Graph theoretical methods for understanding student social interactions in physics classrooms

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Social network analysis has become a common methodology within physics education research to quantify the impacts that student interactions and classroom structure have on student outcomes. These relationships are typically quantified using a degree centrality metric based on the number and range of connections a student has, such that a higher degree centrality would indicate a more central position in the network. However, when looking at these interdependent metrics as independent parameters, they do not consistently show any statistically significant relationship with motivational outcomes like self-efficacy or sense of belonging. In this study, we instead characterize students' network positionality using various "network actor roles" and measure the strength of their connections through network paths, within the context of social capital. In this framing, we are less interested in the impact and importance of individuals than we are in the overall social integration of most students in the class. Using data from an interactive calculus-based physics 1 class, we find that students who are network isolates (no incoming or outgoing connections) or weakly connected report a lower sense of belonging compared with other students, but, consistent with prior research, the number of connections was not correlated with sense of belonging. Similarly, students who were strongly connected to at least one other person reported a higher sense of belonging compared to those who were weakly connected. This indicates the potential for graph theoretical methods to enhance our understanding of student interactions in physics classrooms.

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I. INTRODUCTION AND BACKGROUND

The application of social network analysis (SNA) in education research has produced key insights into classroom dynamics from both individual (student-focused) and collective (class-focused) perspectives. This method is being increasingly used to analyze social-psychological and academic outcomes within a range of educational settings [1]. Applying SNA to physics classrooms is motivated by sociological theories that highlight the importance of social integration and interpersonal connections in shaping students' experiences. Tinto [2,3] theorized that these social interactions at both the classroom and institutional levels are key components of academic success and degree completion.

The impacts of research-based instructional strategies on student conceptual understanding and academic performance are well documented and supported by quasiexperiments, meta-analyses, and randomized controlled experiments [4–8]. For example, Cámara-Zapata and Morales saw both increased learning, as measured by the Force Concept Inventory (FCI) and higher rates of persistence in engineering following an active learning approach to physics 1 [9]. Moreover, it has been shown that active learning can enhance student motivation and collective problem-solving skills [10].

Because active learning almost universally relies on some type of group work [11,12], SNA provides a natural framework to measure how interpersonal dynamics in active learning environments relate to student outcomes. For example, Pulgar *et al.* applied SNA to study students' problem-solving abilities and found relationships between the number of social interactions and the ability to solve ill-structured problems [10]. In particular, the study found that students in three undergraduate sections of an introductory physics course for engineering majors who actively pursued information from multiple peers performed better on ill-structured problems but ultimately did worse on well-structured problems [10], perhaps because well-structured tasks are not perceived as "group worthy" [13]. Another study performed by Dou *et al.* examined the change in students' self-efficacy during a Modeling Instruction course using their centrality within the course network [14]. In the study, a bootstrapped linear regression was employed to determine whether indegree (number of incoming connections), outdegree (number of outgoing connections), and PageRank centrality were statistically significant predictors for post self-efficacy scores collected using a 33-item survey [14]. PageRank centrality is akin to calculating the probability of arriving at a particular student via the interactions from their neighbors [15,16], thereby not only considering the indegree of the student of interest but also the indegree of their neighbors. They found that PageRank centrality was the only statistically significant predictor of overall postcourse self-efficacy as opposed to other centrality measures like indegree and outdegree, even when controlling for students' incoming self-efficacy levels [14].

Other studies have utilized SNA to explore how performance and engagement are impacted by a student's social interaction both in and outside the classroom [10,17,18]. For example, Williams *et al.* used centrality measures like indegree, outdegree, betweenness, and closeness to quantify students' connections in a Modeling Instruction classroom [17]. Betweenness centrality measures the likelihood that a student resides on the shortest path between two other students. The betweenness metric can highlight students who act as bridges between more tightly connected components of the network. Closeness measures the distance between a student and all other students in their respective network. Closeness shows how ingrained a student is within a group, such that they can directly access others without interacting through intermediaries. They found that closeness centrality predicted future academic performance beyond prior grade point average alone [17]. They further found that models using outdegree were best able to predict performance early on in the semester, while indegree gained predictive power only toward the end of the course; betweenness was not a significant predictor [17]. Zwolak *et al.* further examined both in- and out-of-class networks for a Model Instruction introductory physics course to assess their impact on grades and persistence in science, technology, engineering, and mathematics (STEM) majors [18]. Their study focused on the closeness centrality measure and found that for students with intermediate grades (B, B−, and C+ grades: or 2.3–3.0 grade points out of 4), out-of-class outdegree or out-of-class closeness were predictors of persistence, whereas the persistence of students with top or bottom grades was predicted only by course grade [18].

Similarly, another study by Zwolak *et al.* used network analysis to examine students' academic and social interactions and the effect on persistence in an introductory mechanics Modeling Instruction course [19]. When only considering centrality measures (indegree and outdegree, eigenvector, betweenness, and closeness), they found that students with a higher level of interactions at the end of the semester were more likely to enroll in a second semester of the Modeling Instruction course (electricity and magnetism) [19]. They found statistically significant correlations of the odds ratio of persisting with indegree, outdegree, and closeness. However, when including other factors like gender, ethnicity, declared major, and final grade, they found that only final grade provided a statistically significant improvement to the predictive power of persistence rather than centrality [19]. Moreover, they found that students' indegree was not a statistically significant predictor for persistence when course grade was considered [19].

Indegree and outdegree centrality are related to the number of interactions received by a student and the number of interactions initiated by the student, respectively. Often, these interdependent metrics are studied as distinct parameters, particularly in regression models, to understand whether there is a statistically significant correlation to an outcome of interest like a social or psychological factor hypothesized to be a strong predictor of academic success [14,17,20]. However, looking at them as distinct parameters may not provide a clear representation of the broader network structure or may not adequately predict important outcomes. Indeed, this is a potential reason that the relative importance of different centrality measures varies widely between prior studies, and why indegree and outdegree alone are rarely predictive of student outcomes. For this study, we used the indegree and outdegree centrality to define roles commonly used in other applications of SNA (outside of physics courses) to highlight how students interact within the network. We applied these tools to examine students' sense of belonging in an active-learning physics 1 course using a social capital lens. Our research questions are as follows:

1. Do we observe significant changes in students' sense of belonging during the course?
2. How do students' network roles change during the course?
3. Do students' connectedness and network roles significantly predict their course grades and/or sense of belonging at the end of the course?

II. ANALYTICAL FRAMEWORK

The interpretation and methodology of the current study are grounded in Bourdieu's theory of social capital, which is defined as the set of resources that result from different social structures [21]. This has been widely applied in educational research to understand inequities. From a network analysis perspective, Traxler *et al.* define social capital as an individual's access to resources in a social network or the collection of connections an individual has within a particular social setting [22]. For example, in a professional workplace setting, identifying the resources available to an individual through their social connections can promote more effective and efficient workplace dynamics. Though one can identify many types of social capital, the primary capital being transferred through network connections in a classroom is information relevant to learning. Therefore, a student with more connections should have more opportunities to both transmit information and receive information. Given Vygotsky's notion of the zone of proximal development [23], the exchange of information related to course content between peers is likely more impactful than the transmission of information from the instructor to the students.

Centrality in social network analysis illustrates an individual's importance or influence within their respective networks. Individual-level metrics are typically characterized by indegree and outdegree. Indegree, the number of connections reported by others to a specific individual, is often thought of as a measure of popularity, while outdegree, the number of connections reported by an individual to others, can be viewed as sociability or influence [1,20]. These metrics have helped to highlight relationships between student outcomes and social dynamics in the classroom, but looking at these measures independently may provide a limited view of the impact that social interactions have on students in a classroom setting. For example, indegree may show a student's popularity; however, their outdegree or sociability within the classroom may be contributing to their overall indegree. So, to better highlight that interdependence specific to directed relationships, we have elected to define roles commonly utilized in social network analysis based on their ingoing and outgoing connections.

Closeness, betweenness, and PageRank centrality go beyond the individual nodes to consider long-range interactions in the network. Closeness provides an aggregate measure that quantifies the distance between a node and all the other nodes in the network; an individual with high closeness would therefore be able to have more direct access to resources like information or educational support [1,20,24]. Betweenness measures how often an individual is on the shortest path between other pairs of nodes in the network, implying a "brokerage" of the flow of social capital between other students. Finally, PageRank centrality quantifies the likelihood of arriving at a particular individual by randomly walking between nodes on the graph. Therefore, if a student were to seek out information, they would be more likely to be directed to individuals with higher PageRank centrality. While these metrics are useful, they are still primarily focused on the importance of individuals within the network rather than network structures. From a social capital perspective, we may hypothesize that simply being strongly integrated into the network would have a substantial impact on sense of belonging, whether or not an individual within a strongly connected network has high closeness, betweenness, or PageRank centrality. Indeed, the goal of active learning is not to promote the emergence of particularly important individuals acting as sources or brokers of information, but to encourage widespread collaboration and information exchange throughout the network.

