Engagement, integration, involvement: supporting academic performance and developing a classroom social network

Eric A. Williams,1,∗ Justyna P. Zwolak,2,3 Remy Dou,3,4 and Eric Brewe5,6,3,2,1

1 Department of Physics, Florida International University, Miami, Florida 33199
2 STEM Transformation Institute, Florida International University, Miami, Florida 33199
3 Department of Teaching and Learning, Florida International University, Miami, Florida 33199
4 Department of Physics, University of Maryland, College Park, Maryland, 20742
5 Drexel University, Department of Physics, Philadelphia, PA 19104
6 Drexel University, School of Education, Philadelphia, PA 19104

Theories developed by Tinto and Nora identify academic performance, learning gains, and involvement in learning communities as important facets of student engagement that support student persistence. Collaborative learning environments, such as those employed in the Modeling Instruction introductory physics course, are considered especially important because they provide students with the academic and social support required for success. Due to the inherently social nature of collaborative learning, we examined student social interactions in the classroom using Network Analysis. We used student centrality, a family of measures that quantify how connected or “central” a particular student is within the classroom network, to measure student engagement longitudinally over multiple times during the semester. Bootstrapped linear regression modeling showed that student centrality predicted future academic performance over and above prior GPA for five out of the six centrality measures tested; in particular, closeness centrality explained 29% more of the variance than prior GPA alone. These results confirm that student engagement in the classroom is critical to supporting academic performance. Furthermore, we found that this relationship emerged from social interactions that took place in the second half of the semester, suggesting the classroom network developed over time in a meaningful way.

Keywords: social network analysis, centrality, engagement, integration, involvement

I. INTRODUCTION

Students from historically underrepresented backgrounds in physics face unique challenges: of all the physics bachelor degrees awarded nationwide, only 4% go to Hispanic students and 3% to African American students [1]. One pathway to address this issue and move toward equity in physics is by making systemic changes to physics classes and departments that promote the retention and persistence of students from minority groups.

Tinto’s model of student integration links both retention (the successful completion of a course) and persistence (the successful completion of a course sequence) to student engagement [2,5]. At the same time, it has been shown that performance, engagement, and persistence are linked, and active learning offers key advantages over traditional lecture in these areas [6]. One particular example is the Modeling Instruction (MI) course at Florida International University (FIU), where students experience superior outcomes in learning gains, odds of success, attitudes, and retention rates of women and historically underrepresented minority students compared to their lecture-based counterparts [7-9]. In MI, the classroom represents a community of learners of which each student is an integral part [10]. Students work together in small groups to conduct experiments and solve problems on a shared whiteboard. These small groups then meet in a large circle in so-called ‘board meetings’ where students ask questions, present solutions, and discuss underlying physical phenomena. In short, students collaborate and interact with one another to construct their own understanding. The community structure is the defining feature of a Modeling Instruction classroom and offers fertile ground for examining student engagement.

Student engagement is a broadly defined, multifaceted meta construct that describes the behavioral, emotional, and cognitive ways in which students immerse themselves into the academic system [11]. Its meaning has grown and become more nuanced over the years; it has gone by other names such as integration and involvement, which we will also use in this paper; regardless, decades of work are united by the common theme that engagement is critically important to students, especially during their first year of college [6].

To bring some much-needed specificity to the idea of student engagement, we turn to the toolkit offered by Network Analysis. Network analysis brings attention to aspects of engagement that are related to peer interaction, which are particularly salient in active-learning classrooms. This set of tools allows us to operationalize student engagement in terms of the connections formed between students. These connections are mapped and can then be analyzed in a variety of quantitative ways. Network methods can be used to understand student interaction patterns, characterize the role that a specific student plays, and identify preferential positions in the network based on “access” to other people. In this pa-
per we compute several types of centrality, which are measures of how embedded a particular student is in the classroom network based on direct and indirect connections to and from their peers. By doing so, we can learn how students are engaging with each other. This methodology has been used before to link students’ network characteristics to a variety of outcomes, including academic performance, concept inventory scores, self-efficacy, and persistence [12, 18]. Ref. [15] even incorporates past performance in a study of the relationship between integration and academic outcomes. What other studies have not done, as far as the authors know, is show that engagement predicts academic outcomes over and above prior academic history using longitudinal engagement data collected multiple times throughout the duration of a whole course. Nor have other studies considered when is the best time to measure engagement, nor which centrality measure best represents engagement. This paper discusses all of these points.

This paper is organized as follows. We begin with a review of the literature in Section II followed by a discussion of our theoretical framework in Section III. Then in Section IV we describe the methodology used, followed by a presentation of our results with relevant discussion in Section V. Finally, we close by drawing meaningful conclusions suggesting future lines of inquiry in Section VI.

II. LITERATURE REVIEW

Despite being well-studied, or indeed because it is well-studied, student engagement is challenging to define succinctly due to its rich, nuanced, and subtle character that only takes on a specific meaning from the context in which it is viewed. Indeed, it even goes by several interchangeable names: integration, engagement, and involvement are all popular terms that convey the heart of this idea [3, 5, 19, 20]. Regardless of its name, this construct describes the extent to which a particular student is involved with, engaged in, and woven into the academic and social fabric of a learning institution.

Integration has taken on many forms: a student’s social connections, both formal and informal, occurring both inside and outside the classroom, to both peers and faculty, all contribute to a student’s integration. These may be self-directed or a result of membership in some kind of group, either university-sponsored or not. However, as Tinto writes, “though we have a sense of why involvement or integration should matter (e.g., that it comes to shape individual commitments), we have yet to explore the critical linkages between involvement in classrooms, student learning, and persistence” [9]. While several researchers have stepped forward to answer this call [12, 18] there is still much work to be done; this study is a step toward filling that gap.

