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Using Social Network Theory to Design a Teamwork Equity Dashboard for Team-Based Learning in Engineering

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I. INTRODUCTION

This is a full empirical research paper for the Educational Research and Methods Division. Team-based pedagogies are an important aspect of undergraduate engineering learning experiences, thought to facilitate important professional skills necessary for professional practice [1], [2], [3]. These professional skills include teamwork, technical communication, design thinking, prototyping, and fabrication [4]. However, the degree to which students realize these outcomes depends on the extent to which they gain meaningful access to the learning activities that are designed into such teamwork pedagogies [5]. Meanwhile, existing research has frequently documented how team-based pedagogies can be experienced inequitably, particularly for students from historically marginalized backgrounds [5], [6], [7]. Thus, team-based pedagogies present a significant pedagogical challenge: instructors often find it difficult, if not impossible, to monitor student teams to ensure that students participate equitably and experience equitable learning [8], [9].

Existing scholarship has documented several approaches to addressing such challenges. Researchers highlight aspects of team-based pedagogies that support equitable participation and learning outcomes. For example, existing research suggests educators avoid “stranding” students from historically marginalized backgrounds during team formation processes [10]. Meanwhile, peer evaluations such as “rate-the-teammate” surveys are widely used in team-based learning environments [11], [12]. However, these strategies are often only as effective as they are (a) timely and (b) accurate in assessing the specific processes and practices that result in inequities. For example, end-of-term evaluations may be administered too late to support students during learning activities. Similarly, approaches that capture only overall contributions to a project may overlook task-based inequities, such as the well-documented pattern of students dividing and conquering work, whereby individual students take tasks with which they are familiar, leaving some students with fewer learning opportunities.

The purpose of this research study was to develop an online dashboard that highlights teamwork inequities in team-based learning environments to support faculty interventions in inequitable teams. This study proceeded in three parts. First, we collected self- and teammate evaluation data to document patterns of participation in student teams. Second, we drew on social network analysis (SNA) theory and related metrics to depict teamwork dynamics in an entry-level engineering course at a public university. Finally, we developed preliminary equity reports that captured teamwork processes such as communication, task allocation, and performance perceptions, iterating on the reports with faculty feedback from semi-structured interviews. This paper describes SNA statistics, faculty feedback, and the development process.

II. LITERATURE REVIEW

A. Learning Analytics for Supporting Teamwork

Learning analytics (LA) frames data-informed instruction as a reflexive teaching practice that can help instructors adapt their pedagogy as well as help students regulate their learning [13], [14]. In studies of teamwork, researchers have drawn on several data sources to capture students’ collaborative experiences. Peer assessment remains the most common approach, with many teamwork tools asking students to rate themselves and teammates on prosocial and proteamwork behaviors [15]. Other LA research leverages richer but harder-to-collect traces, such as tracking emergent roles during communications about open-ended problem solving [16] or monitoring physiological responses during team decision-making [17].

Despite rapid growth in educational data mining and teamwork support tools, LA tools have not been widely taken up by teachers in authentic classroom settings [18]. One key reason is that LA-based decisions depend on instructors' ability to interpret metrics, considering the social and technical contexts in which the data are produced. Without such contextualization, analytics may not translate into meaningful classroom change [19]. That is, the effectiveness of LA tools depends on how instructors interpret and act upon the data. Research shows that the interpretations of measurements, such as test scores or peer ratings, are often shaped by instructors' expectations and social stereotypes related to students' race, gender, and socioeconomic status [20], [21], [22], [23], [24]. Therefore, we argue that LA system design should account for how instructors' understandings of equity and the broader institutional context shape how they interpret and use these metrics. Doing so can help ensure that data-informed interventions promote inclusion, rather than reinforcing existing biases or reifying discriminatory practices [25].

