Paper ID #51320

Work-In-Progress: Edges of Interaction: Graph Theory in Engineering Team Dynamics

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Introduction

Group work in Science, Technology, Engineering, and Math (STEM) courses has been shown to deepen students' understanding and foster a sense of community within their cohorts [1]. Despite these benefits, the challenge of determining how to effectively form student groups remains for instructors. This challenge is particularly acute in first-year courses, where students are new to the university environment and largely unfamiliar to their instructors. In addition to the instructors' limited knowledge of students, time constraints play a significant role in pedagogical decisions. Instructors have minimal class time to observe student interactions and even less time to manually assign groups based on these brief and often incomplete observations.

The examination of group dynamics through the content of conversations has been extensively studied in both psychology and education. Much of this prior work has focused on identifying indicators of group effectiveness within that content. This study, however, focuses on the dynamics of the groupings through the patterns of communications modeled using graph-theoretic structures. By identifying key features of these graphs and their associated calculations, we aim to explore features of these interactions that may contribute to the effectiveness of the groupings.

This Work-In-Progress presents a proposed method for gaining valuable insight into student interaction patterns through the lens of graph theory. Student small group interactions are represented as networks, enabling the analysis of interaction structures throughout their first-year engineering courses. As this research continues, these interaction-based observations will be compared with quantitative and qualitative outcomes from a course-wide group project to explore communication characteristics associated with effective groupings. Ultimately, this method has the potential to support near-automation of the group formation process, reducing instructor burden while maintaining the quality of student group learning experiences.

Definition of Groups and Teams

In this study, we define a *group* as a collection of two or more students collaborating to achieve a goal. This collaboration may not necessarily be centered on a communal goal, such as a singular shared deliverable, but may instead support individual goals, such as the understanding of a computational problem during class [2]. The common collaborations present in this study vary by course and by progression through each course. Opportunities for whole-table discussions (typically involving 4-6 students), testing sample equipment in smaller groups (3 or fewer students), or completing mini-projects with a partner are all present throughout the first-year engineering curriculum.

A *team* has a more specific definition. In this study, a team refers to a group of four or fewer students working together toward a longer-term communal goal [3]. This term will be reserved for their third course project, detailed in the Methods section. However, because the benefits and characteristics of group work and team work are largely similar, the term *group work* will be used throughout this paper when discussing these benefits.

The Importance of Group Work

The focus on group work in this study stems from its well-documented importance in STEM education. Group work provides many opportunities for student growth, both in their personal skills and in understanding course content. By working with peers from differing backgrounds, students learn how to communicate their ideas, listen to others, and collaboratively integrate multiple perspectives [4]. Group work also supports cultural growth. University students often come from diverse geographic and cultural backgrounds, and opportunities to collaborate with peers who have different lived experiences can expose students to ideas and world views they may not have previously considered [5]. These so-called "soft skills" are important, not only in academic contexts but are also key attributes sought by future employers [4]. Academically, group work has been associated with deeper understanding of course material and increased motivation to pursue further learning. This is especially prevalent in project-based learning environments, where students are encouraged to engage with new material and seek out additional knowledge to support creative solutions [4].

The benefits of group work are especially pronounced when groups are cohesive and effective. The effectiveness of a group or team can be categorized in multiple ways, particularly when accounting for differing group work goals. In this study, effectiveness is categorized into two primary factions: social effectiveness and academic effectiveness. At the conclusion of the main project in the third course in the first-year engineering sequence (which will be detailed in the Methods section) each team will generate both qualitative and quantitative data on their performance. Each team member will complete a survey in which they rate their own participation, communication, and effort as well as those of their team members. This survey is split into two sections for each member: Section One where students can rank the member in categories relating to their participation, communication, and effort (never, rarely, sometimes, usually, or always) and Section Two where students provide an overall ranking of the member's performance in the team (no show, superficial, unsatisfactory, deficient, marginal, ordinary, satisfactory, very good, or excellent). Their course instructor will also complete a similar survey based on the observations they have made of the team and its members during class time. During the first-year project showcase, external judges, typically instructors from adjacent departments and/or invited members of the community, will score each team's 5-7 minute presentation including metrics related to communication quality and the distribution of responsibility among team members. Together, these measures form the basis for assessing social effectiveness. Academic effectiveness will be derived from the grade each team receives on their project from their instructor and the technical aspects from the judges' score cards.

