given that the vast majority of their ties are observed within their friendship group, which in principle are tied to each other (i.e., transitivity). Differently, as hybrid students explore new partnerships with those beyond their friendship clusters, it is more likely to observe individuals bridging ties across pairs of unconnected students.

The literature on online learning highlights accessibility to information as one of its key benefits, as it provides developmental opportunities for learners worldwide by overcoming geographical distances [3]. In addition, remote teaching became, in many countries, the only possible teaching method during the sanitary crisis, and allowing millions of students a rather stable and continuous educational experience. Yet, as seen in our results, online learning adds certain relational limitations that, in turn, could be detrimental to accessing information, resources and further opportunities. First, according to the theory of the strength of weak ties [59,60,72], these enable access to novel and simple ideas from diverse portions of the network, and thus allow individuals with new conceptual or practical perspectives for problem solving, for instance. Yet, the construction of knowledge and further development of problem solutions depends of a cohesive group and a collective dynamic that allows questioning, reflection and analysis of the content for the emergence of solutions, defined as knowledge exploitation [57].

Consequently, students under online and hybrid teaching are likely to experience the same opportunities for in-depth content reflection and development, due to their similar reliance on preexisting friendship groups (i.e., strong ties). Nevertheless, and because online students seemed confined to their clusters, they would be limited in the inflow of new approaches, ideas and perspectives accessible through weak ties in the classroom. Conversely, the face-to-face sessions held during hybrid teaching, as argued earlier, ease interactions beyond the close circle of friends, and therefore afford individuals access to such new ideas. Yet, the unique opportunities of weak ties need to be assessed with caution, given that these social relationships facilitate learning of factual and highly codified ideas (e.g., mathematical definition of instant velocity; initial conditions in kinematic problems) that require little effort to diffuse [60]. Differently, complex information (e.g., conceptual understanding of forces) is more easily transferred among strongly tied students (e.g., friends) [62]. Furthermore, and even though in hybrid sessions students are more likely to explore new ideas through weak ties, it is also likely they continue working with friends, and therefore experience the benefits of social exploration and cohesion, both valuable conditions for information access (i.e., exploration) and development (i.e., exploitation) [58].

Students with high levels of perceived academic status are more socially active in the collaboration network as shown across all regression models, and occupy strategic positions by being located in the shortest paths between two untied peers—as shown by high betweenness centrality [73]. As evidenced in various studies, in the pursuit of academic gains and the possibility to scale up in the social ladder, students would mobilize their social relationships driven by academic status [23,74], or by accessing those physically available to them [12]. Further, the mobilization of resources through social ties is possible because these individuals might have constructed a mental schema of the social structures in the classroom, recognizing their presence and their skills, along with their surrounding networks, in order to establish strategic interactions [28]. Interestingly, students in online and hybrid physics classrooms seem to have utilized different mechanisms to mobilize information from high-status individuals, as depicted in the significant interactions between teaching modality and academic reputation nominations. Here, the effect of being recognized as a proficient student on online physics courses is strongly associated with social engagement in the collaboration network, whereas such status does not show its same importance in hybrid classrooms. Presumably, and because online students have limited access to their peers' behaviors during learning activities, they are therefore, more likely to enact social strategies by relying on their previously constructed understanding of the classroom social systems, accounting for friendship relationships and status [49]. In this scenario, online teaching seems to have encouraged a higher tendency to respect academic hierarchies as sources of task-related advice, and thus limiting advice-seeking in less-nominated portions of the network. For this to happen, accumulated social and academic experience with classmates is fundamental, first for the emergence of social and academic hierarchies [37–39], and then for the collective recognition of such hierarchical distribution of resources to draw upon. Conversely, face-to-face interactions in hybrid classrooms seem to ease advice-seeking strategies beyond previously established academic hierarchies, presumably a benefit of physical proximity, as embarking on new collaborative relationships is less costly and might give immediate insight into their relative effectiveness. Consequently, it is possible to suggest that one's physical presence in a social system affords access to different behaviors that could be associated with academic status and beyond traditionally perceived hierarchies [8,42]. This process could reduce the cognitive relevance of status for the emergence of social network ties and the collective perception of the capital allocated among students. Finally, the relative value of the information strongly depends on the performance expectation, that is, whether students are set to pursue performance achievements (i.e., grades) or learning achievements in the form of deep physics ideas, or innovative physics-related solutions [2,31].

A. Pedagogical implications in physics education

The social network analysis conducted for this study allows us to discuss its implications in terms of pedagogical guidelines for physics educators and researchers. Along with this, there are several key questions for future research that might need to be explored before achieving a robust comprehension of the benefits and limitations of online and hybrid education across a wide range of physics education contexts.

First, it is critical to recognize the value of a cohesive group of friends and peers, with associated benefits in social capital, identity, and learning potential. For those with preexisting friendship networks at the start of the course, the affordances of their network are likely to translate from in-person to remote classroom experiences. However, the scenario for individuals who are new to the classrooms might be different due to the lack of social exploration through weak ties observed in online education, which could hinder their chances for learning and success in response to their limited options for community development. Furthermore, the opportunities for attending in-person sessions periodically (e.g., once per week, or every other week) would ease the process for tie formation, particularly with teachers and instructors having the presence and the evidence (e.g., direct classroom observation) to strategically organize students' work in the classroom.