A. Persistence and Performance

Student engagement is often discussed in relation to persistence. Indeed, Tinto’s student integration model is intended to explain student persistence. Nora expanded Tinto’s model to incorporate additional concerns, such as individual pull factors that act as barriers to student engagement. Further, he focused on traditionally under-represented students at an Hispanic-Serving Institution (HSI) to examine how student engagement, and the barriers that obstruct it, affected student persistence. Astin’s student involvement model went even further and reframed the decision to persist or drop out as polar ends of an involvement spectrum. Under this reframing, dropout represents the most extreme form of non-involvement (disengagement) at the low end of the spectrum while the rest of the spectrum corresponds to the many possible gradations of involvement, including consistently active engagement that supports a student’s successful persistence [20]. Astin categorizes involvement into different types, including residing on campus, academic involvement, interactions with faculty, and extracurricular activities (such as student government, honors programs, and athletics).

Integration has also been linked to a student’s academic performance. Tinto identifies a two-step critical linkage “between involvement and learning, on one hand, and between learning and persistence, on the other” [3]. After all, persisting in a program of study is impossible without some successful academic performance along the way. In addition, academic performance is often considered an explicit element of student engagement models [19, 20]. Nora goes a step further, calling academic performance “possibly the most influential factor” on Hispanic students’ persistence [19]. Academic performance has been connected to students’ sense of belonging and perception of their own ability to earn a college degree; course grades were found to influence Hispanic students’ drop-out decisions three times as much as they did for non-minorities [19]. In both Tinto’s and Nora’s models, the theoretical grounding for a relationship between integration and performance is clear. Furthermore, several studies have found a positive relationship between a student’s academic performance and their social interactions with other students in the classroom [12, 14, 17, 18, 21, 22]. Smith and Peterson found a nuanced relationship between academic performance and indegree centrality dependent upon the type of interaction: course advice-related interactions yielded a positive correlation, while general advice-related interactions resulted in a negative one [21].

The literature indicates that engagement, performance, and persistence are related to each other. In our theoretical framework, described in detail in Sec. III we conceive of engagement and performance asprecursors to persistence, though this study does not address persistence explicitly.
B. Classroom involvement

Of all the possible places for student engagement to develop, the college classroom is perhaps the most important social hub. As Tinto writes, “It is evident that participation in a collaborative or shared learning group enables students to develop a network of support ... engaging them more fully in the academic life of the institution” [3]. This is especially true for first-year students, who have not yet established a support network, and commuter students who do not reside on campus and must attend to a variety of off-campus responsibilities throughout the day. The classroom learning community “becomes a gateway for subsequent student involvement” within the academic and social fabric of the institution.

C. Quantifiable interactions

In order to understand the idea of integration in a quantitative way, it may be operationalized using Social Network Analysis (SNA). Network methods are “a unique way of understanding social integration and [Tinto’s] Student Integration Model” by expressing integration as a function of the individual peer-to-peer and peer-to-instructor ties in a given classroom community [12]. Tinto himself explicitly called for its use, saying “we would be well served... to study the process of persistence with network analysis and/or social mapping of student interaction patterns” [3]. The literature since then has answered this call [23]. Thomas used the network paradigm to examine student integration and found a nuanced relationship between student interaction patterns and multiple outcomes, including GPA, goal commitment, and persistence into subsequent courses. Several researchers have followed up on his work, connecting network measures to self-efficacy [15], academic performance [14, 17], sense of community [24], and persistence [16, 25]. Hommes et al. included network centrality as an explicit term in a structural equation modeling analysis and found several key results: that it predicted students’ integration scores on the College Adaptation Questionnaire [26] and thereby motivation on the Academic Motivation Scale [27]; that it was predicted by high school GPA; and that it predicted exam performance better than any of these three variables [15].

Other scholars have used network analysis methods to characterize integration in a variety of interesting and meaningful ways. Yuan et al. used connectedness to quantify social capital “as resources embedded in network relationships that people can mobilize to facilitate purposeful action” both within and across student groups in a collaborative course, in order to study its development over time as well as its impact on academic performance [28]. Gasevic et al. also used network measures to operationalize social capital in a study of academic performance [17]. Mayer and Puller used network methods and Facebook “Friend” data to study the formation of cliques at 10 public universities in Texas, based on both environmental factors of each school and personal attributes of the students [29]. Smith and Peterson looked at indegree to study how prestige and advice-seeking in a course affect academic performance [21]. Yang and Tang also used indegree to examine three different types of ties (friendship, adversarial, advice) to discriminate among the different ways students interact with each other, in effect creating three different networks from the same group of people [30]. Quardokus and Henderson computed a variety of network measures (three at the whole-network level, two at the individual level, and one at the subgroups level) to map the informal social structure of academic departments in order to identify efficient routes of information flow for disseminating new teaching ideas [31].

There is precedent for the use of network analysis in education research specifically [23]. Recent work by Bruun and Brewe found that academic performance was predicted by the centrality measures Hide and Target Entropy in addition to Force Concept Inventory pre-score [22, 32]. This study is particularly interesting because they found the best predictive power from a primarily social communication network, rather than from the two content communication-based networks they also constructed. Brewe et al. used network analysis extensively to understand and categorize student responses to the FCI, in order to identify patterns of incorrect responses and thus infer student conceptions of physical phenomena [13]. Bodin created networks of students’ epistemic frames from recorded interview data to gain insight into their problem-solving knowledge structures [33]. Forsman et al. framed network analysis within a complexity science perspective to interpret existing persistence literature and describe how “the networked interactions, the social system, and the academic system are all coadapting” over time [34].