An *effective* team is defined as one in which member are rated as "usually" or "always" in Section One of the survey and receive an overall rating of "satisfactory" or higher in Section Two. These ratings should be reflected consistently in the corresponding sections of the instructor survey and the relevant portions of the judges' scorecards and/or the team receives a final project grade of "A" or "B" from the course instructor and demonstrates comparable performance on the technical criteria of the judges' scorecards.

To categorize teams that do not meet the criteria for effective, the classifications *mildly effective*, *low effective*, and *ineffective* are used. *Mildly effective* teams are those in which one or more members are rated as "sometimes" in the majority of Section One of the survey categories and/or receive an overall Section Two rating of "ordinary" or "marginal." Similar patterns should be evident in the instructor evaluation and judges' scorecards, and/or the team receives a final project grade of "C." *Low effective* teams are those in which one or more members are rated as "rarely" in the majority of Section One of the survey categories and/or receive an overall Section Two of the survey rating of "deficient" or "unsatisfactory," and/or earn a final project grade of "D." *Ineffective* teams are those in which one or more members are rated as "never" in the majority of Section One of the survey categories and/or receive an overall Section Two of the survey rating of "superficial" or "no show," and/or earn a final project grade of "F." Because each team member provides ratings, individual evaluations may vary; therefore, average ratings will be used for team classification.

Previous Work in Group Effectiveness

The question of best practices for the formation of student groups is not new in education. Three main categories of group selection are most commonly observed in classroom settings: self-selection, random assignment, and criteria-based assignment [6]. Each of these methods has its own benefits and limitations. Self-selection refers to the process by which students choose the members of their own group, typically with group size as the primary constraint imposed by the instructor. This method is popular due to the time-saving benefits for instructors; however, it has been criticized for its potential to produce homogeneous groupings and feelings of isolation for some students who may not have preexisting relationships within the class [6]. Random assignment is often viewed as a middle ground. Because group membership is randomly determined, the issue of isolation may be reduced, however, some research suggests this method may take groups longer to establish effective working relationships [6].

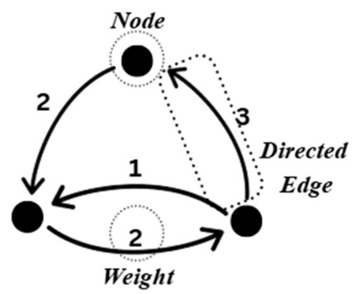
Criteria-based assignment serves as a broad umbrella for a range of grouping strategies that depend on the specific criteria selected. One commonly used criteria-based approach, particularly in K-12 education, aims to create heterogenous groupings based on academic performance. This approach groups higher performing students with lower performing students with the expectation that peer support may enhance learning outcomes. While this strategy has theoretical potential when groups are thoughtfully balance, it has been shown in practice to produce frustration among both higher and lower-performing students [6]. Assigning groups based on personality type has also been explored in recent years with some success, although effectiveness appears to be highly dependent on the nature of the group work [7].

Overall, the effectiveness of group selection methods varies depending on the outcomes being considered. Some approaches tend to support stronger interpersonal relationships, others emphasize project outcomes, and some provide a balance between the two.

Previous Work in Graph Theory

Graph theory, a branch of mathematics which studies relationships between objects, defines a *graph* as a combination of *nodes* and *edges* [8]. *Nodes* can be objects or points and *edges* the lines connecting them. Graphs can be *directed*, meaning they can have an explicit directionality on the edges, or *undirected* [8]. There is also a measure of *weight* which indicates a number associated with an edge. Figure 1 provides an example of graph theoretic structures that are common to this study.

Figure 1. Illustration of Graph Theoretic Structures



While graph theory has been recognized for its applications in understanding different networks of interactions for decades, its use in making pedagogical decisions has been largely unexplored. One area previously investigated in education is the use of graph-theoretic models to track the interactions of students with each other and educational materials [9]. Many methods described in prior research did not fit the needs of this study, as they tracked interactions outside the scope of our focus apart from the method described by Chai et al. [1], from which our method draws influence. In their paper they describe a methodology for creating the graphs from observations of student interactions by treating students as nodes and forming directed, weighted edges between nodes for every "Talk-Turn." Specific details of this method will be discussed in the next section, along with the calculations used. In their study, the graphs were created manually through in-person and video observations by tracking the flow of conversation. Our goal, however, is to adapt their method in a way that better automates many parts of the process. In a university engineering course, using the Chai et al. [1] method would be impractical for many instructors due to the significant time commitment; therefore, our adapted method provides a more feasible approach for instructors to utilize this tool. Previous research also focused heavily on the creation of the graphs, but not on their potential application, which is why this study also emphasizes extracting key information from these graphs to support the formation of more effective student groupings.