With students naturally resorting to their preexisting social networks, in online learning contexts it might be particularly relevant for teachers and instructors to promote collaboration through group-level activities. Yet, simply asking students to form groups to address physics tasks might not be enough for those in isolation, given the social gravity of prior relationships. Teachers and instructors could decide on different strategies for group formation, for instance, by distributing friends across various groups, thus allowing space for the integration of isolates. Furthermore, educators could decide upon a multiplicity of variables (e.g., gender, learning strategies, motivation, social background, race, etc.) to form either homogeneous or heterogeneous groups in order to promote social exploration and knowledge development. Both homogeneous and heterogeneous groups offer chances of a successful performance across many activities, but also certain limitations. Highly homogeneous groups could be better equipped for engaging in collaboration more rapidly compared to heterogeneous ones, mainly due to preexisting familiarity and relationships. Heterogeneous teams, for instance, would need adjustment and time for understanding their diversity, a process arguably easier to achieve in more homogeneous working units. Additionally, homogeneous groups might be associated with a network of peers strongly connected, because of homophily, and therefore, after some time, these might achieve high levels of information redundancy. Alternatively, heterogeneous groups could benefit from information diversity, but might lack the initial cohesiveness for questioning and constructing deep understandings. Regardless of the decision, it is important to weight in the group-level attributes within the learning context, and seek out instances for either homogeneous groups to find diverse perspectives in the class (e.g., between group interactions and information sharing), and heterogeneous working units to build up the needed cohesion (e.g., long term problem solving or projects).

Even though the face-to-face sessions might encourage interactions with unknown peers, there is a didactic dimension that could optimize, or limit even more students' social engagement in both online and hybrid classrooms. From this didactic perspective, one should account for the wide range of teaching models and methods existent in physics education research and beyond. For instance, social mobility and the recognition of proficiency beyond traditional physics performance (e.g., standardized testing, solving textbook physics activities, etc.) might be difficult to access in a traditional lecture-based classroom grounded on the exposition of physics content, and with students assuming a passive role through observing and listening. As classroom norms and activities enforce higher levels of student engagement, and active participation through group level activities of diverse nature (e.g., group problem-solving, unstructured labs), the expectations towards communication and collaboration could nurture new social relationships, along with a wider range of capabilities for students to recognize and add to their concepts of physics proficiency (e.g., leadership, communication skills, organization, artistic and design, etc.). Consequently, the defining properties of active learning methodologies might be preferred for promoting collaboration, and more suitable for those seeking a community and its associated benefits.

Finally, the effectiveness of these pedagogical and organizational suggestions should be further explored through research and assessment. In this study, we did not address the pedagogical nature of the activities performed in schools 1 and 2 through online and hybrid semesters besides. Consequently, it is important to find evidence pointing out in the direction of the previous claims regarding the mechanisms for group formation, and the type of activities addressed in the classroom.

B. Limitations

We acknowledge several limitations in our study. First, our sample comes from just two schools in southern

Chile, which represents a specific social and cultural setting. Therefore, the results may not be universally applicable. The small sample size also means that the findings should be interpreted cautiously. To make broader claims, we would need data from more students and schools. Second, we did not have detailed information about classroom teaching styles or activities, which could have given us more context for our findings. The role of teachers in shaping student behavior is also missing from our analysis.

We could not track the same 11th-grade students from 2020 to 2021 due to the elective nature of physics courses. We also could not include 8th and 9th graders in 2020 because of school restrictions. Although our class sizes were similar, ranging from 20 to 29 students, age differences could have influenced the results. Factors like maturity and social awareness might have affected student behavior, such as willingness to explore new social relationships or avoid bullying.

Lastly, we used linear regression models to analyze network data, which has been a point of debate. These models may not capture the full complexity of social networks. However, simpler models like these have been useful in initial analyses and have been shown to correlate with student performance [25,27]. Future research should consider these limitations and explore whether our findings hold true for different age groups and educational settings.

VI. CONCLUSIONS

Human interaction and collaboration are fundamental to learning and development, influenced by a myriad of factors ranging from individual traits to organizational structures. Our study honed in on high school physics classrooms, examining how online and hybrid teaching modalities affect students' social networks and collaborative behaviors.

Our findings reveal distinct patterns of social engagement between the two teaching modalities. In hybrid classrooms, where students have the benefit of face-to-face interactions, we observed higher levels of social engagement and collaboration. These settings also appeared to mitigate the impact of academic hierarchies, allowing students to form more diverse social connections. In contrast, online classrooms seemed to amplify existing social and academic hierarchies, likely due to the absence of nuanced social cues that face-to-face interactions provide.

These results have significant implications for physics education and potentially for other disciplines as well. Hybrid teaching environments, with their blend of online and in-person interactions, seem to foster a more inclusive and collaborative learning atmosphere. They offer students a richer social landscape, which can enhance learning outcomes and encourage the development of creative ideas. On the other hand, online-only settings may perpetuate existing social divides and academic hierarchies, potentially hindering both social inclusion and educational progress.

In summary, our study underscores the critical role of teaching modalities in shaping social interactions and academic outcomes. It provides valuable insights for educators, policymakers, and researchers aiming to optimize the social and educational benefits of different teaching environments in the digital age.