In the context of high-school students and drop-out risk, Coleman posited that a network with "closure"—a network in which everyone is connected—can even *produce* social capital because dense networks can foster trust between the individuals in the network with effects on educational achievement [25,26]. In particular, he suggested that lack of social capital was associated with higher drop-out risk, while strongly connected family and community networks might be able to produce the otherwise lacking social capital needed to stay in school. Granovetter, however, emphasized the significance of weak social connections in the diffusion of information and formation by focusing on how people access job opportunities via their social networks [27]. Granovetter argues that weak ties, characterized as infrequent interactions and low emotional intensity, are vital in connecting different social groups and facilitating the spread of innovative ideas, such that peripheral weak connections can also be beneficial as a way to infuse new information into the network and avoid groupthink [27].

These studies motivate the need to think beyond importance/centrality metrics and look at topological network features like connectedness. In this study, we focus on the sense of belonging as the outcome that will result from the exchange of capital in the context of *how* students are connected, rather than focusing primarily on the number of connections. This follows Coleman's suggestion that highly connected networks can foster a sense of trust between individuals. Additionally, prior studies have illustrated a strong, bidirectional relationship between sense of belonging and academic performance [28–30]. Ideally, an active-learning classroom format promotes more social interactions and enables students to gather information from diverse sources while minimizing the potential for brokers or gatekeepers who may obstruct the dispersion of information.

III. METHODOLOGY

A. Course structure

Data were collected from students enrolled in a Fall 2023 calculus-based physics 1 course that utilized active learning at a public research university in the southeastern United States. The majority of students who take this course are majoring in engineering, with approximately 5% of students studying another physical science or mathematics, and, in rare cases, science education. The course covered Newton's laws of motion, forces, torques, momentum, and energy in its various forms (kinetic, potential, chemical, etc.), though the sequencing of these topics used a forces-first approach and was designed around the framework of deliberate practice applied to scientific decision making [31]. The high-level learning goals outlined in the syllabus for students to achieve by the end of the course were as follows:

1. Be able to use principles of physics to solve real-world engineering problems.

2. Practice problem-solving skills that can be applied in later courses and throughout your career.
3. Work effectively with others to solve complex problems.
4. Gain confidence in your ability to “do” physics, regardless of who you are or where you come from.

The teaching team for the course included two co-instructors who were responsible for creating course content and leading class activities. One learning assistant (LA) and one supplemental instruction (SI) leader assisted the instructors in facilitating activities in the classroom but had no grading responsibilities. All four instructional team members held two to three nonoverlapping office hours per week for students to meet and ask questions. Moreover, there were five graduate teaching assistants who were responsible for running the lab sessions, teaching lab-specific content, and grading homework and laboratory activities. The laboratory activities followed the traditional “content-focused” model [32–34]. In this course, students were allowed to resubmit homework and quizzes to earn up to two-thirds of missed points back, but these resubmissions were primarily graded by the co-instructors.

As described in Ref. [31], the focus of this course was primarily on supporting students to engage in real-world problem solving, including skills like making simplifying assumptions, deciding what information they may need that is not given, and deciding whether the answer is physically realistic. A typical class period would begin with either a clicker question to review previous material, or an invention activity where the students would use physical models or PhET simulations to invent a particular physical principle—like balance of torques. The students would then practice applying that model in scaffolded real-world problems with periodic check-ins to review the activities and answer some clicker questions for understanding. This is a mix of collaborative problem-solving, peer-instruction, and modeling instruction, which we have been calling “Reflective Problem-Solving” instruction. Notably, this course was conducted in a large lecture hall with a screen and podium at the front of the room, but the chairs in the room were movable so that students could interact easily with one another.

This course covered much of the standard content in an introductory physics course, including forces, torques, conservation of angular and linear momentum, conservation of energy, and periodic motion. However, the content is taught in a different order: beginning with static equilibrium, introducing conservation of momentum and Newton’s second law before kinematics, and concluding with conservation of energy, which includes real-world examples such as estimating battery capacities and household power usage. The assessment structure of the course included preclass quizzes to check understanding of previous material (5%), in-class participation points (15%), long-answer homework assignments (36%, lowest grade dropped), in-class tests (24%, lowest grade dropped), content-focused labs (9%, lowest dropped), and a final exam which was shared with another instructor teaching a parallel section of the course following a traditional model (11%). Students were allowed to submit homework and test reflections to regain up to 50% of their missed points back and were given the opportunity to take a timed practice final exam in the same format, which would replace their actual final exam grade if higher. These measures were intended to emphasize learning through feedback and reflection and to reduce test anxiety.

TABLE I. Demographic breakdown of students who completed both pre- and postsurveys.

Demographic	Percentage (%)
Binary gender	
Male	78.3
Female	21.7
Race	
White	74.5
Asian	8.7
Other	8.7
Hispanics of any race	5.6
Black or African American	2.5
Student status	
First-time freshman	79.5
Transfer	14.3
Other	6.2

B. Participants

A total of 195 students were enrolled during the first week of class, of which 187 students consented to have their course data used for research. In addition to standard course grades and demographic information, pre- and postsurveys were given at the beginning of the first and last lab meetings of the semester (described in the next section). A total of 161 students completed both the pre- and postsurveys and consented to have their data used, out of 189 students who completed the course. The demographic breakdown of the students who completed both the pre- and postsurveys is listed in Table I. These data were drawn from institutional records that only use binary measures of gender.

C. Measurements

1. Sense of belonging measurement

The pre and postsurveys included a physics diagnostic test as well as a survey that probed various social-psychological constructs. The diagnostic was designed to measure students’ incoming conceptual understanding of fundamental physics and math concepts such as vector math, geometry, derivatives, kinematics, forces, and energy.

TABLE II. Survey items utilized to measure belonging for the pre- and postsurveys.

Survey items
1. I feel like I belong in this physics class.
2. I feel like an outsider in this physics class.
3. I feel comfortable in this physics class.
4. I feel like I can be myself in this physics class.
5. Sometimes I worry that I do not belong in this physics class.

This diagnostic was previously shown to be an effective predictor of performance in introductory physics at another institution [35]. The social-psychological survey consisted of Likert-scale questions (see Table II) that had been validated in prior studies in this and similar populations [30,36,37] to measure sense of belonging and a variety of other constructs. For this study, we will focus primarily on the sense of belonging, as we hypothesized it would be the most relevant construct to compare with students' social connections. Students were asked to rate their level of agreement with the following statements from 1 (strongly disagree) to 7 (strongly agree); items 2 and 5 were reverse-scored.

These questions have been revalidated with a comparable student population from this same university in prior studies. Those studies computed Cronbach's alpha of $\alpha = 0.81$ for precourse sense of belonging and $\alpha = 0.79$ for postcourse sense of belonging [38,39]. The confirmatory factor analysis from this study found that all questions in Table II loaded onto a single construct [38], with loadings greater than 0.6 and most items greater than 0.7, illustrating that the constructs effectively illustrate the variance within each item [40]. Thus, we constructed a single composite score ranging from 5 to 35, with a higher score indicating a higher sense of belonging.

2. Social interaction measurement

To collect the social interaction data, a question was included in the pre and postsurveys for students to list their interactions with other students and the strength of that interaction. At the beginning of the course, the instructor designated a portion of the class for students to introduce themselves as well as discuss and establish social norms among their respective groups. The class then collaboratively developed social norms from individual group contributions, which were included in the course materials on the Learning Management System (Canvas) page. For the presurvey, they were asked:

> Please list the students in your course that you already knew prior to the start of class.

to establish an initial baseline for the students' social connections prior to the start of the course. The students were then provided with a text-entry field to input the first and last name of the individual they may have known prior to the course, as well as a field to enter how well they knew the person on a scale of 1 (not very) to 5 (very well). We recognized there might be difficulty with remembering the specific names or legal names; therefore, we provided instructions to utilize the "People" tab on Canvas so participants could find last names or match names to faces as appropriate.

For the postsurvey, students were asked (with the same answer format):

> Please list the students in your class that you had a meaningful interaction with (related to this class) in the past two weeks.