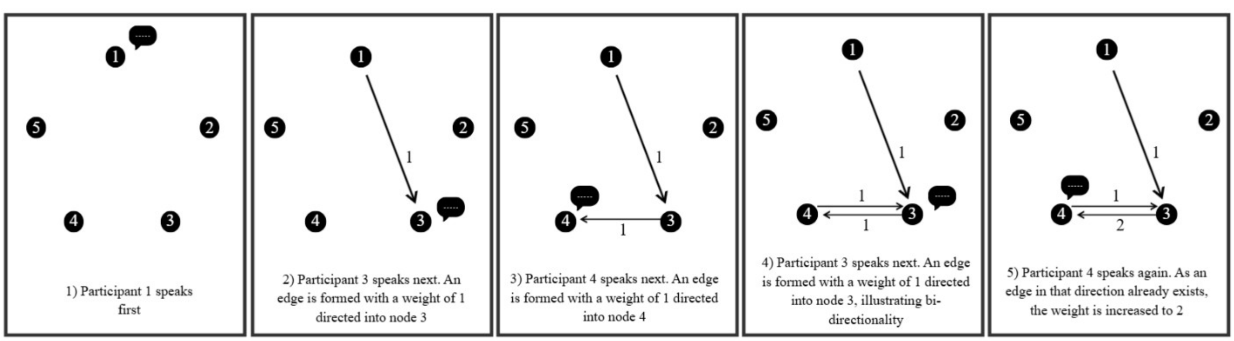
Methods

In this study, we chose to focus on the honors first-year engineering sequence at Louisiana Tech University. As we are a quarter-system school, this sequence is comprised of three courses (Engineering Problem Solving I, II, and III) that emphasize blending early engineering concepts with hands-on learning opportunities and projects. The honors courses were chosen primarily due to their size and retention rates. The total number of students registered for any Engineering Problem Solving I course in Fall 2025 was 510, while the honors sections accounted for 135 of those students, making the honors sections a more manageable size for this study. These sections also historically have higher retention rates from quarter to quarter, allowing us to retain more participants in this study. In Fall 2025, we began with 135 participants and in Winter 2025-2026 we had 116 participants, resulting in a retention rate of 85.9% from the first to the second quarter of data collection. This sequence of courses culminates in a first-year engineering design showcase where teams of 3-4 students present a project of their own creation that they worked on as part of their Engineering Problem Solving III course. From this project, the groups receive scores from the judges, grades from their instructors, surveys for students to rate their own and their teammates' communication, participation, and cooperation (Section One), along with overall ratings (Section Two), and a similar survey for the instructor to evaluate communication observed during class time. This data will provide a robust pool for assessing both social and academic effectiveness.

The primary source of data collected throughout the courses is audio recordings from each instance of group work during class. This includes times when students are working on a computational problem at their tables, collaborating on projects in partners or small teams, or using the "fabrication stations" located around the perimeter of the room (these stations include tools such as milling machines, soldering irons, clamps, drills, etc). The type of group work is flagged for each recording and corresponding graph to support comparisons of structural features and interaction patterns across different group work contexts. The length of these recordings varies based on the activity being done, with typical recordings of computational problems being 5-15 minutes, project collaboration ranging from 20 minutes to entire class times (110 minutes), and fabrications station work being 15-30 minutes. The average recording length for all recordings is approximately 30 minutes. To capture audio, each table and fabrication station is equipped with an audio recorder and microphones. Students were assigned participation numbers to ensure anonymity, which they state at the beginning of each recording. After collecting the audio recordings, they are uploaded to an AI transcription software that produces a detailed transcript with speaker identification. While the settings on the recording devices are adjusted to capture the voices of those at the table or station, there is a chance the voice of another student or instructor outside of the group is caught. This is rectified by quickly inspecting the AI transcription. If the voice did not state their participation number, then it is simple to identify the voice was from an outside source and to strike it from the transcript. From this transcription, we obtain the sequence in which the students spoke during their group work. This sequence is then used as the input for the SageMath code to create the graphs and runs the relevant calculations.