ACKNOWLEDGMENTS

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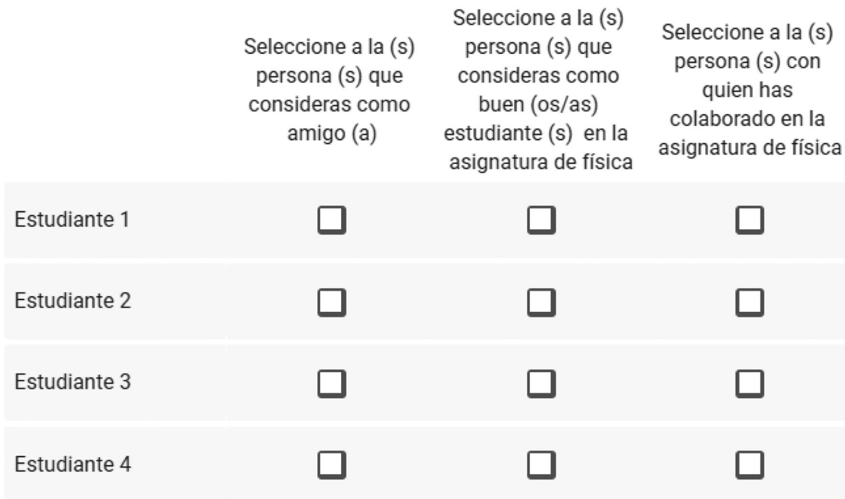
APPENDIX

The Appendix contains the following tables and figures: descriptive statistics and the normality test of log-transformed variables (Table V); Spanish example of the network survey items used in the study (Fig. 5); Graphical depiction of the distributions and correlations between nonfactor raw variables (Fig. 6); graphical depiction of the distributions and correlations between nonfactor log-transformed variables (Fig. 7); graphical depiction of the interactions between academic reputation and classes by school and its association with indegree centrality (Fig. 8), outdegree centrality (Fig. 9), weak ties (Fig. 10), strong ties (Fig. 11), and betweenness centrality (Fig. 12); multilevel regression model results for nontransformed social network variables (Table VI); bootstrapping regression coefficients for multilevel models 1–9 (Tables VII–XV); and variance inflation factor (VIF) reported for predictors and control variables in multilevel models 1–9 (Table XVI).

TABLE V. Summary of descriptive statistics for the dependent social network variables (indegree, outdegree, weak ties, strong ties, and betweenness centrality), and the continuous independent variables (academic prestige and friendship degree). A p value < 0.05 rejects the hypothesis of a normal distribution according to the Shapiro-Wilk test for normality.

	Shapiro-Wilk test			
Variable	W	p	Median	Mean
ln(indegree)	0.89	$p < 0.01$	1.39	1.2
ln(outdegree)	0.90	$p < 0.01$	1.39	1.19
ln(weak ties)	0.88	$p < 0.01$	0.69	0.87
ln(strong ties)	0.91	$p < 0.01$	1.39	1.33
ln(betweenness)	0.85	$p < 0.01$	2.18	1.80
ln(academic rep)	0.91	$p < 0.01$	1.39	1.36
ln(friendship deg)	0.93	$p < 0.01$	1.95	1.68



	Seleccione a la (s) persona (s) que consideras como amigo (a)	Seleccione a la (s) persona (s) que consideras como buen (os/as) estudiante (s) en la asignatura de física	Seleccione a la (s) persona (s) con quien has colaborado en la asignatura de física
Estudiante 1	☐	☐	☐
Estudiante 2	☐	☐	☐
Estudiante 3	☐	☐	☐
Estudiante 4	☐	☐	☐

FIG. 5. Visualization in Spanish of the online survey applied to the students. The instrument was applied to each student, specifying the names of classmates.

