When There Is No Right Answer: How Computing Students Navigate Open-Ended Problems through Collaborative Discussion and Peer Evaluation

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Abstract

Computing students often encounter real-world problems that are open-ended, ambiguous, and lack a single correct solution. This paper examines how computing students navigate such problems in collaborative team settings and how these experiences shape peer evaluation. Using data from a project-based visualization course, we analyze team Discord discussions, participation and activity metrics, and written peer evaluations across multiple teams through a mixed-methods approach. Our findings show that teams commonly encounter decision conflict when working on open-ended problems, which they address through negotiation, resource sharing, and iterative discussion. Disagreement often coincides with sustained engagement and collaborative sensemaking while avoiding breakdown. Instructors are typically treated as collaborative resources, with teams retaining ownership over decisions. Peer evaluations reflect these processes only weakly: visible participation and time investment show limited association with peer ratings, while peers emphasize the relevance, timing, and impact of contributions. Differences between self- and peer evaluations further highlight the socially situated nature of peer judgment. These findings provide empirical insight into collaborative open-ended problem solving in computing education and how peer evaluation captures students' perceptions of contribution.

CCS Concepts

• **Social and professional topics** → *Computing education.*

Keywords

Open-Ended Problem Solving, Collaborative Sensemaking, Peer Evaluation, Computing education

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1 Introduction

Computer science students are often trained to solve problems that are well-defined and objective [40]. In many courses, students learn to apply algorithms or systematic procedures to arrive at a correct or optimal solution under a given set of constraints. However, students frequently struggle with open-ended problems that lack a single correct answer or a clearly prescribed solution path [38]. Such problems are common in real-world computing practice, where understanding context, exploring alternatives, and iteratively refining decisions are often central to effective problem solving.

Open-ended problem solving becomes more challenging in collaborative settings. When students work in teams, different interpretations of the problem, competing ideas, and varying expectations can lead to disagreement and conflict. Unlike well-structured problems, open-ended tasks rarely provide a clear goal state that teams can use to resolve differences. As a result, teams must rely on discussion, negotiation, and shared sensemaking to move forward. Prior work has shown that group-level social and collaborative skills play an important role in managing conflict and supporting effective teamwork [28]. In practice, students often seek help from instructors when disagreements arise, but in open-ended contexts instructors are typically unable to provide definitive answers, leaving teams to resolve tensions themselves.

Prior research in computing and engineering education has examined open-ended and project-based problems, reporting benefits such as increased engagement, self-efficacy, and in some cases improved performance [39]. Other work has focused on different team project dynamics by emphasizing communication and collaboration skills [35]. Despite this growing body of work, there remains limited empirical understanding of how computing students navigate open-ended problems in situ, particularly in collaborative team projects. In addition, little attention has been paid to how these collaborative processes shape students' perceptions of one another when formalized through peer evaluation.

From a learning perspective, collaborative work on open-ended problems aligns with the social constructivist views of learning [34], where understanding is developed through interaction and dialog, as well as with theories of distributed cognition. These perspectives suggest that examining students' interactions, including team discussions and peer feedback, can provide insight into how teams make progress and how students judge each other's contributions.

In this paper, we examine how computing students navigate open-ended problems in a collaborative, project-based course, and how these experiences influence peer evaluation. Using data from a semester-long visualization course, we analyze team Discord discussions, participation and activity metrics, and written peer feedback across multiple teams. We adopt a mixed-methods approach that combines quantitative analyses of participation and engagement with qualitative analyses of collaborative discussions and peer evaluations, capturing both observable activity patterns and students' interpretations of contribution and disagreement. We focus on:

- **RQ1:** How do computing students navigate open-ended problems in a collaborative team project setting?
- **RQ2:** How do these collaborative experiences shape students' perceptions of their peers, as reflected in peer evaluation?

Our analysis shows that teams working on open-ended projects frequently encounter decision conflict, which they address through negotiation, resource sharing, and iterative discussion, often leading to deeper engagement. Instructors act as collaborative resources and avoid authoritarian behavior. Peer evaluations weakly reflect these processes: visible participation measures show a limited association with peer ratings, while contribution quality, timing, and impact play a larger role, highlighting the nuanced nature of peer judgment.

2 Related Works

This literature situates our study within two related strands: (A) collaboration, learning, and engagement patterns in open-ended problem contexts, and (B) peer evaluation and perceptions of contribution in team-based projects.

2.1 Collaboration, Learning and Engagement Patterns in Open-ended Problems

Collaborative problem solving has been widely studied across educational contexts, particularly for its role in supporting learning, with many studies demonstrating positive effects on learning outcomes [21–23, 44]. Prior research has also shown that collaborative groups can outperform individuals across a range of domains, including debugging tasks [18], computational modeling [17], intelligent tutoring systems [36], liberal arts education [26], and mathematical problem solving [3, 7]. Researchers have further examined the dynamics of collaboration in open-ended and complex problem-solving settings [2, 8, 11]. In parallel, a substantial body of work has focused on designing and evaluating instructional interventions to support open-ended collaborative problem solving, often through experiments conducted in collaborative learning environments [6, 9, 12, 16, 24]. Building on this literature, our work examines naturally occurring collaboration in a project-based computing course, focusing on how students engage in brainstorming, negotiation, and decision-making while working on an open-ended visualization project.