III. THEORETICAL FRAMEWORK

Our theoretical framework is based heavily on Tinto’s student integration model, but also draws from Nora’s work on student engagement and Astin’s theory of involvement [24, 19, 20]. We apply these theories to build a coherent scaffold for understanding about students’ immersion into the social and academic spheres of their learning community, and its effects on them. If there is a succinct way to describe the basis for our work, Tinto has said it best: “[T]hough we have a sense of why involvement or integration should matter... we have yet to explore the critical linkages between involvement in classrooms, student learning, and persistence” [3].
A. The nature of engagement

There exists a large body of research on student engagement, which yields a multidimensional understanding of what it means in varying contexts; Fredricks et al. navigates the myriad conceptions of engagement and distills the construct into three facets: the behavioral, the emotional, and the cognitive [11]. From a participationist view of learning, social and academic interactions are not mutually exclusive; this means that students’ peer interactions bridge all three of these engagement facets.

Student interactions may occur in a variety of ways. They may take place in the classroom or outside of it; they may be related to course content or extracurricular activities; they may occur with other students or with faculty, in settings formal or informal. All of these types of connections, and more, contribute to a student’s integration with the social and academic fabric of the institution.

We are especially attentive to particular engagement factors from the work of Tinto [2, 3] and Nora [19]. These elements are specific ways and mechanisms in which student integration manifests. From Tinto we focus on supportive, informal peer group associations; perceptions of “social fit”; bridging the academic-social divide; and gaining a voice in the construction of knowledge. From Nora we highlight in-class experiences and collaborative learning as ways to be part of a learning community; peer group interactions as a meaningful social experience; and academic performance as an important cognitive outcome.

Finally, we draw from Astin’s model of student involvement which unifies engagement and persistence [20]. Instead of viewing these as two separate ideas, Astin’s unification conceptualizes engagement as a spectrum in which attrition is considered to be the zero-value of involvement at the low end. In other words, dropping out amounts to the ultimate form of disengagement, viz. the zero-state of involvement, while persistence is represented by the remaining non-zero part of the involvement spectrum.

Yet engagement does not always come easy: there exist many possible barriers that might hinder, interfere with, or otherwise preclude meaningful student engagement. Among these, Nora identifies “pull factors”, both tangible and intangible, that serve to pull students out of the community, such as family and work responsibilities; the need to commute to school; financial need, that might prevent a student from ingratiating themselves fully out of fear that they cannot afford next semester’s tuition; and for underrepresented groups, including minority students and women, the presence or perception of prejudice and discrimination on campus [19].

B. The relationship between engagement and performance

Based on a synthesis of the literature, our framework leads us to hypothesize a direct positive relationship between student engagement and academic performance. Starting from the collaborative MI curriculum, our logic is as follows: we measure students’ social engagement with each other, and since their learning happens through social engagement, there is a case to be made that more frequent and more effective engagement corresponds with better learning, which we expect leads to better academic performance (and ultimately persistence). Tinto identifies performance as a critical intermediate link in a two-stage relationship between engagement and learning on one side, and learning and persistence on the other [3].

Nora explicitly includes academic performance, in particular student GPA, as well as cognitive gains (both perceived and actual) as elements in his engagement model. Thus we have sufficient theoretical grounding to expect that engagement contributes to academic performance. However, we are also aware that the relationship may point the other way. For example, a student who performs well on an exam may then become a sought-after study partner as other students seek them out, or receive a confidence boost that leads them to speak more freely in class discussions; on the other hand, performing poorly on an exam may discourage a student from participating as much in the future. These are but a few examples of how past performance may influence future engagement, but the point is clear. We propose that both directions of this influential pathway are possible, i.e., that student engagement and academic performance exhibit a reciprocal, iterative relationship: past performance influences engagement, which in turn influences future performance (The authors recognize that alternate paths of influence from past performance to future performance are also possible.). There is evidence for such a reciprocal relationship [18].

C. Formation of social networks

In this study we are interested only in the student-student social interactions occurring within an MI classroom, so it is natural to use a relational data analysis tool. Network Analysis allows us to (i) study the connections that form between students by constructing a network of these connections, and (ii) map the structure of these interactions to see who is engaging with whom. Thus we can study the relational position of a given student with respect to the rest of class, and therefore quantify that student’s integration into the classroom community.

Integration into a community does not, however, happen instantaneously; it is a gradual process. We hypothesize that over time, two things will happen: students will get to know each other better and students will get to
know more of their peers, i.e., both the quality and quantity of interactions will increase. The MI curriculum is expressly designed to encourage, even require, collaborative work and the course instructors explicitly promoted its benefits. Since this course structure differs from traditional physics classrooms, students might need some time to adjust but will, as time passes, engage more often and more effectively with each other. It is natural that in-class interactions occur more often between students in close physical proximity, but we expect to see this preference for within-table interactions to decrease significantly over time. We hypothesize a progression from little interaction at first, to interaction with only seatmates, to some interaction outside of their table, leading finally to moderate interaction with many peers outside of their table.

IV. METHODOLOGY

Our study was conducted at Florida International University, a large HSI serving 54,000 students in Miami, FL. The self-reported demographics are 64% Hispanic, 12% Black, 11% White, and 13% belonging to other groups[35]. Over 90% of the students are commuters[36]. Many FIU students come from working class families[37]; over half are first-generation college students[38].

The classroom of interest was a large-scale Modeling Instruction introductory physics course taught in Fall 2015 over 16 weeks. There were 73 students, 1 professor, 2 teaching assistants, and 3 learning assistants[39]. The demographics of the classroom were 74% Hispanic, 11% Black, 5% Asian, 5% White, and 4% Other. The gender distribution was 67% male and 33% female.