B. Using Network Theory to Examine Teamwork Equity

This research draws on social network theory and methods to depict teamwork processes, such as communication dynamics, task allocation, and interpersonal conflicts between students. In SNA, each student is represented as a node in a network of a team, and in survey-based networks, an edge from student A to student B represents A's rating for B. Studies relying on social network theory have explored team dynamics in various disciplines, including with: (a) basic descriptive network visualizations, (b) metrics for measuring individual participation, (c) metrics for capturing individuals' roles in coordinating team interaction or information, and (d) measures for team cohesion or centralized participation and leadership. For example, several studies use network density at the team level as a measure of team cohesion that captures participation. In these cases, density, which ranges from 0 (i.e., no participation) to 1 (i.e., full participation), is thought to be a relative measure that increases as more students participate in the team (e.g., [26], [27], [28]). Authors also rely on individual-level network metrics, such as one's in-degree centrality. In-degree centrality captures how frequently a student is nominated by others on the team for a specific social relationship. For example, if ties represent perceptions that a student is contributing ideas, higher in-degree centrality captures the belief amongst teammates that the student is contributing to the team.

We propose that SNA offers distinct advantages in detecting potential teamwork inequities in engineering education. First, by representing teamwork as a set of directed and weighted relations, SNA captures the underlying interaction structure that aggregate teamwork scores often mask. For example, prior work demonstrates that engineering teams may disproportionately allocate managerial or documentation labor to women while associating technical work with "real" engineering [29]. To operationalize these role-differentiation processes, we construct task-specific networks for managerial work (e.g., organizing meetings), documentation work (e.g., writing reports and creating presentations), and technical work (e.g., coding and fabrication/prototyping). This design enables us to test whether students become structurally positioned as primary contributors within task domains (e.g., higher in-degree centrality in a task network) and whether such positions are systematically associated with gender and race/ethnicity. Second, because collaboration patterns can shift as teams learn and projects unfold, presenting network metrics longitudinally helps instructors to identify time-varying teamwork dynamics.

III. METHODS: INTERACTIVE DESIGN AND IMPLEMENTATION PROCESS

This project aimed to explore tensions in how equity-related data about teams in team-based, project-based courses are interpreted and acted upon by engineering educators, including the potential for non-intervention, such as avoiding race-related discussions [30]. To do so, this study employed a sequential mixed-methods design [31], constructing an equity report data dashboard with SNA metrics and collecting instructors' feedback in interviews. After the interviews, we revised the equity reports iteratively to produce a more comprehensive dashboard that better aligns with the broader pedagogical goals identified by the participants.

A. Designing a Data Dashboard with SNA Metrics

First, we generated a preliminary dashboard using survey data from Tandem, a teamwork support learning analytics platform developed at a research-intensive public university in the Midwestern U.S. [32], to distill initial reports on equity in teamwork. While our full dataset contains several years of teamwork data from multiple courses across several disciplines (e.g., engineering, business, law), the data utilized in the designs depicted in this paper were collected from students enrolled during Winter 2024 in a team-based, project-based, entry-level engineering (ENGR) course aiming to enhance students' engineering design and problem-solving skills.

While we drew on beginning-of-term survey data for sociodemographic characteristics, our calculation of SNA metrics to depict teamwork processes utilizes the midterm and end-of-term survey data administered on the TeamCoach platform. In the ENGR course, students typically worked in teams of three to five students on semester-long projects. This research made use of teamwork data collected through periodic surveys at three points: (a) shortly following initial team meetings, (b) at the project midterm mark, and (c) at the end of the term. These surveys captured both self- and peer ratings of contributions to various team tasks, using the prompt: "How much did you and each of your teammates contribute to the following tasks for your team assignments and in-class activities?" When constructing networks for each team by task in the ENGR course, each student is represented by a node in a network of a team; an edge from student A to student B represents that student A has rated student B with a high score (4 or 5 on a 5-point scale).

Additionally, we merged the University's administrative records with TeamCoach's survey data to depict students' sociodemographic characteristics. Table 1 shows the sociodemographic characteristics of the ENGR students. The course consisted of 50 students. The participants were predominantly White (42 percent) and male (64 percent). Most students were United States citizens (88 percent), with 8 percent international students. Nearly all the enrolled participants were non-transfer students.