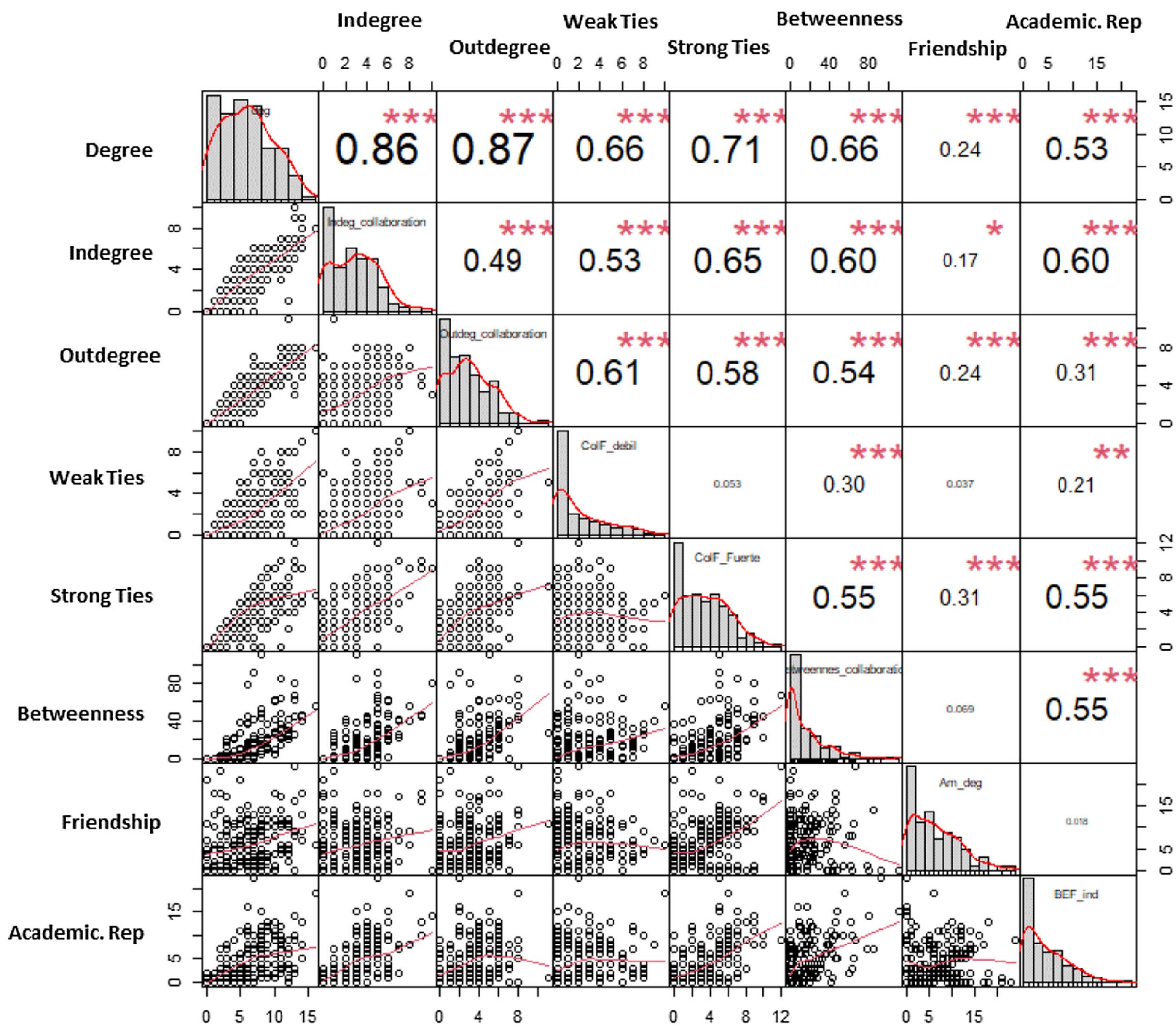


FIG. 6. Matrix of correlations between nonfactor raw variables, and excluding categorical variables.

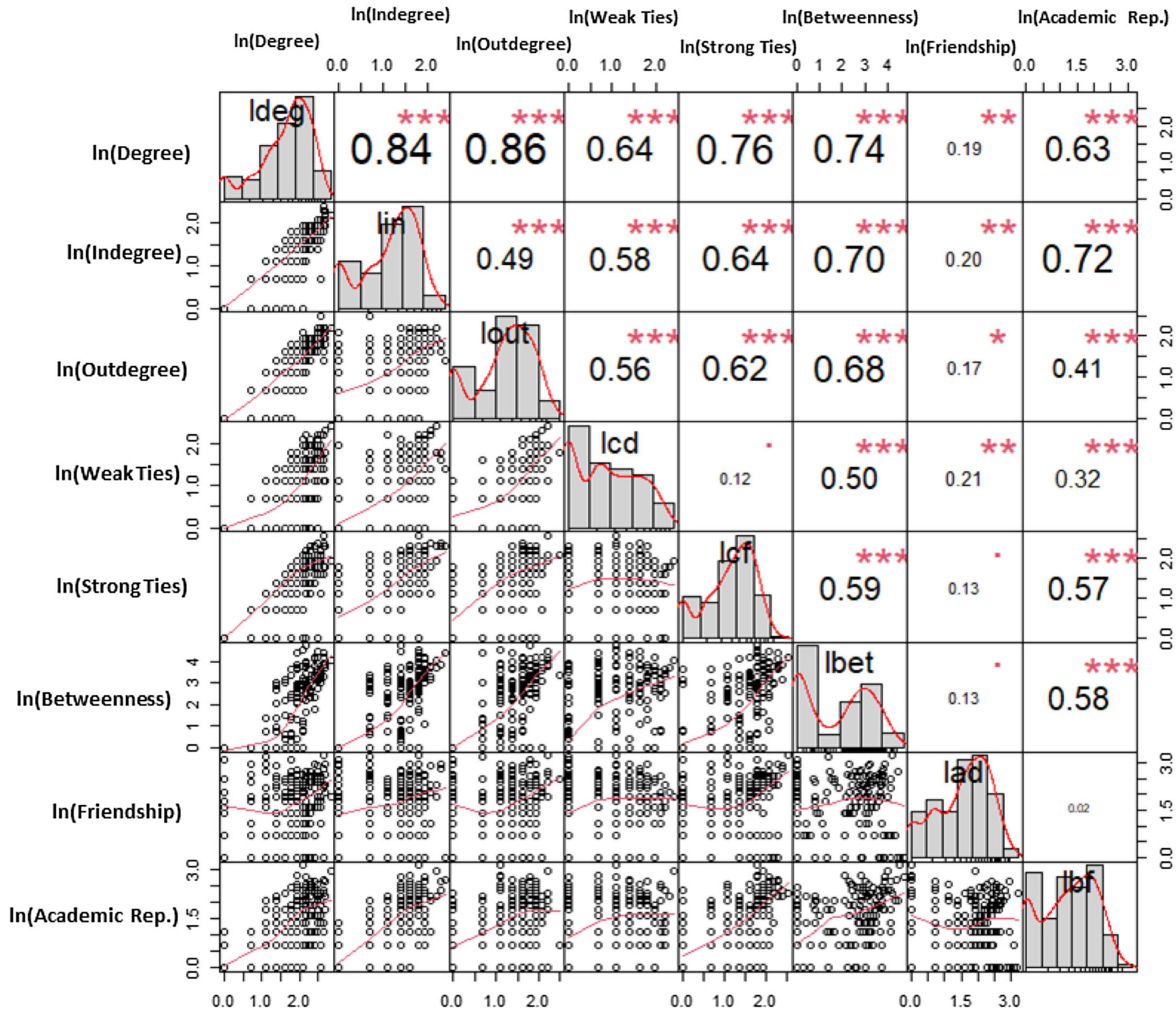


FIG. 7. Matrix of correlations between log-transformed variables used in the models, and excluding categorical variables.