It is important to note that the way the questions are posed in the postsurvey is different in order to distinguish students' incoming social capital from the social connections they developed during the course. This is because we anticipated that students entering with more social connections might have an advantage in building social capital during the course. We chose to use a two-week window because it had been used in prior SNA studies in the literature (Ref. [17] used a one-week window), and we did not anticipate that students would have a fully accurate recall of interactions prior to that.

Because the data collection required students to self-report, there were a total of five presurvey interactions and 17 postsurvey interactions that could not be matched to course or institutional records. These interactions were removed, perhaps resulting in a slight underestimate of the interactions occurring in the class. This might occur because students used initials in their reporting that could not be uniquely tied back to an individual student, or in the case that the student used a preferred name that was not reflected in the course roster (though this is an option provided to all students when enrolling in Canvas).

3. Performance metrics

We also analyzed student grades at the end of the course, as well as their one-year persistence rates, to see if there were notable consequences of their social capital on aspects of their education other than belonging. The grade distribution was heavily skewed toward an A (90% or higher) because of the generous test and homework corrections policy, so the statistical analysis compares students who received an A with students who received a lower grade using logistic regressions rather than treating grades as continuous. For persistence, we analyzed the 151 students in the sample of 161 who were engineers during the class (it was a class specifically for engineering majors) and categorized whether they were still in any kind of engineering major one year following the class (Fall of 2024).

D. Social network analysis

We analyzed the data using techniques from social network analysis (SNA) to characterize the data's structure and form. The social interaction data we collected were considered asymmetric, meaning a student may report that they had a meaningful interaction with another individual that individual may not reciprocate. Because these data had a directional relationship, we represented it using a directed graph (digraph), which contains a set of nodes (students) and ties (connections) that illustrate the interaction from student A to student B [24]. The difference between a digraph and a standard graph is that the direction of the tie between two nodes is specific. For a directed network, it will contain two key items of information, which are the set of nodes, or in this case, students, and a set of ties, where each tie is consequently an ordered pair of distinct nodes.

To analyze these networks collected by pre- and postsurveys, we used the R packages `igraph` and `intergraph` [41,42]. We focused on the degree centrality of each node (a student-level metric) and the network density and connectedness (class-level metrics).

1. Global network level analysis—Density and connectedness

Coleman highlights that a source of social capital is the structural cohesion of the "global" network of student connections. These connections are theorized to support a structure in which community norms, a climate of trust, and a sense of belonging can be built [25,26].

A common network-level metric used to characterize directed social networks is the network *density* [24]:

$$\Delta = \frac{l}{g(g-1)},$$

where l is the number of ties in the network, g is the number of nodes, and Δ represents the density of the network, such that $g(g-1)$ represents all possible ties for a given network with values ranging from 0, meaning no connections, to 1, which illustrates that everyone is connected. The network density allows us to examine the overall network cohesion [20].

To look at the network closure—*how* connected is everyone—we analyzed the structural connectedness of the network. Connections are defined in terms of *paths* and *semipaths*. A path in a directed network is a closed set of unique interactions linking one student to another. For example, in Fig. 1, there is a *path* formed by student 1 interacting with student 2, student 2 interacting with student 3, and student 3 then indicating an interaction with student 1. A semipath is a sequence of interactions among unique students that may not be closed, in the sense that the "vector sum" is zero [24]. For example, a semipath in Fig. 1 would be the link between student 1 and student 2 "through" student 3, even though this is counter to the indicated flow of information or capital.

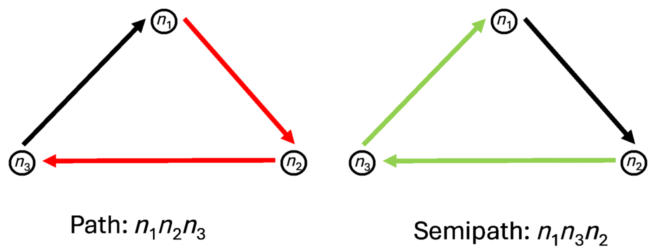

FIG. 1. Illustration of paths and semipaths in a directed network. For a directed network with a set of nodes $N = \{n_1, n_2, n_3\}$ and ties $T = \{\langle n_1, n_2\rangle, \langle n_2, n_3\rangle, \langle n_3, n_1\rangle\}$, a (left) path in the network is defined as n_1 to n_2 to n_3. While a (right) semipath in the network is defined as n_1 to n_3 to n_2 such that the direction of the tie does not need to be considered.

In Fig. 2, we illustrate how to characterize the connectedness of a pair of nodes n_1 and n_4 [24]. They are (a) weakly connected if they are joined by a semipath; (b) unilaterally connected if they are joined by a path from n_1 to n_4 or a path from n_4 to n_1 (i.e., the interactions are not reciprocated); (c) strongly connected if there is a path from n_1 to n_4, and a path from n_4 to n_1, where the path from n_1 to n_4 can have different nodes and ties than the path from n_4 to n_1; and (d) Recursively connected if they are strongly connected, and the path from n_1 to n_4 uses the same nodes and ties as the path from n_4 to n_1, in reverse order.

We were interested in characterizing whether the network that results from the course is strongly connected. A strongly connected network would show that each pair of nodes is reachable from any other pair. However, even if the network as a whole is not strongly connected, there may be components within the network with strong connections. Additionally, an isolated node or one with no connections to any other node is by definition strongly connected with

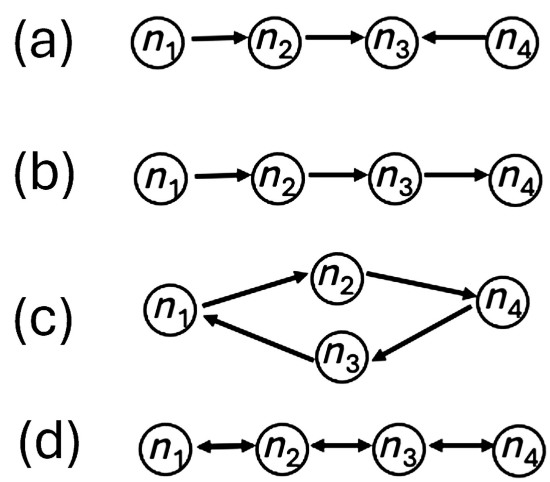

FIG. 2. Illustration of the different connectivity types from Ref. [24]. (a) Weakly connected, (b) unilaterally connected, (c) strongly connected, and (d) recursively connected.

itself. So, when evaluating the components of our network that are strongly connected, we will have "components" containing only one person and components with two or more people. The components containing only one person will include both those who are isolated and those who may be weakly connected with another individual. With this grouping, we then explored whether there is any added benefit for an individual student's outcome in academic performance or effect on sense of belonging.

2. Student-level network analysis: Network roles

Putnam proposes that social capital, in terms of interactions, collectively defined social norms, and trust, helps to establish a paradigm of mutual benefit from collaboration [43]. To better understand if this was taking place in our classroom environment, we characterized the roles that students took on within the classroom via their reported interactions. Characterizing students' degree centrality in a directed graph required us to distinguish between indegree (the number of interactions terminating at a specific node) and outdegree (the number of interactions originating from a specific node). To study the evolution between the pre- and postnetworks, we examined the distributions of the number of indegrees and outdegrees per node, as well as a "degree-informetric" to categorize the *roles* of each node in the network. The informetric considers a node's indegrees and outdegrees simultaneously [24] to define the following roles:

1. Isolate: Indegree = Outdegree = 0.
2. Sender: Indegree = 0 and Outdegree > 0.
3. Receiver: Indegree > 0 and Outdegree = 0.
4. Communal: Indegree ≥ 1 and Outdegree ≥ 1.
5. Bridge: Indegree = 1 and Outdegree = 1.

An isolate is a student who reports no interactions with others and whom no others report interacting with. A sender reports interacting with at least one other student, but none of these interactions are reciprocally reported. A receiver is a student who reports no notable interactions, but who is identified by other students as someone they meaningfully interacted with. Bridges and "communal" students have both ingoing and outgoing connections, but a bridge has exactly one indegree and outdegree (i.e., an isolated partnership or bridging two groups within the network), and a communal node's indegree and outdegree are both greater than or equal to 1, such that both indegree and outdegree are not both exactly equal to 1. In doing this, our intention is not to assign a value judgment for each specific role, but rather to understand the exchange of capital that may occur via the interactions reported by the students, and if that may translate to an effect on the sense of belonging in the class. Note that we use slightly different language than the roles used in Ref. [24] as the role names connote spread of disease, which we do not want applied to students.