A. Academic performance data

We divided students’ academic performance data into two categories: past and future. We represented past performance by a student’s pre-existing GPA prior to the MI course, which was maybe expressed on the typical 4.0 scale. Future performance was represented by the final grade they received in the course in full letter grades, which were coded according to the standard grade point per unit conversion scheme (A=4.0, B=3.0, C=2.0, D=1.0, F=0.0). Any student who dropped was assigned a final grade of zero. Both of these data sets were downloaded from FIU’s electronic record system; there was no missingness in either one. Data management and analysis was done using the statistical programming language R[40][42].

B. SNA data collection

Student interaction data were collected by a pen-and-paper survey we developed, which asked students to identify who they had a meaningful interaction with during that week of class.

In order to explore different values of “meaningful” the survey presented students with a table as shown in Fig. 1 to allow each respondent to simultaneously indicate how often they interacted with each person they identified. Presence of a reported interaction was coded as an edge from the survey respondent to each indicated name, and the frequency of interaction was coded as a three-valued edge weight parameter. We also provided a roster of all students enrolled in the course and the full instructional staff to aid name recall.

The survey was administered five times throughout the semester, spaced approximately three weeks apart (weeks 2, 6, 8, 11, and 13). Each data collection was treated as an independent data set. Response rates were on average 84% but never less than 77%.

C. Conceptualizing student engagement

Although engagement takes on many forms, the focus of this study is on interpersonal student-to-student social interactions occurring inside a Modeling Instruction classroom at FIU. Network analysis allows us to quantify classroom interactions by framing the student community in a relational way: we conceptualize the community as people (nodes) and the interactions between them (edges, i.e. ties or links)[43]. To identify a node with high centrality is to identify a person who is important, to the network. However, there is more than one way to be important. In order to understand the different ways that students integrate within the classroom, network ties may be accounted for in different ways when calculating an entire family of centrality measures. We divide these measures into three groups: local (ego-level), which deal only with a student’s nearest neighbors, global, which consider all of the nodes and edges in the entire network, and intermediate, which bridge the two other categories. These three different levels provide three dif-
different cross-sections of the network structure.

For the local measures, each reported interaction is represented as a tie going away from the survey respondent and pointing towards the names listed. The number of these outgoing ties away from student A is called outdegree. Outdegree is exclusively self-reported, and thus represents a student’s beliefs about their own engagement in the classroom. Indegree describes the number of a node’s incoming ties, i.e., the sum of interactions other students have reported having with student A. Therefore in-degree may be considered a metric of popularity or sociability as perceived by other students in the network. To capture the sum total of engagement that a student exhibits with their nearest neighbors, we calculate the sum of outdegree and indegree to get degree.

An intermediate case involves not just how many connections student A has, but also the importance of whom those connections are with. Student A’s PageRank is based on their incoming ties from nearest neighbors, and also how important those neighbors are according to their own neighbors from two doors down. It is important to note that PageRank is transferred between nodes: student A’s PageRank increases due to incoming ties and decreases due to outgoing ties. Thus PageRank represents a student’s weighted popularity, reputation, or influence within a group.

Two global measures, closeness centrality and betweenness centrality, describe the position of a student within the full network. Closeness captures how “close” student A is to all other students in the network according to a specific definition of distance: the edge-path length between them, i.e., how many people must serve as intermediaries to make a connection. This distance is similar to an idea that has been popularized in academic circles as the Erdos number and in mainstream media as the Kevin Bacon number. Adding these distance measurements from Student A to everyone in the network and then taking the reciprocal of the result yields Student A’s closeness to all other nodes and thus represents their ease of access to everyone else in the network. Betweenness centrality indicates the degree to which student A is “between” other students. (To be between two students is to lie on the shortest path between them, where path length is measured by the number of edges forming an unbroken connection between them.) In the classroom context, having high betweenness can be visualized as occupying a specific network position in which student A acts as a bridge between two or more tightly connected clusters of students that would otherwise be disparate. Such a position puts the student in a gatekeeper role and gives them control of information flow within the network, as well as the opportunity to “run in multiple circles.”

D. Network Analysis

For each network survey collection, student interaction data were aggregated into an edge list. (Instructors were removed from the network to focus exclusively on students’ peer interactions.) The igraph package was used to calculate centrality scores, which were then incorporated as node attributes. Students’ academic performance data, both past and future, were also stored as node attributes. This ensured consistent one-to-one matching between centrality data and performance data.

1. Edge weights

Interaction survey data were weighted in three levels according to how frequently the interactions occurred during the collection week. Therefore, we used the weighted version of each centrality measure to allow more nuanced analysis. For degree measures, we used the strength function to include edge weights. For PageRank, Betweenness, and Closeness, we utilized the built-in weight parameter for each corresponding function. (Unweighted centrality measures were also calculated as a check. However, they yielded no significant differences in subsequent regression models so they are not reported.)

E. Statistical Analysis

As a first step, we ran a simple linear regression to confirm our expectation that academic performance was predicted by prior academic history (i.e., Performance ~ GPA); this constitutes our base model.

1. Analysis of five collections

Each network data collection was treated as a separate data set, so the statistical analysis procedure was conducted independently for each collection. Since there were five collections, the procedure was performed five times.

We conducted an exploratory series of six bootstrapped simple linear regressions to corroborate our pilot study results and verify our hypothesis that academic performance was predicted by any one of the six centrality measures alone (i.e., Performance ~ Centrality); these constituted our six simple models. Then we performed a series of bootstrapped multiple linear regression tests to determine whether or not academic performance was predicted by the sum of prior academic ability and any one of six centrality measures. Each multiple regression model that we tested consisted of only two variables, GPA and a centrality measure (i.e., Performance ~ GPA + Centrality); these are the full models.