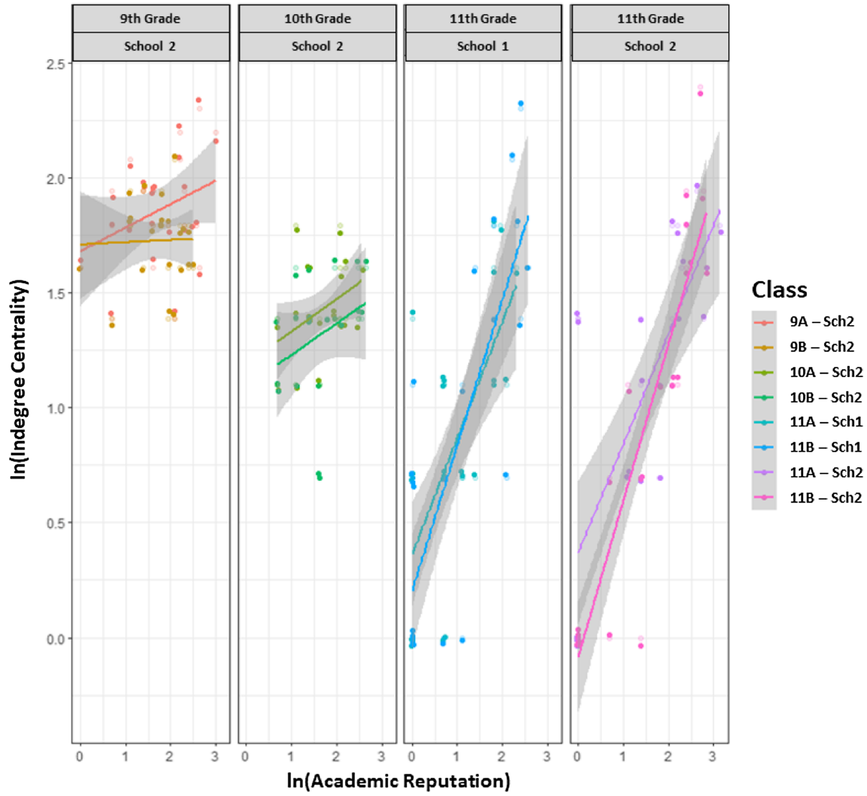


FIG. 8. Interaction between academic reputation and classes by school to predict indegree centrality.

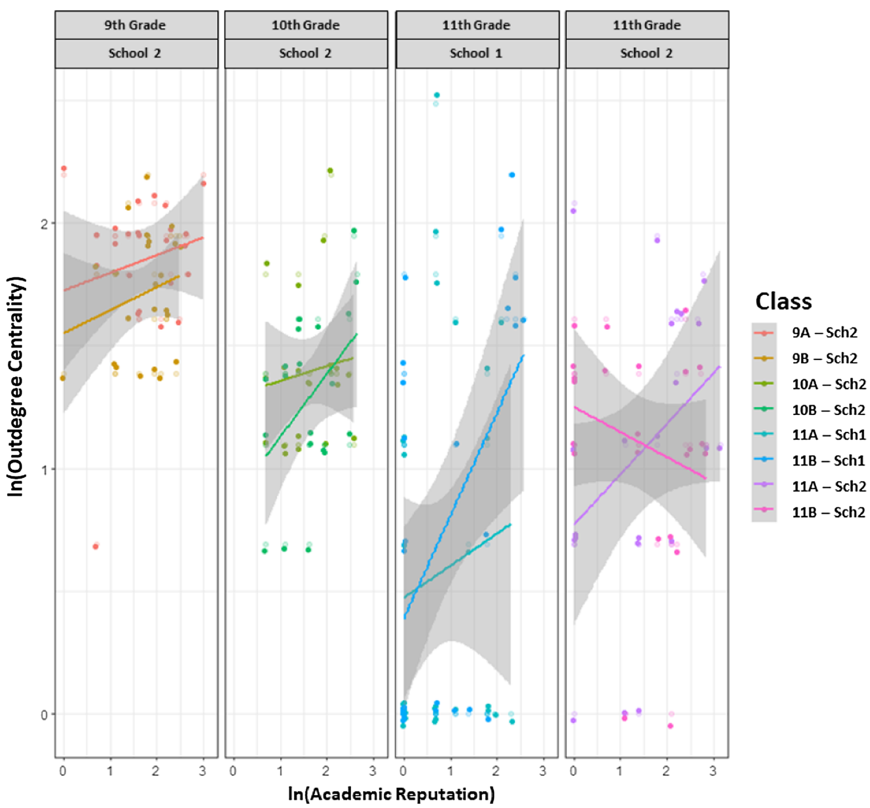


FIG. 9. Interaction between academic reputation and classes by school to predict outdegree centrality.