IV. RESULTS

A. Change in sense of belonging

To understand how a student's sense of belonging changed over the duration of the course, we plotted histograms of the pre- and postbelonging scores in Fig. 3. The average values on a scale of 5 to 35 for the pre- and postmeasures were 25.9 and 25.7, respectively, with a median score of 26 for both pre and post. We used a paired hypothesis test to capture the student-level nature of pre-to-post change. Using a Shapiro-Wilk test, we found that the distribution of the difference in sense of belonging was

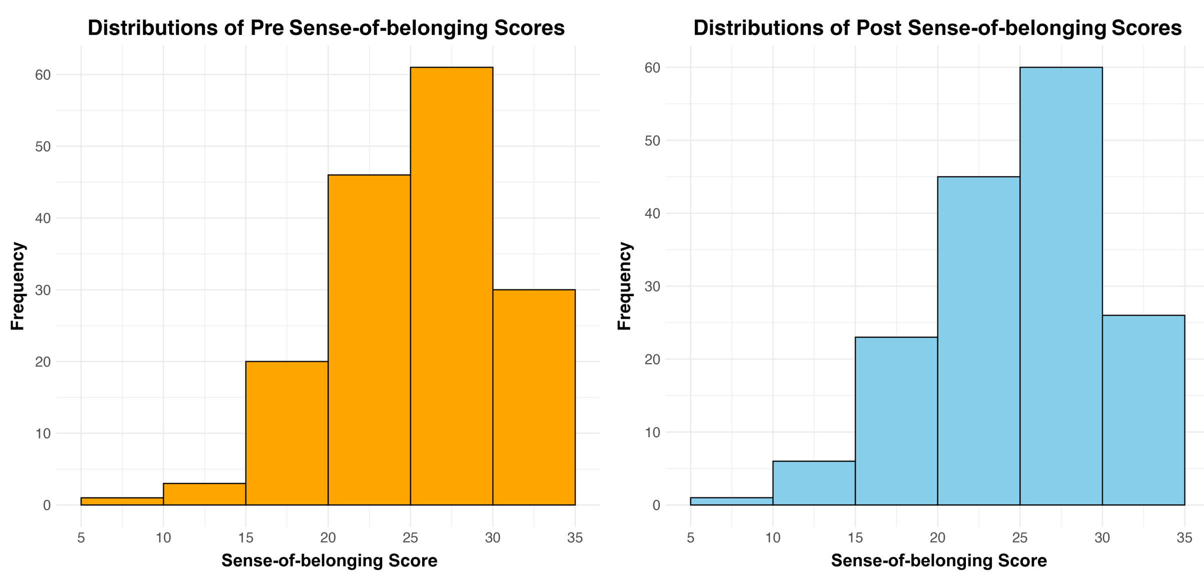

FIG. 3. Left: distribution of the sense of belonging scores collected using the presurvey. Right: distribution of the sense of belonging scores collected using the postsurvey.

TABLE III. Pre and post social network metrics.

	No. of nodes	No. of connections	Average degree	Network density
Prenetwork	161	103	0.64	0.004
Postnetwork	161	454	2.82	0.018

statistically different from a normal distribution ($p = 0.0016$). Therefore, we used the nonparametric Wilcoxon signed-rank test, which indicated that a student's starting sense of belonging was not significantly different than their ending sense of belonging score ($p = 0.56$).

B. Network density and connectedness

To investigate how the social interaction of students evolved at the class level over the duration of the course, we used the collected data outlined in the methodology sections and examined the density and connectedness of the students in the class from pre to post.

1. Network density

Table III provides descriptive statistics for the pre- and postnetworks. There were approximately 4.4 times as many connections reported in the postnetwork compared with the prenetwork, with each node going from an average of 0.64 connections to an average of 2.82 connections. The density of the overall network correspondingly increased from 0.004 to 0.018. This density was expected to be low because a high-density directed network would require a large number of students to report reciprocal relationships with most other students in the network. We note that the average attendance during the 2 weeks prior to the post-survey was 87% (standard error $= 2\%$) compared with 90% (standard error $= 2\%$) for the whole semester, suggesting that the number of in-class interactions captured by the survey is likely an accurate representation. However, we did not distinguish between in-class and out-of-class interactions, and we discuss potential impacts of this in the limitations section below.

2. Network connectedness

Figure 4 shows the strongly connected components for the pre- and postnetworks. Visually comparing the two illustrates that the number of overall components decreases while the number of people in components of two or more increases between pre and post. For there to be a strong connection, there has to be a path from a starting node to an ending node as well as a path from the ending node to the starting node. We note that we did not analyze network connectedness at the beginning of the term because the network was extremely sparse, so the number of strongly connected individuals would not have provided much information.

In the context of our analytical framework, we examined how strongly connected components of two or more people compare with components of single individuals. We plotted the distributions of postcourse sense-of-belonging scores (Fig. 5) for those who were in components of one person (left, $N = 38$) and two or more people (right, $N = 123$). By inspection, we can see that those in strongly connected components of two or more people, on average, have a higher sense of belonging than those in strongly connected components of one person. The average sense of belonging for those in components of two or more was 26.03, and for the components of individuals, it was 24.58, and their medians were 27 and 23.5, respectively.

To test whether this was statistically significant, we used a statistical test to determine whether those in components of two or more people have a greater sense of belonging than those in components of single individuals. We first tested the normality of the data using a Shapiro-Wilk test and found that the distribution of scores for students in a component of one was not statistically different from a normal distribution ($p = 0.11$), whereas the distribution of

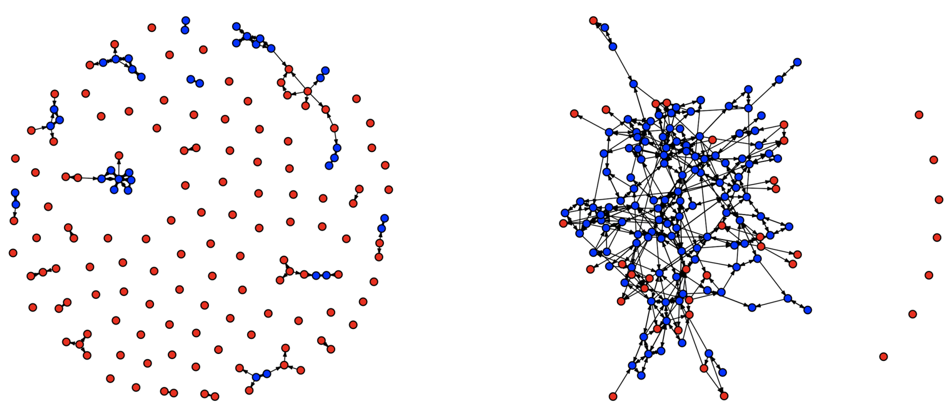

FIG. 4. Left: prenetwork with nodes that are vermillion, representing students who are not strongly connected, and blue nodes representing students who are strongly connected. Right: postnetwork with nodes that are vermillion, representing students who are not strongly connected, and blue nodes representing students who are strongly connected.

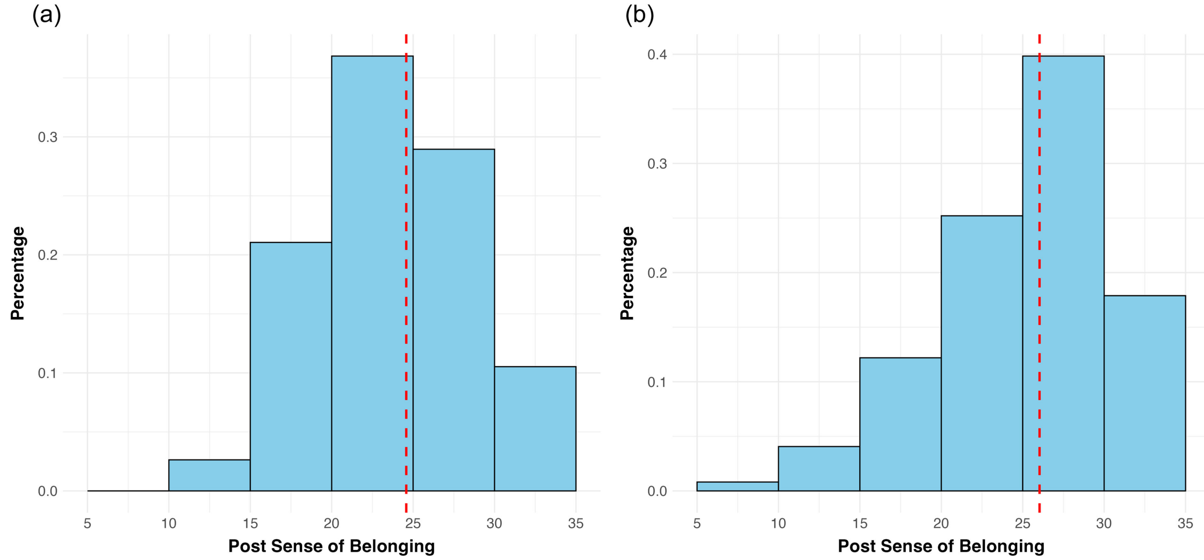

FIG. 5. (a) Distribution of the post sense of belonging for components with one person, with the red dashed line representing the mean (24.58). (b) Distribution of post sense of belonging for strongly connected components of two or more people, with the red dashed line representing the mean (26.03).

scores for components with two or more people was ($p < 0.001$). Thus, we used a Wilcoxon rank-sum test, which showed that the difference was statistically significant at the $p = 0.05$ level ($p = 0.046$): sense of belonging was greater for students in strongly connected components of two or more people.