In order to compare our full models to the baseline, we used the likelihood ratio test. This allowed us to judge whether or not inclusion of student centrality term improves prediction of academic performance over and above GPA. For the multiple regression models, we
checked the Variance Inflation Factor to check for any collinearity between GPA and centrality.

F. Technical Notes

1. Missing network data

The network survey response rate was never 100%, so we had to address the issue of missing nodes. While imputation may generally be used to accommodate missingness in data, it did not seem appropriate for missing network data. This is because imputation “fills in” the missing data values without changing the pre-existing values—often a good strategy, but not appropriate for interdependent centrality values. As a result, imputation of centrality measures was neither necessary nor used.

Instead, we chose to address the issue with a practical approach that is consistent with network methods: by carefully defining network boundaries, i.e. who is and who is not in the network. We could not change the definition of network inclusion based on who responded to/was named on each survey collection; we needed a consistent list for the whole semester. We created our roster of names by listing all of the students who appeared on at least one of the data collections. In this way, any student who appeared on the roster but did not appear in a given survey was added as an “isolate” to that particular collection network. (An isolate is a node with no connecting ties.) Centralities were computed after this step, which means the isolates were accounted for in the computation.

It is important to note that all of the data collections occurred after the add/drop enrollment deadline, so this method preserves any student who dropped out of the course and is immune to additional students enrolling.

2. Multiple testing error

Due to the large number of regression tests performed, there was a concern of encountering Type I error and inferring a relationship spuriously. This was corrected by making Bonferroni adjustments to the p-values in order to maintain valid alpha-levels. Since each survey collection is an independent data set, the Bonferroni corrections were made at the collection-level. These adjusted p-values are the ones reported throughout this paper.

3. Normality and independence

Standard linear regression modeling relies on the assumption that data is normally distributed and independent, but this is often not the case for centrality measures. To account for this, we used the bootstrap method. Bootstrapping is a permutation technique in which data set values are randomly resampled to run a statistical test a large number of times. The bootstrapped statistical test results are then constructed into a distribution of values, from which a confidence interval may be calculated. If this confidence interval excludes zero, then the test result is considered statistically significant. In our analysis, we applied this technique to the results of our linear regression models: for each model of interest we ran a corresponding bootstrapped linear regression with 1000 iterations to build a 95% confidence interval on the regression coefficients (estimates) and $R^2_{adj}$ values. Thus we were able to ensure the validity of our statistical results in spite of interdependence and non-normality. All linear regression models discussed in this paper were bootstrapped in this way.

V. RESULTS AND INTERPRETATION

The results from our analyses may be viewed through two different lenses: the development of student networks, and which network measures are considered. We begin by discussing the significant models chronologically by collection order to summarize our findings. Then we continue by discussing general trends from the study as a whole. Finally, we close with a discussion of the relative merits of each centrality measure that was studied.

A. Establishing the baseline

First the base model, Performance $\sim$ GPA, was tested. We found a significant predictive relationship with $B = 0.780, p_{adj} < 0.001, F(1, 71) = 18.5$, and $R^2_{adj} = 0.196$. Then we tested the six simple models for all five collections; results are shown in Table I.

B. Development of student networks

In the first collection, no centrality measure emerged as a significant predictor of final grade (see Table II). Thus we conclude that integration levels at week 2 do not predict academic performance. We note that at this time, students mostly reported ties with their 4-5 group members sitting at the same table as them (assigned by the course instructor). We believe that this collection occurred too early in the semester for meaningful classroom connections to have formed.

In the second collection, degree and outdegree were significant predictors of final grade. The adjusted $R^2$ values (0.2869 and 0.2867, respectively) showed that these models explained about 10% more of the variance than GPA alone ($R^2=0.1959$). The likelihood ratio test further confirmed that these full models were significantly better than the baseline, as shown in Table III. Since degree is the sum of indegree and outdegree, we expect that if one of the directed degree measures is significant
TABLE I: Summary table of linear regression results for the six simple models (Performance ~ Centrality). Reported p-values have been Bonferroni-adjusted at the collection level. Significant p-values are marked with the appropriate number of asterisks. Models that failed the bootstrap test have been omitted for clarity. Models in which centrality was not a significant predictor have also been omitted.

| Centrality | s1 (w2) | s2 (w6) | s3 (w8) | s4 (w11) | s5 (w13) |
|------------|---------|---------|---------|----------|----------|
| Degree     | -       | B=0.052** | B=0.063*** | B=0.0698*** | B=0.058** |
|            | -       | F(1, 71)=15.2 | F(1, 71)=33.2 | F(1, 71)=27.4 | F(1, 71)=30.1 |
|            | -       | R^2 =0.164 | R^2 adj =0.309 | R^2 adj =0.268 | R^2 adj =0.288 |
| Indegree   | -       | -       | B=0.103*** | B=0.159*** | B=0.092**  |
|            | -       | -       | F(1, 71)=18.9 | F(1, 71)=30.6 | F(1, 71)=16.1 |
|            | -       | -       | R^2 =0.199 | R^2 adj =0.291 | R^2 adj =0.173 |
| Outdegree  | -       | B=0.079** | B=0.101*** | B=0.0752**  | B=0.088**  |
|            | -       | F(1, 71)=15.2 | F(1, 71)=31.5 | F(1, 71)=13.3 | F(1, 71)=27.3 |
|            | -       | R^2 =0.165 | R^2 adj =0.298 | R^2 adj =0.145 | R^2 adj =0.268 |
| PageRank   | -       | -       | B=86.4***  | B=88.2**    | B=64.6     |
|            | -       | -       | F(1, 71)=19.6 | F(1, 71)=17.9 | F(1, 71)=10.8 |
|            | -       | -       | R^2 =0.205 | R^2 adj =0.190 | R^2 adj =0.119 |
| Closeness  | -       | -       | B=1293***  | B=1174***   | B=1573***  |
|            | -       | -       | F(1, 71)=21.6 | F(1, 71)=27.4 | F(1, 71)=31.1 |
|            | -       | -       | R^2 =0.222 | R^2 adj =0.268 | R^2 adj =0.295 |
| Betweenness| -       | B=0.00343* | -       | -       | -       |
|            | -       | F(1, 71)=10.9 | -       | -       | -       |
|            | -       | R^2 =0.120 | -       | -       | -       |