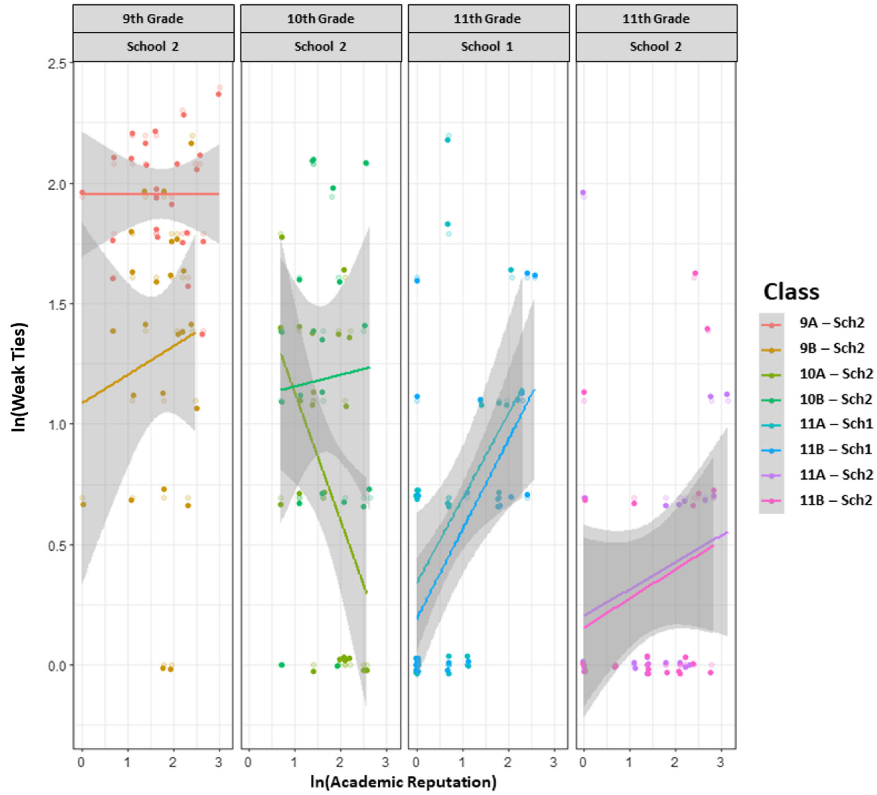


FIG. 10. Interaction between academic reputation and classes by school to predict weak ties.

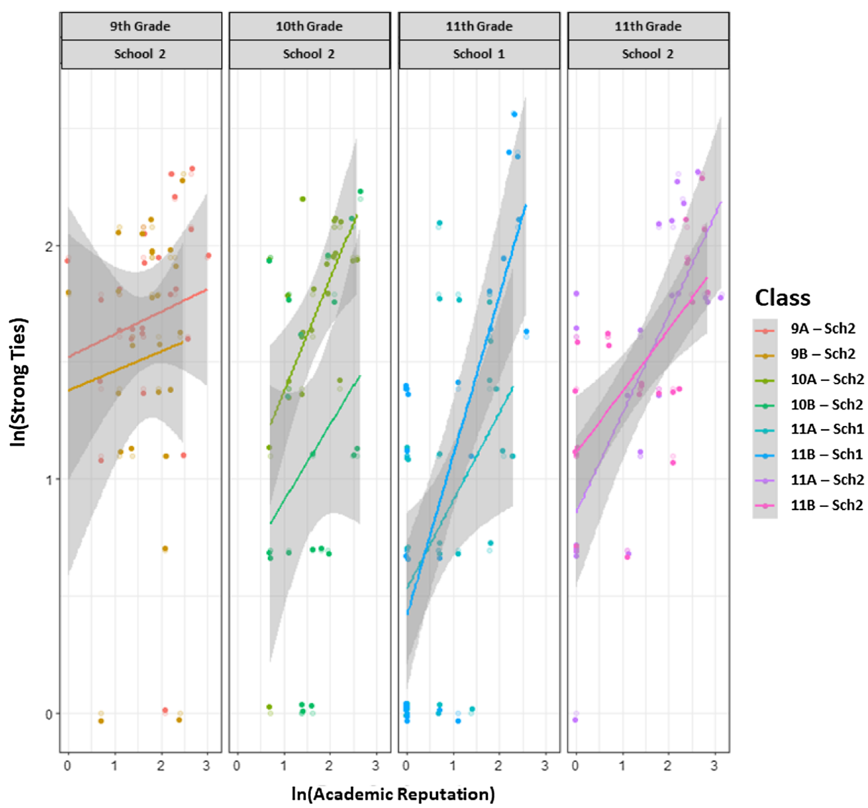


FIG. 11. Interaction between academic reputation and classes by school to predict strong ties.