Table 1: Demographics of the Enrolled Students in an ENGR Course in the 2024 Winter Term
N = 50

Sex		*Citizenship*	
Female	36%	China	2%
Race/Ethnicity		India	4%
Multi-race	16%	Iran	2%
Asian	26%	Korea	4%
Black	4%	United States	88%
Hispanic	2%	*Entry Status*	
White	42%	Transfer	2%
Missing	10%	*Citizenship Status*	
		International	8%

Notes. Citizenship refers to students' country of citizenship, while citizenship status refers to their visa classification. As a result, the share of students with non-U.S. citizenship (12 percent) differs from the share classified as international students (8 percent), as some non-U.S. citizens are recorded as permanent U.S. residents.

We used a Python-based platform, Streamlit, to develop an interactive data dashboard that provides descriptive visualizations at the course-, team-, and individual levels. At the course level, the dashboard summarizes the sociodemographic composition of students, the number of teams, and team sizes within each course (Figure A1 in the appendix). The dashboard also displays distributions of peer rating scores across the seven task domains, disaggregated by sex and race/ethnicity (Figure A2).

In addition, the dashboard provides all the teams' network density, reciprocity, and in-degree centralization by tasks to depict team cohesion across tasks. For example, team-task density ranges from 0 to 1, and a higher density indicates that high contribution attributions are more widely distributed across team members within a task domain, indicating equal participation in the task. Team-task reciprocity is the number of pairs of students both rating each other as 4 or 5, and higher reciprocity indicates that high contribution attributions are more mutual. Higher in-degree centralization indicates that high contribution attributions are disproportionately focused on a small number of students, suggesting a single student is dominating a particular task (Figure A3).

At the team level, the dashboard presents each student's normalized outdegree centrality and normalized indegree centrality by task. Higher out-degree centrality indicates that a student is frequently rating others with high scores. Conversely, a higher in-degree centrality indicates that a student is frequently being rated by others with high scores. The dashboard also includes heatmaps of peer-to-peer ratings for each task domain at both midterm and end term. In these heatmaps, rows represent ratees, columns represent raters, and cell colors correspond to rating scores (Figure A4).

B. Faculty Interviews

We conducted semi-structured interviews with faculty instructors to explore their perceptions of team dynamics and the equity report dashboards generated from the Winter 2024

ENGR course data described above. We used purposive sampling to recruit faculty participants at the same university because they had taught team-based engineering design courses. These courses share similar pedagogical features of the ENGR course: they all include a semester-long team project and emphasize engineering design and ill-structured problem-solving. Seven faculty members participated in the interviews; however, only six members were included in our sample because one recording was unavailable (Table 2). In addition, an instructor who taught the ENGR course in the Winter 2024 term participated during data collection by providing contextual information on assignment details and student interactions when relevant. During the interview, we demonstrated each section of the dashboard to the faculty participants. We then discussed faculty's beliefs about learning goals in team- and project-based learning environments, the types of data they believe would support their pedagogical aims, and their feedback on the preliminary dashboard. These interviews were guided by two primary research questions: (1) **How do instructors interpret the network analysis metrics?** (2) **How do instructors respond to any inequities they identify through the dashboards?** Interviews took place in the summer of 2025, lasted approximately 1 hour, and were audio-recorded. We analyzed the interview data by grouping recurring narratives into themes after rounds of close reading. The findings are organized by theme rather than by participant, and thus, not all the participants are directly quoted in the results session.

Table 2: Demographics of the Faculty Interview Participants

Pseudonym	Gender	Race	Department
F1_Mike	Man	White (non-Hispanic)	Electrical Engineering and Computer Science
F2_Gary	Man	White (non-Hispanic)	Robotics
F4_Lyssa	Woman	White (non-Hispanic)	Robotics
F5_Leo	Prefer not to describe	White (non-Hispanic)	Technical Communication
F6_Astrid	Woman	White (non-Hispanic)	Technical Communication
F7_Yvonne	Woman	Asian/Asian American	Robotics

IV. FINDINGS: FACULTY INSIGHTS ON EQUITY REPORTS AND DISPARITIES

A. Perceptions Towards Equity

We found that instructors' interpretations of "equity" extended beyond demographic categorizations to encompass students' varying levels of preparation and disciplinary experience, elements that we had not included in the first version of the design. While most faculty acknowledged race and gender as visible dimensions of equity, they frequently emphasized subtler, within-group differences shaped by students' prior educational trajectories, socioeconomic background, and familiarity with U.S. higher education. Thus, this information is also necessary for a holistic interpretation of the metrics we utilized to distill teamwork processes and outcomes. Astrid described this complexity:

> Yeah, certainly race and gender, I think, are some of the most salient components of equity that I see. But I also see a lot with students who are first-generation or International students... they have a lot more catching up to do and just learning how

> to be a student, let alone learning all the things about being an engineer... the students who are very well prepared... will sometimes bulldoze those other students.