***p < .001, **p < .01, *p < .05

then the total degree will be significant as well. While checking all three may seem redundant, doing so allows us to understand what types of behavior are and are not significant. It is interesting that degree and outdegree emerged as significant but not indegree. This is to say that a student’s own perception of their engagement at collection 2 matters, but not other students’ perceptions of them at that time. Such a result indicates the importance of a student’s self-beliefs, i.e., their own perception, regarding their integration to the classroom community. Also of note is that these two centrality measures are both ego-level, representing ties only to/from a student’s adjacent partners. This implies that at week 6, only a student’s closest peers with whom they interact directly predict future academic performance.

The final three collections yielded results similar to each other. Bootstrapped linear regression modeling showed that all centrality measures except for betweenness were significant predictors of final grade. The likelihood ratio test corroborated this result by showing the corresponding full models (Performance ~ GPA + Centrality) to be significantly different from the base model (Performance ~ GPA) as shown in Table I. Finally, the R^2 adj values shown in Figure reveal that the full models explain up to 49% of the variance in final grade, compared to the baseline’s explanatory power of 20%. The significance of degree, indegree, and outdegree show the importance of a student’s ego network, i.e. the peers they interact with directly, while the significance of PageRank and closeness indicate the importance of integration into the whole network in a broader sense.

1. Statistical trends over time

We observe that the R^2 adj values generally increase over time, which shows that the predictive power of our full model improves as the semester progresses, as seen in Figure[4]. This has practical implications for the use of SNA in a classroom setting: practitioners and researchers who wish to study classroom integration need only collect data at the half-way/two-thirds mark, rather than multiple times throughout the whole semester. This allows for a much more streamlined, less resource-intensive collection process, and far less data processing/analysis time; this is especially useful considering the widespread, time-intensive coding necessary to prepare the data collected from pen-and-paper surveys into an adjacency matrix or edge list suitable for computer analysis.

C. Which centralities matter?

The only answer we can offer to this question is, “it depends.” Indeed, that is the very reason we conducted this analysis: to determine what the question depends
without a significantly predictive relationship.

Having said this, we must also remember that not all peak at collection 4; outdegree peaks at collection 3.

TABLE II: Summary table of linear regression results for the six full models (Performance ~ GPA + Centrality). Reported p-values have been Bonferroni-adjusted at the collection level. Significant p-values are marked with the appropriate number of asterisks. Models that failed the bootstrap test have been omitted for clarity. Models in which centrality was not a significant predictor have also been omitted.

| Centrality | Regression statistics |
|------------|-----------------------|
|            | s1 (w2) | s2 (w6) | s3 (w8) | s4 (w11) | s5 (w13) |
| Degree     | -       | $B_{GPA}=0.64^*$ | $B_{GPA}=0.52^*$ | $B_{GPA}=0.74^{***}$ | $B_{GPA}=0.58^*$ |
|            | -       | $B_D=0.041^*$ | $B_D=0.052^{***}$ | $B_D=0.067^{***}$ | $B_D=0.049^{***}$ |
|            | -       | $F(2,70)=15.5$ | $F(2,70)=23.6$ | $F(2,70)=30.3$ | $F(2,70)=24.0$ |
|            | -       | $R^2_{adj}=-0.287$ | $R^2_{adj}=0.385$ | $R^2_{adj}=0.449$ | $R^2_{adj}=-0.390$ |
| Indegree   | -       | $B_{GPA}=0.60^*$ | $B_{GPA}=0.73^{***}$ | $B_{GPA}=0.66^{**}$ | $B_{GPA}=0.66^{**}$ |
|            | -       | $B_{I}=0.080^*$ | $B_{I}=0.15^{***}$ | $B_{I}=0.076^*$ | $B_{I}=0.076^*$ |
|            | -       | $F(2,70)=16.6$ | $F(2,70)=32.3$ | $F(2,70)=17.1$ | $F(2,70)=22.54$ |
|            | -       | $R^2_{adj}=0.303$ | $R^2_{adj}=0.465$ | $R^2_{adj}=0.300$ | $R^2_{adj}=0.300$ |
| Outdegree  | -       | $B_{GPA}=0.64^*$ | $B_{GPA}=0.084^{***}$ | $B_{GPA}=0.76^{***}$ | $B_{GPA}=0.60^*$ |
|            | -       | $B_O=0.061^*$ | $B_O=0.084^{***}$ | $B_O=0.073^{***}$ | $B_O=0.074^{***}$ |
|            | -       | $F(2,70)=15.5$ | $F(2,70)=23.6$ | $F(2,70)=19.3$ | $F(2,70)=22.54$ |
|            | -       | $R^2_{adj}=-0.287$ | $R^2_{adj}=0.386$ | $R^2_{adj}=0.337$ | $R^2_{adj}=0.374$ |
| PageRank   | -       | $B_{GPA}=0.57^*$ | $B_{GPA}=0.76^{***}$ | - | - |
|            | -       | $B_p=64.5^*$ | $B_p=86.3^{***}$ | - | - |
|            | -       | $F(2,70)=15.9$ | $F(2,70)=23.3$ | - | - |
|            | -       | $R^2_{adj}=0.293$ | $R^2_{adj}=0.382$ | - | - |
| Closeness  | -       | $B_{GPA}=0.64^*$ | $B_{GPA}=0.81^{***}$ | $B_{GPA}=0.66^{***}$ | $B_{GPA}=0.66^{***}$ |
|            | -       | $B_C=1099^{**}$ | $B_C=1213^{***}$ | $B_C=1423^{***}$ | $B_C=1423^{***}$ |
|            | -       | $F(2,70)=20.4$ | $F(2,70)=35.5$ | $F(2,70)=28.8$ | $F(2,70)=28.8$ |
|            | -       | $R^2_{adj}=0.351$ | $R^2_{adj}=0.490$ | $R^2_{adj}=0.436$ | $R^2_{adj}=0.436$ |
| Betweenness| -       | - | - | - | - |
|            | -       | - | - | - | - |
|            | -       | - | - | - | - |