The graphs created are weighted, bi-directional graphs obtained using the method detailed by Chai et al. [1], where students are represented by nodes. When one student speaks after another, referred to as a "talk-turn", a directed edge is formed from the first speaker to the second. Each subsequent talk-turn in the same direction increases the weight of the edge by one. A separate graph is created for each instance of group work. Figure 2 provides an illustration for the creation of a graph in this manner.

Figure 2. Illustration of Graph Formation

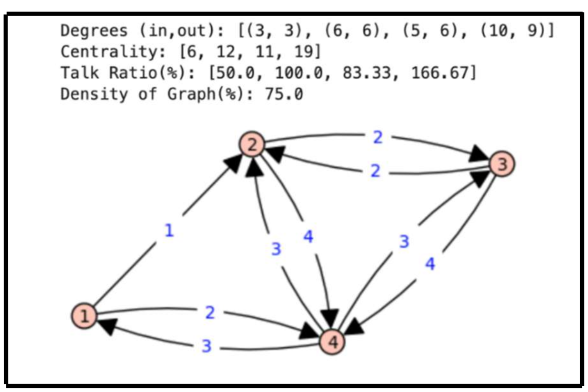


Typical graph-theoretic calculations performed on each graph include the degrees (in and out) of each node, the centrality of each node, and the density of the graph. Degrees in and out of each node are calculated by summing the weights of the edges directed into (degrees in) and out of (degrees out) the node. In this application, degrees in indicate the number of times a participant spoke after another, while degrees out indicate how many times another participant spoke after them. This calculation provides an indication of how involved a specific participant was in the conversation. Centrality, calculated by summing the degrees in and out for each node, provides a reference for the participant's influence in the conversation. Density is a measure of the graph as a whole. To calculate density, we ignore the edge weights and focus instead on the edges present in the graph. Between any two nodes, two edges are possible, one in each direction. Missing edges indicate that two participants did not interact before or after each other in the conversation. For a graph with nodes N and edges E, density is calculated taking the total number of edges present and dividing by the number of edges possible, $\frac{|N|(|N|-1)}{2}$, to get: $density\ (\%) = \frac{2|E|}{|N|(|N|-1)}(100)$ [10].

A calculation used that is not typically found in standard graph theory is the "Talk Ratio" [1]. Using the method described by Chai et al. [1] in their paper, the talk ratio is computed by first calculating each student's "Fair Share" ratio which represents the number of times a speaker would speak if the conversation was evenly distributed among all participants. The Fair Share ratio is calculated as $FS = \frac{\sum d_{in}}{|N|}$, where d_{in} is the degree in of each node and $|N|$ is the total number of nodes. The Talk Ratio for each node is then calculated as $TR(\%) = \frac{d_{in}}{FS}(100)$. The graphs created and their associated calculations are then used to analyze communication pattern within groups and individual students.

To further clarify the application of these methods, a brief illustrative example of the SageMath code output is included. In this example, the sequence in which participants (labeled 1, 2, 3, and 4) speak during group work is [3,2,4,1,4,2,4,3,4,2,3,2,4,1,2,3,4,3,4,1,4,2,4,3,4]. When used as input to our code, the output is given by Figure 3.

Figure 3. Sample Code Output



This study intentionally adopts a high-level, structure-first analysis, focusing on aggregate interaction patterns rather than participant's background or the content of discussions. This allows for a scalable analysis to support the development of graph-based measures that are readily interpretable by instructors. More in-depth analysis is deliberately deferred to future work where additional dimensions will be layered onto the framework established in this study.

Early insights

As this project is still in the main data collection phase, most insights are currently anecdotal but can illuminate areas where results are expected. On average, one to two audio recordings containing each participant are produced a week resulting in approximately 150 total audio recordings available currently. We estimate a total of 250 recordings during the full data collection period, with each participant appearing in approximately 20-30 recordings. Since each audio recording is used to create a graph, each participant should have 20-30 unique graphs for analysis. A benefit of collecting recordings over three quarters is that the participants in the sections change each quarter, allowing us to see the interactions between a wider variety of participants.

Based on these anecdotal observations, graph density is expected to be an informative calculation for evaluating group-level interactions. Groups with lower density percentages indicate that some participants do not communicate before or after certain others. This is especially enlightening when this pattern appears in multiple graphs involving the same participants, suggesting that these participants may not effectively collaborate together as they do not continue the flow of ideas. Conversely, groups exhibiting consistently high density may indicate that participants interact well, particularly with respect to their social effectiveness.