Astrid's reflection shows an understanding of teamwork equity that reflects more than the characteristics often cited in the literature—race/ethnicity and gender disparities. These observations illustrate how instructors view equity as relational and cumulative, encompassing and extending back to students' pre-college preparation. From this standpoint, the dashboard's equity indices were understood as indicators of a lack of access and preparedness for engineering learning activities.

Many instructors adopted a similarly pragmatic stance toward interpreting patterns related to race and gender. Rather than framing all disparities as race- or gender-based inequities, they emphasized students' preparation. Yvonne, for instance, noted that team differences in contribution patterns often stemmed from variation in technical expertise rather than demographic divisions, such as taking the university's required robotics course and Python knowledge. Aligning with this perspective, Mike also expressed his hesitation about presenting data by race and gender groups, arguing that it would reinforce the race and gender stereotypes attached to the disadvantaged group: "It feels like it would lead to stereotyping… Maybe that would be helpful for me to learn [the race and gender relationships]. But I don't know."

In response, the research team made two iterative changes to the dashboard design. First, recognizing that instructors sought more nuanced and contextually relevant measures, we integrated additional variables, including socioeconomic status and citizenship, by leveraging the institution's administrative data. Second, we incorporated students' prior course taking by leveraging the institution's administrative data, as well as beginning-of-term survey data, to extract students' self-reported technical skills (e.g., programming and hardware experience). These modifications help offer a more holistic evaluation of students' backgrounds for interpreting the data patterns.

B. Interpretations of the Indices and Decisions (Not to) Act on Data:

We found that whether instructors decided that a data pattern warranted attention was highly contingent on their own understanding of what constitutes equitable teamwork in entry-level STEM courses. When reflecting on group-level (density) and individual-level (normalized in-degree centrality) network metrics, most instructors agreed that a downward trend represented by a leftward arrow indicates a group's declining shared engagement and students' declining contribution to a specific task. Yet whether instructors believed they should intervene varied markedly. For example, while commenting on Figure 1, Yvonne emphasized that declining density might signal disengagement or logistical breakdowns requiring follow-up:

> I would worry about arrows that go down… especially if it's drastic, that tells me that something has changed, maybe someone's not pulling their weight, or there's some dynamic shift, at least a prompt for the instructional team to follow up.

Also, Astrid connected group cohesion to students' opportunities for holistic learning:

> I would worry that that means they are siloing too much… the objective of a team project is to learn how to share responsibility… if they specialize too early, they reduce their opportunity to explore new skills.

For Astrid and others, though they acknowledge that specialization may become more common and acceptable in advanced and capstone courses, equal participation is a pedagogical condition for equitable learning in entry-level STEM courses. Thus, a downward trend in either group-level density or individual-level in-degree centrality requires an instructor's attention or even reaching out.

Figure 1. Changes in the Density of All the Teams by Tasks from the Midterm to the End of the Term in an ENGR Course on the Dashboard