***p < .001, **p < .01, *p < .05

TABLE III: Summary table of the likelihood ratio test comparing full models (Performance ~ GPA + Centrality) to the base model (Performance ~ GPA). Significant p-values are marked with the appropriate number of asterisks. Non-significant values have been omitted for clarity.

| Centrality | df | s1 (w2) | s2 (w6) | s3 (w8) | s4 (w11) | s5 (w13) |
|------------|----|---------|---------|---------|----------|----------|
| Degree     | 1  | -       | 9.80*   | 20.6**  | 28.6**   | 21.2***  |
| Indegree   | 1  | -       | -       | 11.5**  | 30.8**   | 12.1**   |
| Outdegree  | 1  | -       | 9.78*   | 20.7*** | 15.1***  | 19.4***  |
| PageRank   | 1  | -       | -       | 10.4**  | 20.3***  | 8.09*    |
| Closeness  | 1  | -       | -       | 16.6**  | 34.2***  | 26.9***  |

***p < .001, **p < .01, *p < .05

on. Let us now discuss our results from this lens.

It is interesting to consider where the $R^2_{adj}$ peaks occur in Figure 4. Closeness, indegree, degree, and PageRank all peak at collection 4; outdegree peaks at collection 3. Having said this, we must also remember that not all centralities were significant predictors of performance at all times: without a significantly predictive relationship in the linear regression model, the model’s $R^2_{adj}$ does not mean much for that particular centrality measure. (Since betweenness was never a significant predictor in the full models, it is not shown in the figure.)

Of the six centrality measures we tested, closeness seems to us to be the best representation of Tinto’s student integration model. This is because closeness rep-
represents a student’s ties to the classroom as a whole – granting easy access to academic and social support from a robust group of peers directly, without the need to go through intermediaries. Thus closeness may be the most valuable centrality measure to study when considering questions of student engagement and persistence, as it seems to be the closest analogue. Another point in favor of closeness is that it explains the most variance of all measures, in its peak at collection 4 with $R^2_{adj} = 0.49$. Therefore a mid-semester closeness measurement represents the best way we discovered to predict the end-of-semester final grade.

We found the outdegree model peaked at collection 3, and was also the best predictive model available at that time with $R^2_{adj} = 0.386$. Furthermore, the outdegree model’s predictive power emerged even earlier at collection 2 with $R^2_{adj} = 0.2869$. It may be that outdegree is the best choice for predicting performance as early as possible.

It is also worth mentioning that degree and outdegree showed nearly identical predictive power at collection 2 ($R^2_{adj} = 0.2869$ and 0.2867, respectively) and collection 3 ($R^2_{adj} = 0.3853$ and 0.3859, respectively). They were also similar to each other at collection 1 and collection 5. (Indeed, they were the only two measures to emerge as significant predictors so early.) However, recall that degree is the sum of outdegree and indegree and indegree was not significant at this time. From this we conclude that outdegree is the “truly” meaningful centrality measure here, and degree merely “inherits” this significance.

Betweenness was never a significant predictor in the full models, so it was excluded from further analysis. Although this result is not exactly what the authors expected, it is consistent with our theoretical framework because betweenness represents a very specific type of position in the network characterized by being a bridge between otherwise-disparate groups. Such a position may be indicative of an ancillary status as an “outsider” member of a multiple small groups, rather than a “strong member” well-connected within any one group. Our study indicates that this type of engagement, while important to the cohesion of the network as whole to prevent fragmentation, does not serve the interest of supporting a student’s own academic performance.

D. Formation of student networks

We observe that as the semester progresses, interpersonal interactions become more significant. At the local level this is indicated by degree, indegree, and outdegree; at the global level by closeness; and at the intermediate level by PageRank. In the first collection none are significant and in the second only two ego-level measures are significant; in the latter three collections, five of the six centrality measures are significant. This indicates that in the first half of the semester, there is little to no effective integration occurring; the little integration that does occur exists only with nearest neighbors and is predicated on each student’s self-perception of their own behavior. Yet in the second half of the semester, the reverse is true: interactions at the local, intermediate, and global scales all predict higher performance. Such a change indicates a time-development of the classroom community, wherein the student interactions in the second half of the semester effectively predict final grade at the end of the course. This time development is also apparent from viewing the network diagrams of the classroom as in Figure 2. In the first collection, the majority of ties exist between same-group members and the six-person seating arrangement is readily apparent. In the fourth collection, seating groups are almost completely indistinguishable in favor of a more unified “hairball” shape, indicating classroom-wide integration.