Centrality and Talk Ratio are also predicted to provide insight when evaluating participants individually rather than the group are a whole. Because centrality describes how integral a specific node is to the graph, it can identify participants who interact with a wider range of peers. Talk-ratio, based on early observations, appears to reflect different communication styles. For example, a participant with a Talk Ratio well below 100% may feel less comfortable contributing to the conversation. If this pattern persists across multiple groupings, the participant may simply be more introverted. However, if it occurs only with certain peers, that may indicate that those specific groupings are less optimal for that participant.

Anecdotal observations further suggest that task type (computational problem solving, partner or small group tasks, or larger project work) may influence the interaction structures and calculated graph measures. Comparisons and further analysis will be made to explore the effects of these task interactions.

These early observations provide possible insights into the social effectiveness of the groupings. Predictions regarding academic effectiveness must await data from the first-year project showcase and instructor grades.

Limitations

A limitation of this study is that, as previously discussed, we account for the frequency and order of communication rather than the content of the discussion. This has the potential to include off-topic conversations within our graphs, however, this inclusion may also have a significant impact on the effectiveness of our groupings, which is why we have chosen not to manually review the recordings to exclude such interactions. Meaningful group interactions do not solely have to revolve around the task at hand, and an argument can be made for the importance of off-topic utterances in relationship building as well [1].

This also highlights another limitation in that the directionality of utterances is not explicitly tracked. In other words, we do not track whether a student's utterance is directed to the group as a whole, a subset of the group, or a specific individual. Additionally, demographic data about participants or their prior experience is not collected. While these limitations are outside the scope of the present study, they represent areas for future expansion of this work.

Our method for data collection is also not fail-safe. It relies on several factors, including equipment functionality, ambient noise levels in the classroom, and students remembering to record their group work. Because of these factors, there will be instances of group work that are not captured or included in the data. We have put in place several strategies to mitigate these challenges as much as possible. Equipment is checked and charged at least once per week, audio recording device settings have been adjusted to capture usable audio in most classroom environments, and students receive reminders both on their tables and from instructors to record their audio.

From a scalability perspective, equipment cost can also be a limitation for future instructors implementing this method. In larger classes with more tables and/or equipment stations, there would be an added cost of additional recording materials that would need to be considered. The equipment we have chosen, such as handheld style recording devices and simple lapel microphones secured to the tables with gaffer tape, offers a more obtainable price point when compared to some of the other recording options available on the market.

Future Work

At the conclusion of the Spring 2026 quarter, data from the first-year engineering project showcase will become available for analysis. Using this data, each team and each individual team member will be classified as effective, mildly effective, low effective, or ineffective. This classification will allow us to evaluate patterns observed in the interaction graphs generated throughout the academic year and to identify graph-based features and calculations that correspond to each effectiveness category. Considering both perspectives, the graph as a whole and individual nodes, will enable us to examine whether effectiveness is driven primarily by team-level interaction structures, individual participation patterns, or a combination of both. Conclusions from this study are expected in Fall 2026.

Validation of this framework is planned through shorter-span studies following only the Engineering and Problem Solving III courses, with the goal of assessing whether the model can be condensed to a more practical timeline for instructors while preserving its core insights.

Expected outcomes include the identification of predictive patterns in early interaction graphs that signal group effectiveness prior to project completion, as well as patterns at the individual level that indicate which students may be well suited to form effective groups together. From these findings, we aim to outline a method instructors can use to assign student groups quickly in a way that promotes higher overall effectiveness when compared to student self-selected groups.

Beyond the scope of the present study, additional aspects of interaction data may provide further insight into how students communicate. One metric discussed in prior work is *episode length*, defined as the number of talk-turns that occur before a new topic or question is introduced. When combined with the methods presented in this study, episode length may offer insight into the depth of group discussions and how discussion depth relates to both group and individual effectiveness [1]. Factors such as student demographics and prior experience, utterance length, and AI-based identification of key terms to distinguish on-task from off-task discourse are planned extensions to the current framework and will be incorporated in future work to examine their effects

Another anticipated direction for future work is the development of a SageMath code capable of autonomously processing audio recordings, generating interaction graphs, computing relevant metrics, and applying effectiveness classifications. Such a tool could ultimately support instructors by providing data-informed group assignments with minimal manual effort.

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