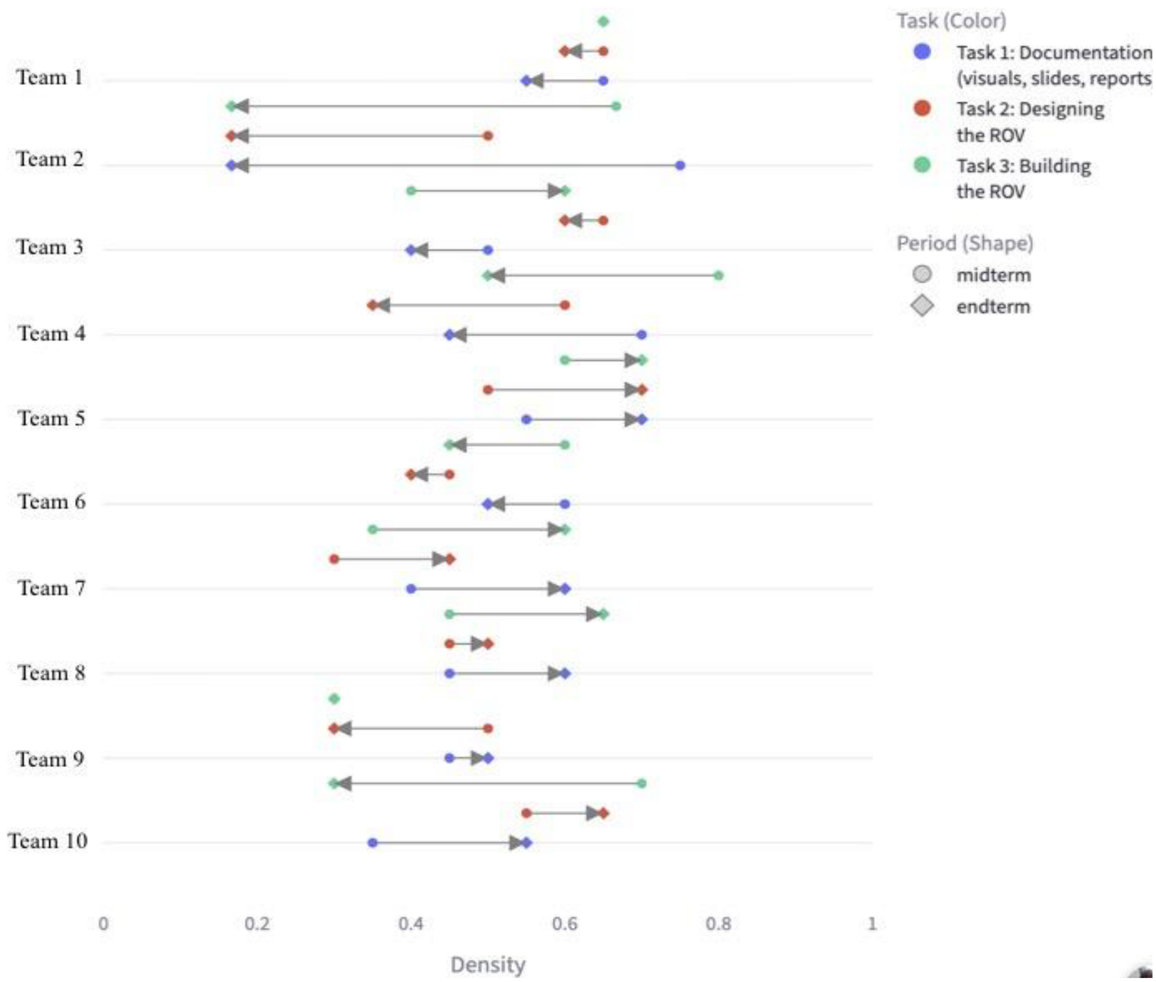

Figure 1. Changes in the Density of All the Teams by Tasks from the Midterm to the End of the Term in an ENGR Course on the Dashboard
Notes. Instructors can select the term, course, team, and student of interest from the drop-down menus in the data dashboard. All information in the figure, including the team names, is anonymized to ensure confidentiality.

In contrast, some faculty, such as Gary, treated variation in contribution as an expected and sometimes productive feature of teamwork. He made the following comments when interpreting the presentation that most teams' density metrics trended downward for all the tasks:

> In industry, no one is ever contributing to all parts of the project equally… I want to see some collaboration. But also, that's a good way, especially when things get tough, to be like, I'm going to focus on this, you know, and then if they're all equally doing that [specialization], which almost looks like it is, well, yeah, I

mean, the measurement is not zero, which is good, except for one person... It's almost like, yeah, one person is doing each of those, each task, which is good.

Gary suggests that specialization could represent functional equity: each student contributing uniquely according to their strengths. Thus, no strong intervention is required even when the measures are trending downward, though he acknowledges instructors should also pay some attention to these teams. This juxtaposition reveals a tension between fairness and specialization. The same density pattern, therefore, could be read either as a signal of inequity or as evidence of productive differentiation.