Additionally, we found that integration, as measured by centrality, changed in a nonintuitive way during the semester. Although one might expect the number of reported interactions to increase over time, we found that centrality values on average tended to remain relatively constant (decreasing only slightly) over time as shown in Figure 3. The slight decrease may be attributable to the decreasing response rates between collections. However, this does not mean the classroom integration is stagnant. Considering the flat-line trend of median centrality value simultaneously with the upward trend of centrality’s predictive power described above, our theoretical framework leads us to interpret these figures as evidence of a selection effect. While the average quantity of a given student’s reported interactions remains the same, their quality improves. It seems that in the beginning, students cast a wide net to interact with each other but these interactions do not support their academic performance effectively; whereas in the second half of the semester, students interact with (slightly fewer) people who do. It may be that students need enough time to find the “right” people with whom they collaborate well and who can support their academic development.

VI. CONCLUSION

This study found that engagement in the classroom indeed predict academic performance, but in a way that is more nuanced than we expected. We will begin this section by discussing the subtleties of this relationship to provide necessary context. Then we will follow with our key predictive findings, methodological lessons for the use of network analysis, and recommendations for future study.

A. A nuanced relationship

This study found that engagement in the classroom did indeed predict academic performance, but in a way that is more nuanced than we expected. We hypothesized
that centrality values would increase over time because more time affords more cumulative opportunities for engagement to occur, but this did not happen. Instead, average centrality scores remained relatively constant or decreased slightly. Yet at the same time, the predictive power of our models did increase as the semester progressed! This apparent disparity suggests that the relationship between student engagement and academic performance defies a simplistic narrative. It is emphatically not the case that aggregate classroom interactions increase over time, leading to better academic performance. (Indeed, the number of reported interactions actually decreased over time.) Rather, there is a time-development of the network. Student interaction patterns change over time such that they begin the semester by interacting primarily with their seatmates, but end the semester by reaching out beyond their tables.

This change can be interpreted in several ways. It could be that students require a certain amount of time to find “the right people” with whom they can effectively collaborate beyond their table-mates; it may also be that they need enough time to “buy in” to the concept of a collaborative-learning based physics classroom and see each other as valuable learning resources. Another possible interpretation is that students’ understanding of “meaningful interaction” changes over time, perhaps due to an evolving comprehension of which peer interactions, both social and academic, are important to their classroom experience. However, it could simply be the case that the mid- and end-stage of the semester is just the most important time in a given semester: whether a student begins the semester strongly or weakly, if they work hard and do well in the middle and end of the semester they will earn a high final grade purely due to the algebra of how course grades are calculated. We acknowledge that these interpretations are speculative — network analysis alone is inadequate to understand how students think about this integration. Qualitative follow-up would be necessary to provide a more detailed understanding.
FIG. 3: Scatterplot of median centrality values for five centrality measures, shown by data collection. We observe a general trend that median value decreases slightly or remains constant as time passes. Note that each median centrality value has been normalized individually (according to [43]) to allow for comparison of trends despite different units.

B. Engagement predicts academic performance

Five out of six centrality measures, acting as proxies for student engagement, predicted academic performance over and above prior GPA. Of particular note is closeness centrality from collection 4, which yielded the best predictive power: our closeness full model (Performance $\sim$ GPA + Closeness) explained 49% of the variance in final grade. This result is powerful because closeness is most theoretically similar Tinto’s conception of student integration and closeness was the most empirically predictive centrality measure. Therefore, measuring closeness centrality at week 11 is the prime way to investigate student engagement according to this study.

We found that meaningful student network integration occurs as early as collection 3 (week 8). In particular, the outdegree model from this time explained 39% of the variance in final grade. The fact that predictive power emerged so early is empowering to course instructors. Since predictions about students’ future academic performance are accessible as early as week 8, there is still enough time for instructors to enact interventions to promote student engagement and success.

C. Implications for network methods

The results from this study have broad implications for the use and applicability of network methods generally. First, the inclusion of interaction weight did not drastically affect our predictive models. We found that frequency of interactions did not matter as much as the mere occurrence of interactions. This result implies that a streamlined survey with no weight ranking requirement would yield a similar amount of information and predictive power. Second, we found significant predictive power primarily at weeks 8, 11, and 13 of a 16-week course, and the results were similar. This implies that researchers need only collect SNA data at one of these times in a given semester with no major information loss. Streamlining the data collection process would benefit three groups: researchers, who need collect and analyze less data; student participants who need face less survey fatigue; and instructors wishing to use network methods to inform their pedagogy, who need disrupt their class on fewer occasions for data collection thus facing a lower barrier to implementation. These benefits represent a sure, three-fold win for education researchers.

D. Limitations and future work

There are some limitations to the results of this study. First, this study looks only at one semester of one section (N=73 students) offered at one university. This could be overcome by studying additional sections during different semesters to evaluate how generalizable our findings are. Second, our interpretations of why certain centrality measures at certain times, and not other measures at other times, predict academic outcomes are speculative. Although we have offered several possible interpre-
tations based on our theoretical framework, qualitative work must be done to determine which of these interpretations, if any, represents the mechanism underpinning our results.

Future work should further explore the reciprocal relationship between performance and engagement. Structural Equation Modeling could be used to disentangle (1) the direct effect of past performance on future performance from (2) the indirect effect of past performance on engagement, thus influencing future performance. It would also be valuable to study interpersonal social connections occurring outside of the classroom in a more casual setting, how they are related to in-class performance, and how they affect persistence in the introductory course sequence. In addition, network edge weights can be utilized to capture different information. While this study used them for increased nuance of quantity (frequency of social interaction in a collection week), they could instead be useful for increased nuance of quality: students could be asked to rank their meaningful interactions on a scale to compare the relative importance of different interactions with different people. Finally, qualitative methods should be used as a follow-up to understand how students perceive their integration into their learning communities, both inside and outside the classroom.

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