C. Centrality and network actor roles

1. Degree centrality

Though there was an average increase in network connectivity, Fig. 6 shows that there was a distribution of connectedness at both time points. The distributions illustrate that, for the prenetwork, a large fraction of the students had an in and outdegree less than or equal to 1, while in the postnetwork, there were more students with in and outdegrees greater than 1. In fact, we found that for the prenetwork, there were 137 students with an in and outdegree less than or equal to 1, such that there were 93 and 100 students who had an in and outdegree equal to zero, respectively. In the postnetwork, there were only 13 students with an indegree equal to zero and 27 students with an outdegree equal to zero.

Due to the interdependence of centrality measures, distributions of indegree and outdegree are typically non-normal. Since bootstrapped regressions do not make any assumptions on the distribution of the data, we applied this technique to test for a correlation between post sense of belonging and students' final reported indegree and outdegree centralities. The model we tested was:

$$Post\,Sense\,of\,Belonging \sim Post\,Indegree + Post\,Outdegree$$

We performed 1000 iterations of random resampling of the existing data to calculate a set of regression coefficients for each sample. We then pooled the set of regression coefficients to get an estimate of the effect size for post indegree and post outdegree. The effect size for post indegree was 0.25 with a 95% confidence interval of $[-0.33, 0.85]$, and the effect size of the post outdegree was -0.09 with a 95% confidence interval of $[-0.66, 0.42]$. Therefore, neither correlation was significant at the $p = 0.05$ level.

2. Network actor role

To better understand this distribution, we assigned roles to students based on the definitions defined in the methods section and plotted how these roles were distributed at both time points, as well as how students transitioned between roles [Fig. 7 (Left)]. We found that 74 out of 161 students in the prenetworks were classified as isolates (indegree = outdegree = 0) and only 27 out of 161 were classified as communal (in/out degree > 1) while in the post network, 7 out of 161 were classified as isolates, and 124 out of 161 students were classified as communal. We saw that ~74% of isolates (students with no prior social connections at the beginning of class) transitioned into communal and bridge roles, with ~12% remaining isolates or moving into receiver or sender roles (i.e., only unidirectional relationships). A small number of students transitioned into isolates from more connected roles. Overall, ~4% of students reported fewer connections (reciprocal or otherwise) at post-test.

Figure 7 (Right) illustrates that those who had a post role of isolate had a smaller reported sense of belonging when compared to students with other postnetwork roles.

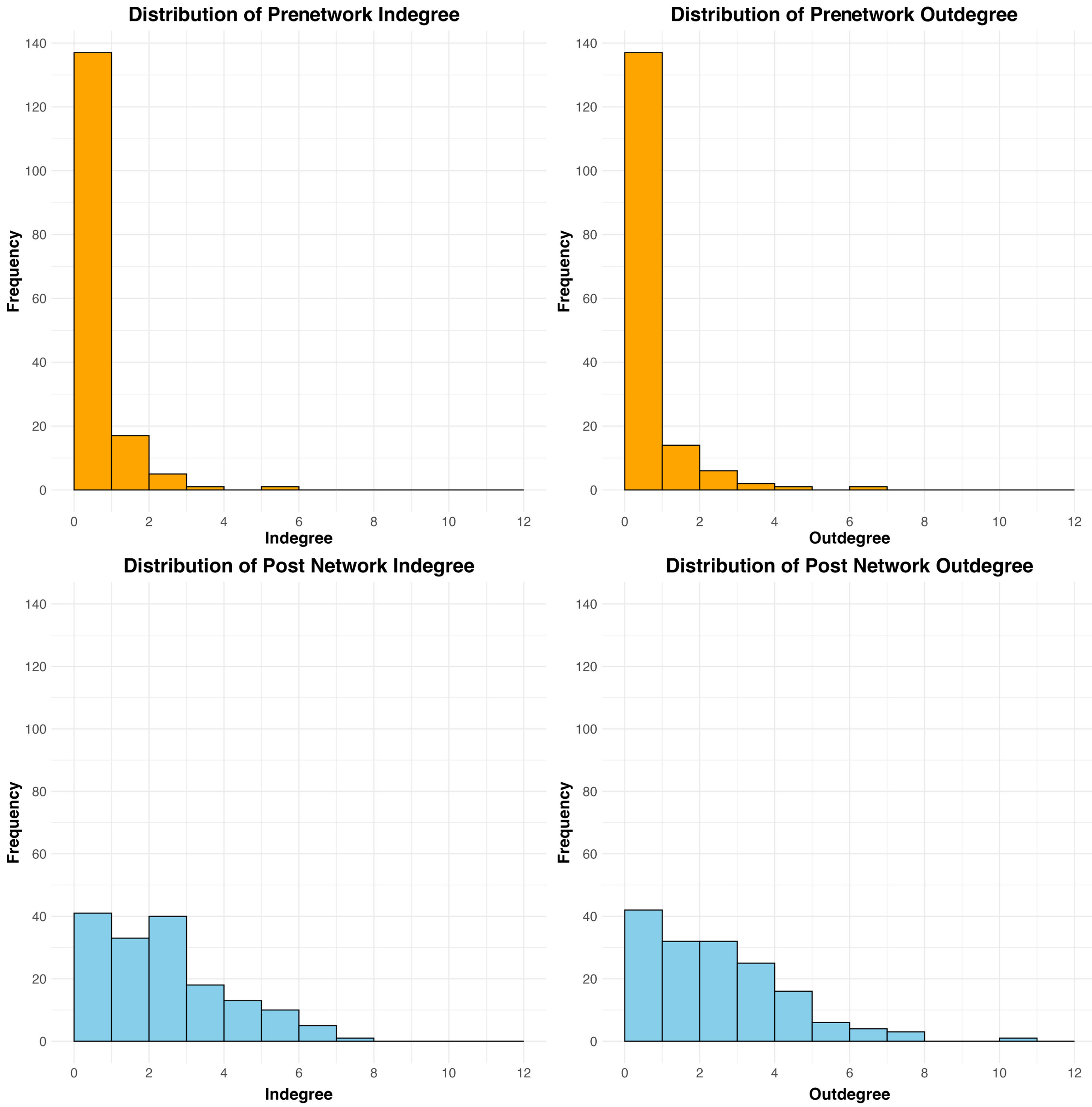

FIG. 6. Top left: distribution of indegree centrality for the prenetwork. Top right: distribution of outdegree centrality for the prenetwork. Bottom left: distribution of indegree centrality for the post network. Bottom right: distribution of outdegree centrality for the postnetwork.

A Shapiro-Wilk test revealed that post sense of belonging was normally distributed for isolates ($p = 0.41$) but not for others ($p < 0.001$). So, using the Wilcoxon rank-sum test, we again found that the sense of belonging of students who did not have a post role of isolate was greater than those whose post role was isolate ($p = 0.044$). Note that a student with a role of isolate is, by definition, in a component of one, but students in a component of one are not necessarily isolated—they just do not have any strong connections with other students in the network.

D. Student performance and persistence

1. Student grades

Because sense of belonging is related to student performance, we wanted to see if that was the case in this course and if students' network roles or connectedness were associated with higher grades in addition to higher levels of social capital. In Fig. 8, we show the final letter grades (categorical) and plot the distributions of sense of belonging for each. We note that an A is a score of greater than 90%, a B is a grade of 80–89%, a C is 70–79%, and a D is 69% or lower. Students need at least a C to continue in their engineering majors.