In response to these insights, the design team restructured several dashboard components to better align with instructors' interpretive logics. Recognizing instructors' sensitivity to visual cues, we removed red–green color coding and standardized all directional indicators to neutral gray arrows. As Leo explained, "our brains are designed to recognize patterns," and color-based associations could bias instructors toward premature value judgments. The new design, therefore, emphasizes neutrality, encouraging users to interpret trends in light of contextual knowledge for whether specialization requires intervention rather than implicit visual hierarchies.

C. A Classroom-Dashboard Combination of Interpretations and Interventions

While the dashboard enabled instructors to visualize potential inequities in teamwork participation, its pedagogical value emerged most clearly when coupled with classroom-based observations. Across interviews, faculty described a process of cross-modality sensemaking, where analytic indicators acted as early warning signals that were subsequently validated, or contested, through direct engagement with students in class. This blended mode of interpretation positioned instructors as diagnostic practitioners who used both digital and classroom evidence to inform equitable teaching practices.

Several instructors viewed the dashboard as a mechanism for identifying potential "at-risk" teams before conflicts escalated. Mike explained that his primary goal was to reduce the number of teams that encounter severe dysfunction each semester:

> [I'm] mainly looking for issues that… about 10% of our teams explode one way or the other. My goal is to reduce that number. Sometimes one or two people feel like they're carrying the whole team… That's what we're looking for—group dynamic issues that we want to put out as quickly as possible.

According to Mike's comment, the dashboard should function as an early intervention tool, helping instructors focus attention where it is most needed.

At the same time, most instructors call for combining dashboard quantitative data and more classroom observations when identifying problems and determining interventions. For example, Leo described how combining dashboard signals with periodic team check-ins provided a layered form of responsiveness that felt less intrusive to students:

> I'll ask questions like, 'What was your contribution?' or 'What are you working on?' to see whether others are participating. When someone stops showing up altogether, that's when I know something's really wrong… Setting aside time to have instructor–team meetings, even once or twice a semester, is extremely helpful… just being able to check in during independent work time, rotating around the classroom, being aware of who is present and who isn't… It all feels reactive, but it's a necessary kind of reaction.

These practices illustrate the synergistic relationship between data interpretation and in-person observation. Faculty did not substitute numerical indicators for judgment and in-class observation; instead, they used them to sharpen their sensitivity to social cues already observable in the classroom.

Guided by these perspectives, the research team refined the dashboard to better support cross-situated sensemaking. A "warning system" feature was introduced to flag teams displaying concerning trends, such as sharp declines in density, persistent missingness, or widening discrepancies between self- and peer-assessments. However, the design intentionally stopped short of automating intervention recommendations, such as bringing in generative artificial intelligence models for data interpretations. Instead, flagged teams would be visually highlighted within the course overview page, prompting instructors to initiate dialogue rather than execute algorithmic judgment.

V. FUTURE DIRECTIONS

This paper shows a preliminary development process of a dashboard based on SNA theory for team-based, project-based learning in STEM education. Utilizing a mixed-method design, our study shows that applying SNA methods and theory in learning metrics design has the potential to detect potential teamwork inequities in project-based courses. By representing teamwork as a set of directed and weighted relations, it may reveal patterns that are masked by the average scores; also, leveraging a longitudinal design of SNA analysis helps reveal how team dynamics change over the term. We also show that instructors' perceptions of equity would shape their interpretation of SNA metrics and interventions; thus, a classroom-dashboard combination approach of interpretations and interventions is adopted and recommended by most faculty.

We propose four future directions of this project. First, we plan to scale the data dashboard to all engineering courses that use team-based, project-based assessment. We also plan to develop an automated data pipeline that can generate instructor-facing feedback shortly after students complete the midterm and end-of-term surveys. This will allow instructors to receive timely information about team dynamics when there is still time to intervene during the course.