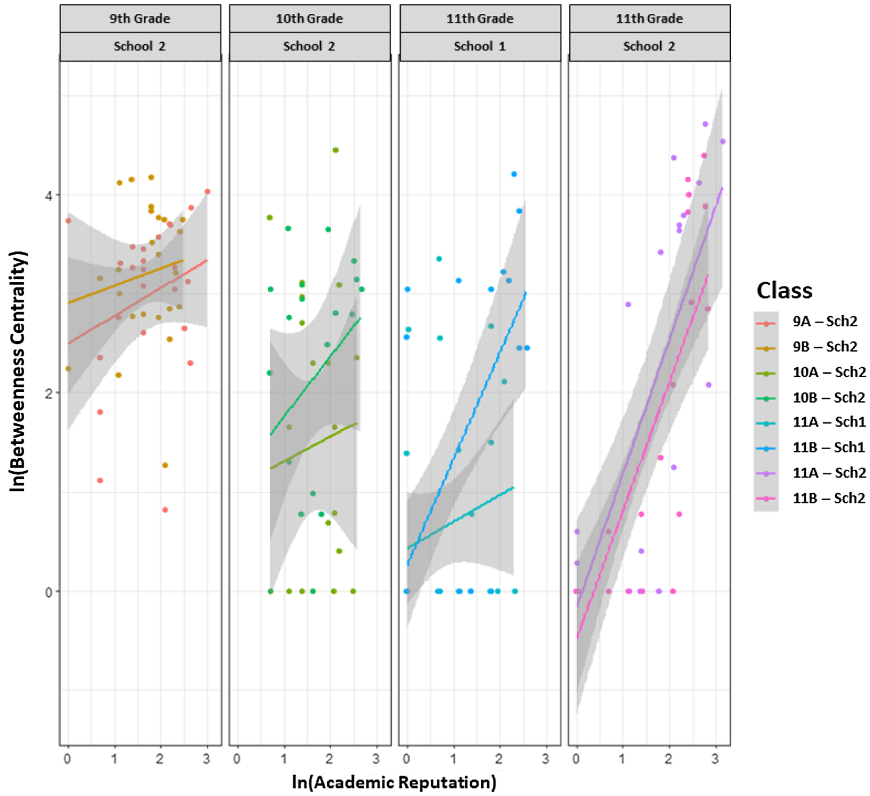


FIG. 12. Interaction between academic reputation and classes by school to predict betweenness centrality.

TABLE VI. Multilevel models illustrating the regression of nontransformed social network variables on teaching modality (online and hybrid) and control nontransformed variables: academic reputation nominations, friendship degree, and gender (female). The models incorporate an interaction term between teaching modality and academic reputation nominations. Notably, the models allow for varying slopes and intercepts for each group as defined by school and classrooms. The observed effects withstand random intercept effects at both school and classroom levels, in addition to the random effects attributed to the variable academic reputation (acad. reputation).

	Dependent variable:								
	Indegree		Outdegree	Weak ties		Strong ties		Betweenness	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Teaching (hybrid)	3.02**	3.96**	2.1**	4.05**	3.96**	1.24*	1.42*	18.3**	20.97**
	(0.27)	(0.37)	(0.40)	(0.89)	(0.86)	(0.57)	(0.63)	(4.21)	(4.24)
Acad. reputation (physics)	0.28*	0.37**	0.13†	0.09	0.11*	0.37*	0.4**	1.7**	2.75*
	(0.13)	(0.05)	(0.08)	(0.07)	(0.05)	(0.15)	(0.13)	(0.6)	(1.24)
Friendship degree	0.03	0.04*	0.09**					0.59*	0.7**
	(0.02)	(0.02)	(0.03)					(0.25)	(0.25)
Gender (female)	0.49**	0.5**	0.34	0.43†	0.46†	0.15	0.15	1.62	1.67
	(0.18)	(0.18)	(0.25)	(0.24)	(0.24)	(0.31)	(0.31)	(2.33)	(2.34)
Grade (10th)	−1.98**	−1.96**	−1.93**	−2.03*	−1.83†	−1.11†	−1.12†	−12.1*	−12.84**
	(0.31)	(0.32)	(0.4)	(1.03)	(1.01)	(0.67)	(0.67)	(5.24)	(4.18)
Hybrid*acad. rep.		−0.29**			−0.1		−0.09		−3.28**
		(0.07)			(0.07)		(0.12)		(0.64)
Constant	0.56	0.17	0.97	0.29	0.29	1.68*	1.64*	−3.02	−4.45
	(0.38)	(0.24)	(0.82)	(0.54)	(0.49)	(0.7)	(0.67)	(2.68)	(2.75)
SD random effect (class-school)	0.5	0.26	0.12	0.87	0.82	0.13	0.1	0.00	1.15
SD random effect (class-school/acad. rep.)	0.14	0.07	0.01	0.03	0.05	0.11	0.11	1.45	0.3
SD random effect (school)	0.37	0.00	1.07	0.28	0.18	0.9	0.84	0.00	0.00

(Table continued)

TABLE VI. *(Continued)*

	Dependent variable:								
	Indegree		Outdegree	Weak ties		Strong ties		Betweenness	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
SD random effect (school/acad. rep)	0.16	0.02	0.1	0.08	0.04	0.19	0.16	0.00	1.65
Observations	191	191	191	191	191	191	191	191	191
R^2 marg.	0.61	0.71	0.39	0.57	0.49	0.44	0.37	0.4	0.334
Log likelihood	−317.06	−314.17	−378.27	−371.55	−372.51	−412.11	−413.07	−791.25	−786.11
Akaike inf. crit.	660.11	656.34	782.53	767.09	771.02	848.22	852.14	1,608.49	1,600.22
Bayesian inf. crit.	702.39	701.87	824.81	806.12	813.3	887.25	894.42	1,650.77	1,645.76
RMSE	1.14	1.14	1.66	1.57	1.57	1.97	1.96	14.92	14.98

†$p < 0.1$.
*$p < 0.05$.
**$p < 0.01$.

TABLE VII. Bootstrapping regression coefficients for model indegree (model 1). Number of permutations = 1000.

Statistic	B	St. dev	CI (95%)
Teaching (hybrid)	0.56	0.27	[0.37, 0.76]
Acad. reputation (physics)	0.35	0.25	[0.17, 0.53]
Friendship (degree)	0.05	0.12	[−0.04, 0.13]
Gender (female)	0.11	0.15	[0.00, 0.22]
Grade (10th)	−0.40	0.23	[−0.56, −0.23]
(Intercept)	0.46	0.46	[0.14, 0.79]

TABLE VIII. Bootstrapping regression coefficients for model indegree (model 2). Number of permutations = 1000.