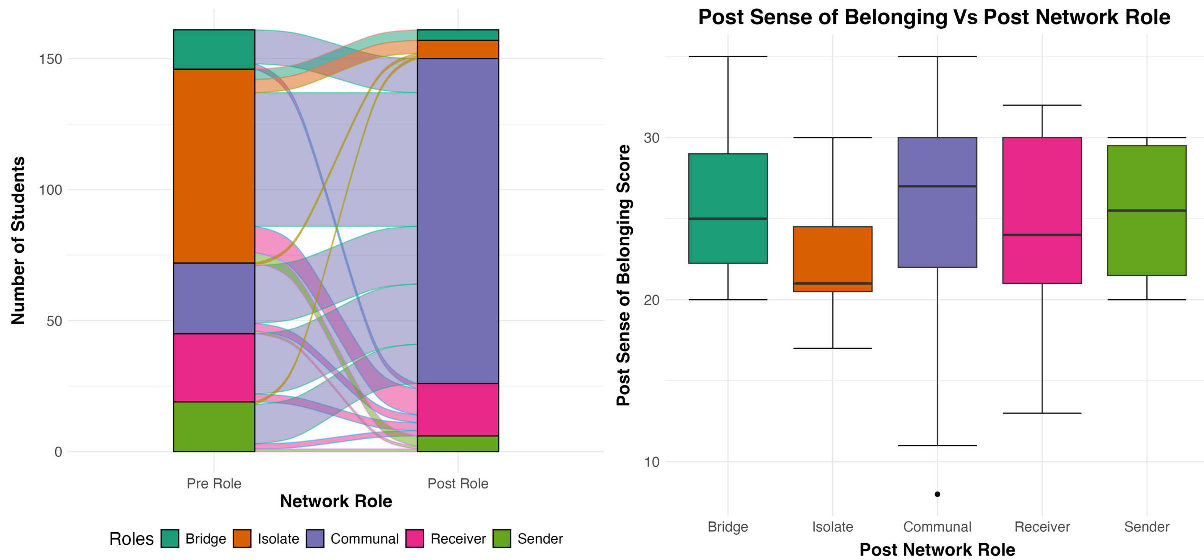

FIG. 7. Left: alluvial diagram illustrating the network role transitions between pre and post. Right: box plot of students' post roles and their reported post sense of belonging.

Figure 8 illustrates that those who received an A had a higher sense of belonging when compared to those who received a B, C, or D. To see if these differences are statistically significant, we first used a Shapiro-Wilk test for normality and found that for those who received an A, the distribution was different than a normal distribution ($p < 0.001$) and those who received a B, C, or D was different than normal distribution ($p < 0.05$) on a $p = 0.05$ level. We, therefore, used a Wilcoxon test to check whether the sense of belonging for students who received an A was greater than students who did not receive an A. We found that the post sense of belonging was significantly higher (at the $p < 0.05$ level) for students who received an A than for those who received a B, C, or D ($p < 0.001$).

We then used a logistic regression to determine whether post sense of belonging, and students' network roles or connectedness, were statistically significant predictors of a student receiving an A. We hypothesized that those who are more strongly connected and not isolated would have greater access to social capital and thus have a higher final grade. We tested the following model(s)

$$logit(P(Final.Grade = A)) = \beta_0 + \beta_1(Post\,Sense\,of\,Belonging) + \beta_2(Post\,Connection\,Category)$$

$$logit(P(Final.Grade = A)) = \beta_0 + \beta_1(Post\,Sense\,of\,Belonging) + \beta_2(Post\,Network\,Role)$$

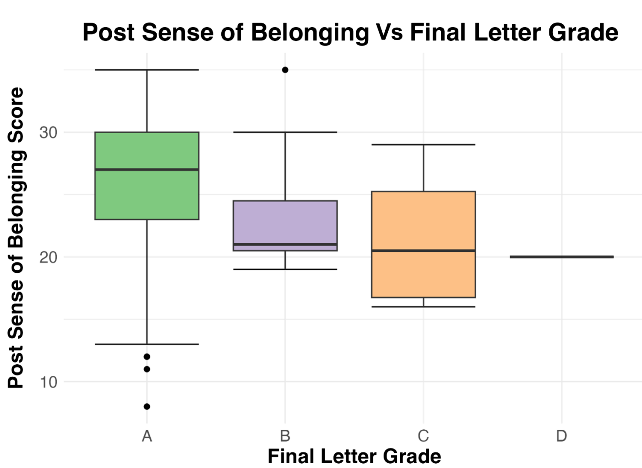

FIG. 8. Box plot of students' grades and their post sense of belonging.

The outcome variable was the log-odds of the probability that a student received an A versus a B, C, or D, and the independent variables were students' post sense-of-belonging scores (ranging from 5 to 35) and the network connectedness (model 1) or role (model 2). The network connectedness was coded as a binary variable, which is 1 when a student is strongly connected and 0 when they are not. The network role was coded as a 0 when a student was an isolate and 1 when they were not. The results are in Table IV.

The results of model 1 have the following interpretations: β_0 represents the log-odds for a student with zero sense of belonging and in a component by themselves, β_1 is the average correlation between a student's post sense-of-belonging score with their likelihood to receive an A in the course regardless of their role, and β_2 measures the difference in log-odds of students in components that are

TABLE IV. Output of logistic regression models. The 95% confidence limits are for the exponentiated coefficients.

		Model 1		
Predictors	β_k	e^{β_k}	95% C.L.	p value
Intercept	−1.29	0.28	0.036–2.046	0.2
Post sense of belonging	0.097	1.1	1.019–1.19	$p < 0.05$
Post connection category	0.95	2.59	1.00–6.55	$p < 0.05$
		Model 2		
Predictors	β_k	e^{β_k}	95% C.L.	p value
Intercept	−1.24	0.29	0.028–3.55	0.3050
Post sense of belonging	0.097	1.1	1.019–1.19	$p < 0.05$
Postnetwork role	0.63	1.88	0.25–9.63	0.4752

strongly connected with two or more people in relation to those in components by themselves. We found that $\beta_0 = -1.29$, which means that the odds of a weakly connected student with zero sense of belonging receiving an A compared with a lower grade was 0.19, which is not statistically different from an odds ratio of 1.0 (or an even chance, which is the null hypothesis in this case; $p = 0.20$). We found that $\beta_2 = 0.95$, which means that a strongly connected student with a zero sense of belonging score is 2.59 times more likely than a weakly connected student to receive an A, which is statistically significant at the $p < 0.05$ level, though the range of the effect is enormous. We found that $\beta_1 = 0.097$, which translates to each 1-point increase in sense of belonging resulting in a 1.1-fold increase in the odds of any student receiving an A ($p < 0.05$). To test a specific case, we set the sense-of-belonging score to 25.7 (the average class post-score) and find that a strongly connected student with average post sense of belonging is 1.99 times more likely to get an A than a weakly connected student with the same post sense of belonging.

The results of model 2 are analogous, with the caveat that β_2 now measures the difference in log-odds of students who are not isolates compared to students who are isolates. We found that $\beta_0 = -1.24$, which means that the odds of a weakly connected student with zero sense of belonging receiving an A compared with a lower grade was 0.29, which is not statistically different from an odds ratio of 1.0 (or an even chance, which is the null hypothesis in this case; $p = 0.31$). We found that $\beta_2 = 0.63$, which means that a strongly connected student with a zero sense-of-belonging score is 1.88 times more likely than a weakly connected student to receive an A, but this is not statistically significant ($p = 0.48$) because of the small number of isolates. We found that $\beta_1 = 0.097$, which translates to each 1-point increase in sense of belonging resulting in a 1.1-fold increase in the odds of any student receiving an A ($p < 0.05$). To test a specific case, we set the sense-of-belonging score to 25.7 (the average class post-score) and find that a nonisolated student with average post sense of belonging is 1.46 times more likely to get an A than an isolated student, though this difference has a large error.

2. Student persistence

We found that the one-year persistence rate of all students was 91.4%, with 138 of 151 engineers staying in engineering one year after the class. Because the number of students who left engineering is small, it is difficult to make any kind of accurate estimates of the effect of network or connectedness. When testing analogous models to the ones mentioned above, we found that a strongly connected student was 1.08 times more likely to persist (95% C.L. $= [0.23, 3.88]$, $p = 0.91$) and a student who was not an isolate was 8.17 times more likely to persist than an isolate (95% C.L. $= [1.0, 54.7]$, $p = 0.029$).