Second, we acknowledge that the SNA metrics we have included are descriptive. Importantly, the sample size for some sociodemographic characteristics, particularly for historically underrepresented groups (e.g., Black students), was very small (N = 2) in our sample course, so any patterns involving these students should be interpreted as exploratory. To complement the descriptive evidence, our future work entails estimating inferential models (e.g., exponential random graph models) to assess whether perceived participation patterns differ significantly by gender and race/ethnicity across task types, after controlling for various group-level features. Third, we recognize that reviewing and interpreting reports may be time-consuming for faculty. As a result, we are working to enhance our visualizations and associated text for more efficient interpretation.

Finally, though we have focused on the faculty's role in identifying, responding to, and mitigating patterns of inequity in student teams, we are aware that students' responses also matter [33]. Since students' reflections on their participation in teams can also afford opportunities for them to craft equitable teamwork without instructor intervention [33], [34], our next efforts might work to investigate how network measures can inform student-facing visualizations. To be more specific, our future work will examine student reflections on dimensions of teamwork equity, asking if the reports, as formulated by the research team and faculty interview participants, adequately capture inequities that students experience. We also plan to document where faculty and student perceptions align and diverge. Our future work is guided by the following questions: What metrics should be included in faculty-facing equity reports? What metrics should be included in student-facing equity reports? And what metrics should be included in both faculty-facing and student-facing equity reports?