Statistic	B	St. dev	CI (95%)
Teaching (hybrid)	1.34	0.43	[1.04, 1.65]
Acad. reputation (physics)	0.56	0.13	[0.47, 0.65]
Friendship (degree)	0.06	0.12	[−0.02, 0.15]
Gender (female)	0.08	0.15	[−0.02, 0.19]
Grade (10th)	−0.39	0.23	[−0.55, −0.23]
Hybrid*acad. rep.	−0.47	0.21	[−0.62, −0.32]
(Intercept)	0.12	0.27	[−0.07, 0.31]

TABLE IX. Bootstrapping regression coefficients for model outdegree (model 3). Number of permutations = 1000.

Statistic	B	St. dev	CI (95%)
Teaching (hybrid)	0.29	0.47	[−0.04, 0.62]
Acad. reputation (physics)	0.177	0.31	[−0.04, 0.39]
Friendship (degree)	0.21	0.21	[0.06, 0.35]
Gender (female)	0.01	0.21	[−0.14, 0.16]
Grade (10th)	−0.42	0.30	[−0.63, −0.21]
(Intercept)	0.42	1.28	[−0.49, 1.33]

TABLE X. Bootstrapping regression coefficients for model weak ties (model 4). Number of permutations = 1000.

Statistic	B	St. dev	CI (95%)
Teaching (hybrid)	1.34	0.57	[0.94, 1.75]
Acad. reputation (physics)	0.16	0.46	[−0.16, 0.49]
Gender (female)	0.11	0.22	[−0.05, 0.26]
Grade (10th)	−0.45	0.66	[−0.91, 0.02]
(Intercept)	0.21	0.26	[0.02, 0.40]

TABLE XI. Bootstrapping regression coefficients for model weak ties (model 5). Number of permutations = 1000.

Statistic	B	St. dev	CI (95%)
Teaching (hybrid)	1.43	0.66	[0.96, 1.90]
Acad. Reputation (physics)	0.23	0.30	[0.01, 0.44]
Gender (female)	0.10	0.23	[−0.06, 0.26]
Grade (10th)	−0.45	0.76	[−0.98, 0.09]
Hybrid*acad. rep.	−0.24	0.40	[−0.52, 0.04]
(Intercept)	0.19	0.27	[−0.00, 0.39]

TABLE XII. Bootstrapping regression coefficients for model strong ties (model 6). Number of permutations = 1000.

Statistic	B	St. dev	CI (95%)
Teaching (hybrid)	0.25	0.52	[−0.12, 0.62]
Acad. reputation (physics)	0.42	0.37	[0.16, 0.68]
Gender (female)	0.01	0.23	[−0.16, 0.17]
Grade (10th)	−0.33	0.60	[−0.75, 0.09]
(Intercept)	0.71	0.73	[0.19, 1.22]

TABLE XIII. Bootstrapping regression coefficients for model strong ties (model 7). Number of permutations = 1000.

Statistic	B	St. dev	CI (95%)
Teaching (hybrid)	0.32	0.61	[−0.11, 0.76]
Acad. reputation (physics)	0.45	0.35	[0.20, 0.70]
Gender (female)	0.01	0.24	[−0.16, 0.18]
Grades (10th)	−0.34	0.58	[−0.75, 0.07]
Hybrid*acad. rep.	−0.14	0.43	[−0.45, 0.16]
(Intercept)	0.69	0.74	[0.17, 1.22]

TABLE XIV. Bootstrapping regression coefficients for model betweenness (model 8). Number of permutations = 1000.

Statistic	B	St. dev	CI (95%)
Teaching (hybrid)	1.98	1.18	[1.15, 2.81]
Acad. reputation	0.70	0.57	[0.30, 1.10]
Friendship (degree)	0.18	0.42	[−0.12, 0.48]
Gender (female)	−0.06	0.46	[−0.38, 0.27]
Grade (10th)	−1.42	1.32	[−2.36, −0.49]
(Intercept)	−0.03	0.77	[−0.57, 0.51]

TABLE XV. Bootstrapping regression coefficients for model betweenness (model 9). Number of permutations = 1000.

Statistic	B	St. dev	CI (95%)
Teaching (hybrid)	2.49	1.31	[1.56, 3.42]
Acad. reputation	1.04	0.89	[0.42, 1.67]
Friendship (degree)	0.26	0.41	[−0.03, 0.55]
Gender (female)	−0.09	0.47	[−0.42, 0.25]
Grade (10th)	−1.32	1.11	[−2.10, −0.54]
Hybrid*acad. rep.	−0.98	0.85	[−1.57, −0.38]
(Intercept)	−0.27	0.74	[−0.79, 0.25]

TABLE XVI. Variance inflation factor statistics reported for predictors and control variables in the multilevel regression models presented in the article.

Model	Teaching (hybrid)	Academic rep. (physics)	Friendship deg.	Gender (female)	Grade (10th)	Hybrid*acad. rep.
ln(indegree) (1)	1.77	1.00	1.35	1.02	1.40	
ln(indegree) (2)	6.89	1.56	1.36	1.03	1.40	7.28
ln(outdegree) (3)	2.83	1.01	2.45	1.03	1.32	
ln(weak ties) (4)	1.49	1.00		1.02	1.48	
ln(weak ties) (5)	1.79	1.18		1.03	1.56	1.43
ln(strong ties) (6)	1.51	1.03		1.01	1.50	
ln(strong ties) (7)	2.56	1.24		1.01	1.49	2.47
ln(betweenness) (8)	1.81	1.09	1.05	1.03	1.68	
ln(betweenness) (9)	2.57	1.08	1.17	1.04	1.52	2.25

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