V. DISCUSSION

In this study, we applied techniques from social network analysis to analyze the relationship between student social interactions and sense of belonging in an active-learning physics 1 class. We found that the network density increased by a factor of 4.4 during the duration of the course, even though no statistically significant change in sense of belonging was observed at the class level. Thus, we observed a substantial change in the average number of student connections but not their sense of belonging. When examining the students' connections in terms of network roles, we found that most students started as isolates (e.g., no prior social connections) and transitioned into a role with at least one incoming or outgoing connection, with the majority having more than one incoming and outgoing connection at the end of the class. Students who did not report any significant interactions at the end of the class (isolates) reported a lower sense of belonging. When looking at the connectedness of individual students, we further found that students who were not isolates but did not report strong connections with other students also reported a lower sense of belonging at the end of the course. Finally, we found that students who were not isolates and were strongly connected to at least one other student were significantly more likely to earn an A in the class, even if they had the same levels of sense of belonging, but we cannot make any strong claims about the long-term outcomes for students with differing levels of connectivity.

In an educational context, sense of belonging is defined as a student's personal feeling of being related to, connected with, and respected by the institution (or in this case, class) they are a part of; this is also referred to as "psychological membership" [44]. Sense of belonging is known to be a strong predictor of performance in introductory physics [36,38], and performance is a known mediator for a student's likelihood to stay in STEM [45,46]. Thus, understanding how student social interactions shape motivational beliefs like sense of belonging is important for understanding long-term student outcomes. Prior studies have shown that looking at the number of interactions at both a student level using metrics like indegree and outdegree centrality, and relative global level metrics like closeness, betweenness, and PageRank does not provide consistent correlations with these outcomes. Indeed, we found that, while the number of reported interactions almost uniformly increased between pre- and post-tests, we saw no statistically significant effect on a student's sense of belonging. This is consistent with a prior study, which found that student post self-efficacy was not predicted by indegree or outdegree centrality [14].

In the context of social capital, centrality provides a limited description of the social dynamics in a classroom because it primarily reflects the importance and influence of individuals. While this is useful to examine resource allocation in a hierarchical organization like a professional environment with designated leadership structures, or in distributed networks like the import or export of materials, we argue that it is not the goal in a classroom. Rather, in an active-learning classroom setting, the goal is to deemphasize the importance of any singular student and maximize the engagement of all by fostering a diverse and inclusive environment. Within a strongly connected network (or component within a network), demographic diversity allows for the inclusion of unique perspectives, resulting in new methods and plans to understand and solve problems [47]. Pulgar *et al.* found that those who interacted with more people performed better on ill-structured problems than well-structured problems [10]. This illustrates that through social connections, a diversity of perspectives can help maximize the potential of an individual to solve novel problems, while conversely, it can hinder a student when looking at rote textbook problems. This relationship warrants closer study, as it could be that well-structured problems discourage collaborative efforts because they are not group-worthy tasks.

While analyzing the post network, we found that the overall network was not strongly connected, but there were subsets of the classroom social network that were. Students in subsets that had strong connections between at least two people reported higher levels of post sense of belonging compared to isolated or weakly connected students. This would suggest that students with stronger connections (and therefore more significant exchanges of social capital) feel more socially integrated in the classroom, which is consistent with Coleman's suggestion that stronger connections within a network can better foster a sense of trust between the individuals in the network. Conversely, Granovetter mentions the benefits that weak social connections or peripheral interactions can have in interjecting new information in groups, but we found that students who were weakly connected reported a lower post sense of belonging. This is likely because Granovetter was discussing how weak *incoming* connections might be helpful to an individual looking for employment. In the classroom, it is possible that a student with both weak and strong connections might benefit from both of those, whereas students experiencing only weak connections might be disadvantaged [48]. This reinforces the need for egocentric network methods, which emphasize who is benefiting from what kinds of interactions.

Another utility of this method is that we can more easily identify students who are not benefiting from or actively participating in the course by defining roles rather than a continuous centrality metric, which would require an arbitrary cut-off value to define a "group" that was not benefiting from the course. Indeed, the goal of active-learning classrooms is not to promote the accumulation of capital by a privileged few or encourage brokering relationships that halt the flow of capital, but to maximize the free flow of information between students so that all of them can benefit from a variety of information sources to support their learning. For example, students who change from a communal to an isolate role may highlight students being intentionally isolated by their peers because of some facet of their identity [49]. Again, this is something that could be more richly explored through egocentric methods.

VI. LIMITATIONS

It is important to acknowledge that this study is purely observational and does not provide any causal explanations for the observed changes in students' sense of belonging, network positionality, or academic performance. Its primary purpose is to show that this approach toward analyzing student networks might provide a different way of thinking about how we support students' social connections in the classroom. A limitation of this study is that we did not do a comprehensive comparison of network roles to other measures of network density, like PageRank centrality, and whether those were correlated with students' sense of belonging. We did find that indegree and outdegree were not correlated with sense of belonging, but chose not to do an exhaustive test of centrality correlations because (i) we did not want to risk p-hacking without a strong hypothesis about *why* one centrality measure would or would not be correlated with belonging and (ii) the interpretation of those correlations is still fundamentally focused on supporting an individual rather than a cohesive class structure.

One limitation of the study is that we do not know precisely what *types* of student interactions are being captured by our network survey. While student in-class participation and attendance were high, it is possible that students consider most of the meaningful interactions to be outside of the classroom. For example, Zwolak and coworkers [17] found that the out-of-class interactions were more predictive of student persistence, and we do not make that distinction. Anecdotally, the authors knew that students who may not be close in the classroom frequently worked together outside of the class, and that this may not have been related to the instruction in any way. Similarly, we do not know what students were discussing in or outside of the classroom and whether that had a notable impact, as has been shown in some prior studies [50].

Another limitation is that we do not have longitudinal data to suggest whether these postnetworks are truly representative of the class as a whole. We are currently conducting a study to look at longitudinal network evolution using these methods and comparing the impacts of the physical space—active learning versus lecture classrooms—on students' connectedness and network role. This may shed insight as to whether the effects observed here are due to any deliberate in-class actions by the instructional team, or perhaps due to some other feature like the emphasis on real-world problems that require multiple perspectives from students to solve, as seen in Ref. [10].

VII. CONCLUSION

We examined the social dynamics of an active learning calculus-based physics 1 class using techniques from social network analysis not typically used in physics education. We found that degree centrality by itself may obscure the nuances of how students' social interactions do or do not foster a greater sense of belonging. We instead use methods that define roles in the network based on the interdependent metrics of indegree and outdegree centrality, as well as the strength of connections within the network. We found that a student's postclass sense of belonging was not correlated with their overall number of connections in the class network. However, we found that students who were isolated or only weakly connected to others reported a lower sense of belonging compared to students who were strongly connected to at least one other person. We see similar impacts of connectedness and network role on students' academic performance above and beyond the contributions of these network features to students' sense of belonging.

As this approach is still in an early stage, there are few definitive recommendations for instructors or policies that we feel comfortable recommending. These results do suggest that a student having a strong level of connection to even just one other person may be beneficial to both their sense of belonging and academic success. Thus, an instructor may not have to focus on students forming large study groups but simply making sure that students find one other person they can work with productively and supportively. Another noteworthy finding is that this very dense network was not deliberately nurtured by the instructional team during the semester but seems to be a result of their typical teaching approach. This is not to say that promoting student connectedness requires no instructor support, but it does motivate the need to find out *what about* this method of instruction seems to result in such a dense network, and whether there are particular pedagogical choices that led to these results. For these future studies, these methods provide a clearer way to identify how classroom dynamics are impacting individual students or groups of students and may provide a way to reconcile some of the inconsistencies in the results of other approaches to SNA in the literature.

DATA AVAILABILITY

The data that support the findings of this article are not publicly available because they contain sensitive personal information. The data are available from the authors upon reasonable request.

[1] D. Z. Grunspan, B. L. Wiggins, and S. M. Goodreau, Understanding classrooms through social network analysis: A primer for social network analysis in education research, CBE Life Sci. Educ. **13**, 167 (2014).

[2] V. Tinto, Stages of student departure: Reflections on the longitudinal character of student leaving, J. Higher Educ. **59**, 438 (1988).

[3] V. Tinto, Classrooms as communities: Exploring the educational character of student persistence, J. Higher Educ. **68**, 599 (1997).

[4] S. Freeman, S. L. Eddy, M. McDonough, M. K. Smith, N. Okoroafor, H. Jordt, and M. P. Wenderoth, Active learning increases student performance in science, engineering, and mathematics, Proc. Natl. Acad. Sci. U.S.A. **111**, 8410 (2014).