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VIII. APPENDIX

Figure A1. Course-level sociodemographic characteristics

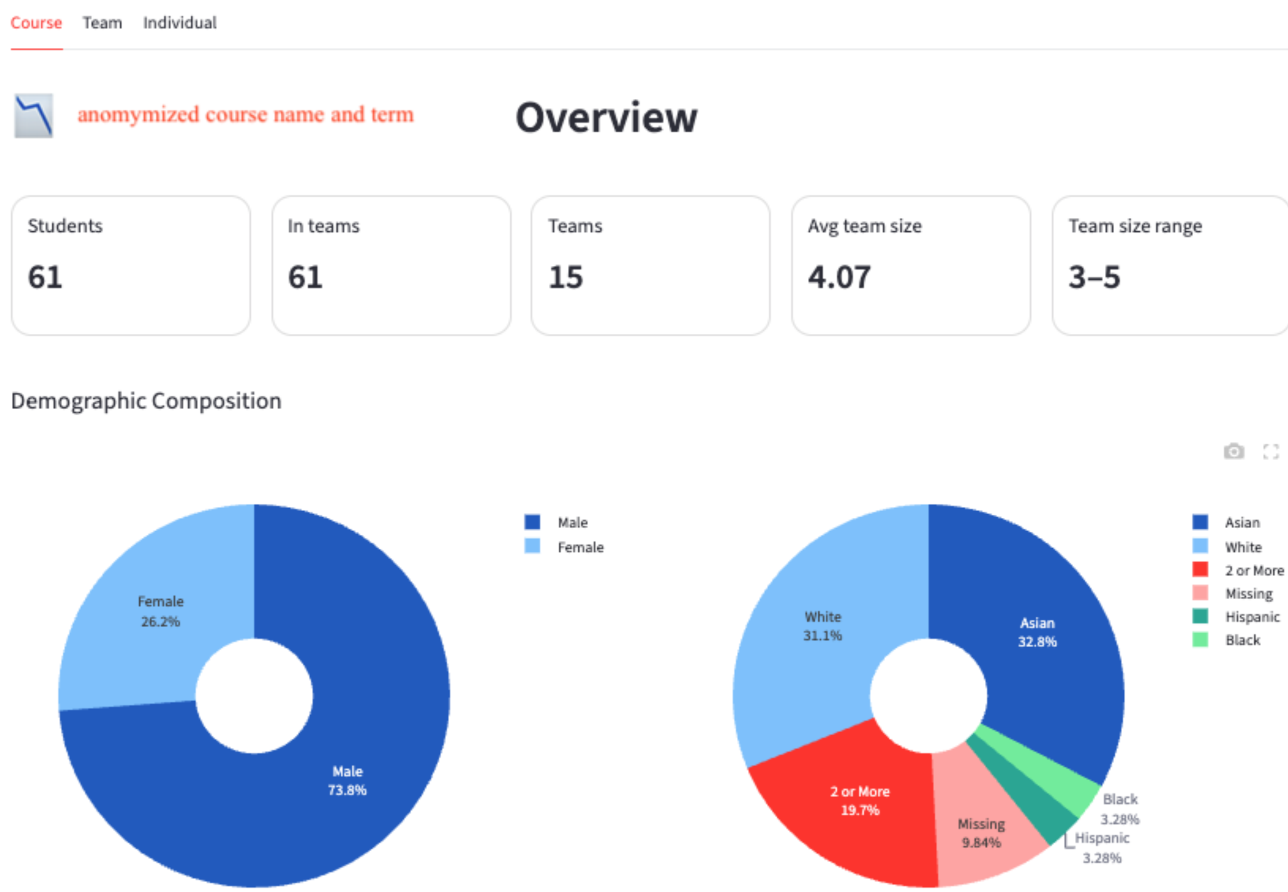

Figure A2. Distributions of peer ratings by gender

Figure A3. Depictions of changes in team network density

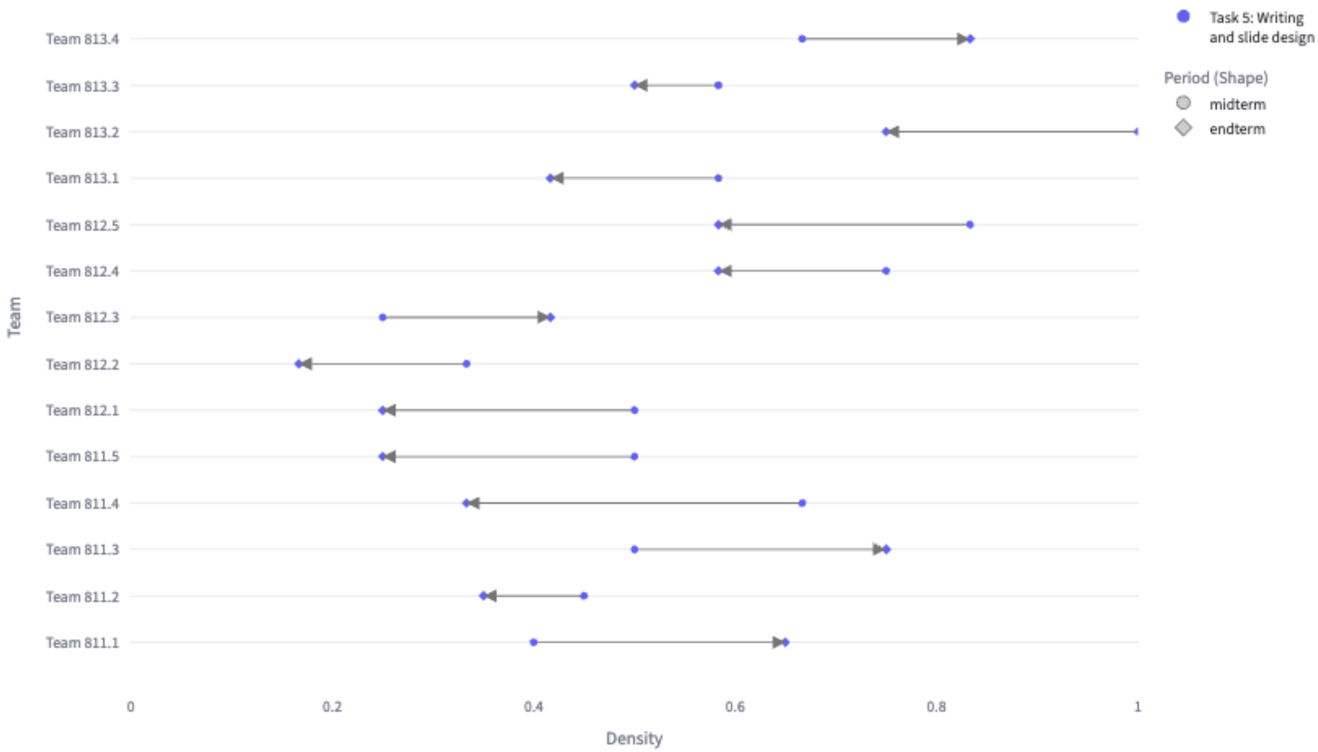

Figure A4. Heat maps depicting self and teammate evaluations at the beginning and end of the term