[5] E. J. Theobald *et al.*, Active learning narrows achievement gaps for underrepresented students in undergraduate science, technology, engineering, and math, Proc. Natl. Acad. Sci. U.S.A. **117**, 6476 (2020).

[6] L. Kramer, E. Fuller, C. Watson, A. Castillo, P. D. Oliva, and G. Potvin, Establishing a new standard of care for calculus using trials with randomized student allocation, Science **381**, 995 (2023).

[7] R. R. Hake, Interactive-engagement versus traditional methods: A six-thousand-student survey of mechanics test data for introductory physics courses, Am. J. Phys. **66**, 64 (1998).

[8] L. Deslauriers, E. Schelew, and C. Wieman, Improved learning in a large-enrollment physics class, Science **332**, 862 (2011).

[9] J. M. Cámara-Zapata and D. Morales, Cooperative learning, student characteristics, and persistence: An experimental study in an engineering physics course, Eur. J. Eng. Educ. **45**, 565 (2020).

[10] J. Pulgar, C. Candia, and P. M. Leonardi, Social networks and academic performance in physics: Undergraduate cooperation enhances ill-structured problem elaboration and inhibits well-structured problem solving, Phys. Rev. Phys. Educ. Res. **16**, 010137 (2020).

[11] A. Rezaei, Groupwork in active learning classrooms: Recommendations for users, J. Learn. Spaces **9**, 1 (2020), https://libjournal.uncg.edu/jls/article/view/1965.

[12] E. P. Driessen, J. K. Knight, M. K. Smith, and C. J. Ballen, Demystifying the meaning of active learning in postsecondary biology education, CBE Life Sci. Educ. **19**, ar52 (2020).

[13] R. A. Lotan, Group-worthy tasks, Educ. Leadership **60**, 72 (2003).

[14] R. Dou, E. Brewe, J. P. Zwolak, G. Potvin, E. A. Williams, and L. H. Kramer, Beyond performance metrics: Examining a decrease in students' physics self-efficacy through a social networks lens, Phys. Rev. Phys. Educ. Res. **12**, 020124 (2016).

[15] S. Brin and L. Page, The anatomy of a large-scale hypertextual web search engine, Comput. Networks ISDN Syst. **30**, 107 (1998).

[16] S. Fortunato and A. Flammini, Random walks on directed networks: The case of PageRank, Int. J. Bifurcation Chaos Appl. Sci. Eng. **17**, 2343 (2007).

[17] E. A. Williams, J. P. Zwolak, R. Dou, and E. Brewe, Linking engagement and performance: The social network analysis perspective, Phys. Rev. Phys. Educ. Res. **15**, 020150 (2019).

[18] J. P. Zwolak, M. Zwolak, and E. Brewe, Educational commitment and social networking: The power of informal networks, Phys. Rev. Phys. Educ. Res. **14**, 010131 (2018).

[19] J. P. Zwolak, R. Dou, E. A. Williams, and E. Brewe, Students' network integration as a predictor of persistence in introductory physics courses, Phys. Rev. Phys. Educ. Res. **13**, 010113 (2017).

[20] R. Dou and J. P. Zwolak, Practitioner's guide to social network analysis: Examining physics anxiety in an active-learning setting, Phys. Rev. Phys. Educ. Res. **15**, 020105 (2019).

[21] P. Bourdieu, The forms of capital, in *The Sociology of Economic Life*, 3rd ed. (Routledge, New York, NY, 2018).

[22] A. L. Traxler, C. M. D. do Amaral, C. Henderson, E. LaForge, C. Hatcher, M. Swirtz, and R. Barthelemy, Person-centered and qualitative approaches to network analysis in physics education research, Phys. Rev. Phys. Educ. Res. **20**, 020132 (2024).

[23] L. S. Vygotsky, *Mind in Society* (Harvard University Press, London, 2019).

[24] S. Wasserman and K. Faust, *Social Network Analysis: Methods and Applications* (Cambridge University Press, Cambridge, London, 1994).

[25] J. S. Coleman, Social capital in the creation of human capital, Am. J. Sociol. **94**, S95 (1988).

[26] J. Coleman, *Foundations of Social Theory*, 1st ed. (Harvard University Press, Cambridge, MA, 1990).

[27] M. S. Granovetter, The strength of weak ties, in *Social Networks* (Elsevier, New York, 1977), pp. 347–367.

[28] S. Cwik and C. Singh, Students' sense of belonging in introductory physics course for bioscience majors predicts their grade, Phys. Rev. Phys. Educ. Res. **18**, 010139 (2022).

[29] J. D. Edwards, R. S. Barthelemy, and R. F. Frey, Relationship between course-level social belonging (sense of belonging and belonging uncertainty) and academic performance in general chemistry 1, J. Chem. Educ. **99**, 71 (2022).

[30] Y. Li and C. Singh, Sense of belonging is an important predictor of introductory physics students' academic performance, Phys. Rev. Phys. Educ. Res. **19**, 020137 (2023).

[31] E. Burkholder, S. Salehi, S. Sackeyfio, N. Mohamed-Hinds, and C. Wieman, Equitable approach to introductory calculus-based physics courses focused on problem solving, Phys. Rev. Phys. Educ. Res. **18**, 020124 (2022).

[32] N. G. Holmes and C. E. Wieman, Introductory physics labs: We can do better, Phys. Today **71**, No. 1, 38 (2018).

[33] N. G. Holmes, J. Olsen, J. L. Thomas, and C. E. Wieman, Value added or misattributed? A multi-institution study on the educational benefit of labs for reinforcing physics content, Phys. Rev. Phys. Educ. Res. **13**, 010129 (2017).

[34] C. Wieman and N. G. Holmes, Measuring the impact of an instructional laboratory on the learning of introductory physics, Am. J. Phys. **83**, 972 (2015).

[35] E. Burkholder, K. Wang, and C. Wieman, Validated diagnostic test for introductory physics course placement, Phys. Rev. Phys. Educ. Res. **17**, 010127 (2021).

[36] Y. Li and C. Singh, Inclusive learning environments can improve student learning and motivational beliefs, Phys. Rev. Phys. Educ. Res. **18**, 020147 (2022).

[37] PERTS Academic Mindsets Assessment (2020), https://www.perts.net/orientation/ascend.

[38] Y. Li, R. C. Bernardi, and E. Burkholder, The effects of active learning on students' sense of belonging and academic performance in introductory physics courses, Eur. J. Phys. **45**, 045705 (2024).

[39] Y. Li and E. Burkholder, Investigating students' self-identified and reflected appraisal of femininity, masculinity, and androgyny in introductory physics courses, Phys. Rev. Phys. Educ. Res. **20**, 010110 (2024).

[40] J. F. Hair, W. C. Black, B. J. Babin, and R. E. Anderson, *Multivariate Data Analysis*, 7th ed. (Pearson Education Limited, London, 2014).

[41] G. Csárdi and T. Nepusz, The IGRAPH software package for complex network research, InterJournal **1695**, 1 (2006).

[42] M. Bojanowski, intergraph: Coercion Routines for Network Data Objects. R package version 2.0-3, https://mbojan.github.io/intergraph/.

[43] B. R. D. Putnam, Social capital and public life, Am. Prospect. **4**, 35 (1993).

[44] C. Goodenow, The psychological sense of school membership among adolescents: Scale development and educational correlates, Psychol. Sch. **30**, 79 (1993).

[45] M. I. Suárez, A. R. Dabney, H. C. Waxman, T. P. Scott, and A. O. Bentz, Exploring factors that predict STEM persistence at a large, Public Research University, Int. J. Teach. Learn. Higher Educ. **10**, 161 (2021).
[46] M. E. Thompson, Grade expectations: The role of first-year grades in predicting the pursuit of STEM majors for first- and continuing-generation students, J. Higher Educ. **92**, 961 (2021).
[47] S. E. Page, *The Difference: How the Power of Diversity Creates Better Groups, Firms, Schools, and Societies*, 1st ed. (Princeton Universty Press, Princeton, NJ, 2007).
[48] M. Y. Ahn and H. H. Davis, Sense of belonging as an indicator of social capital, Int. J. Sociol. Soc. Policy **40**, 627 (2020).
[49] H. B. Carlone and A. Johnson, Understanding the science experiences of successful women of color: Science identity as an analytic lens, J. Res. Sci. Teach. **44**, 1187 (2007).
[50] L. N. Simpendoerfer, M. Sundstrom, M. Dew, and N. G. Holmes, What topics of peer interactions correlate with student performance in physics courses?, Eur. J. Phys. **45**, 035704 (2024).