2.2 Peer Evaluation and Perception of Contribution in Team-based Projects

Peer assessment has been widely used to evaluate individual contributions in group work and has therefore been adopted in numerous studies [13, 27, 29]. Prior research has shown that peer assessment can promote accountability [20], support motivation [33], and influence student engagement [1]. Related work has also examined how disagreement within teams can shape inquiry and collaborative progress [10, 45]. In addition, researchers have leveraged communication platforms [4, 25, 43] and activity logs [5, 15, 31] to study patterns of student collaboration. A separate line of work has documented bias, reciprocity, and disagreement in peer evaluation [32, 41, 42]. Despite this body of research, there has been limited empirical examination of how self- and peer evaluations relate to one another in collaborative team settings. Our work contributes to this area by connecting peer evaluation outcomes to evidence from collaborative discussions and activity traces in team-based, open-ended problem contexts.

3 Methodology

We used a mixed-methods approach combining quantitative participation data with qualitative analysis of collaboration and peer feedback.

3.1 Participants

The study was conducted with undergraduate students enrolled in an advanced, project-based visualization course offered at a large public university. The course was designed to address the theoretical and practical issues in creating visual representations of large amounts of data. It covered the core topics in data visualization: data representation, visualization toolkits, scientific visualization, medical visualization, information visualization, and volume rendering techniques. All students enrolled in this course were computer science undergraduate students with a background in computer graphics or data-intensive fields. In total, there were 40 students in the course. Out of 40 students enrolled in the course, 36 provided demographic information: pronouns were He/Him (42%), She/Her (14%), and not provided (44%); 58% were undergraduates (81% seniors, 19% juniors) and 42% were graduate students.

3.2 Dataset

The dataset used in this paper is collected to a semester-long project in which students in the visualization course worked in small teams (each team had 5 members) to design and implement an open-ended visualization task. These projects consisted a range of concepts including but not limited to the design and demonstration of new visualizations, case studies involving the visualization of actual data, the construction of interactive tools for novel data exploration, or in-depth evaluation of existing tools or techniques.

Each project team had an instructor-created dedicated Discord channel for project discussions, which students were strongly encouraged to use, while external communication channels were not monitored. We used these **teams' discussion on Discord for our mixed-method analysis to answer RQ1**. The dataset includes eight Discord channels corresponding to eight project teams. The

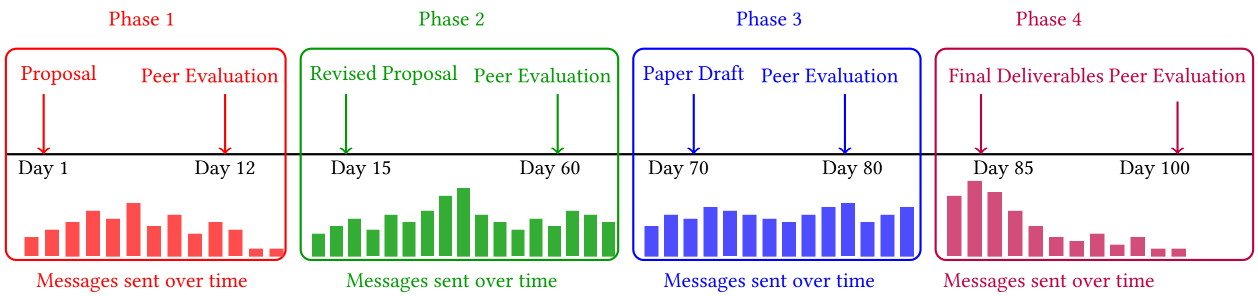

Figure 1: Overview of the visualization project showing four phases of the project, individual milestones, and the distribution of daily messages within each phase.

logs contain timestamped messages, authorship information, channel membership, and message metadata, comprising 5,873 messages (primarily text-based, with links, images, documents, and other file types), with an average of 67.51 messages per day.

As illustrated in Figure 1, the project lifecycle comprised four main phases, each associated with specific deliverable submissions. After each submission, each student completed a self-evaluation and peer evaluation for each member of their team. We analyzed **students' self- and peer-evaluation data to answer RQ2**. Peer evaluation data was collected using structured survey forms [14]. The survey included both quantitative and open-ended components. Students reported their own responsibilities and time investment along with a self-rating through this survey. In addition, they provided numeric ratings for each teammate accompanied by written justifications.

3.3 Mixed Methods Analysis

Quantitative Analysis: We conducted descriptive statistical analysis to characterize students' participation pattern including total message volume and variation in engagement. To examine the relationship between observable participation and peer perception, we computed non-parametric correlations between participation metrics and peer evaluation scores. Given the ordinal nature of evaluation data and the presence of skewed distributions, Spearman's rank correlation coefficient was used to assess whether higher levels of visible activity are associated with more favorable peer evaluations, while avoiding assumptions of linearity or normality.

Qualitative Analysis: To understand how students navigated when solving open-ended problems collaboratively and how their experience shaped their peer evaluation, we conducted a qualitative analysis of both Discord discussions and open-ended peer evaluation. We employed an iterative thematic analysis approach, beginning with open coding followed by iterative axial coding to identify recurring patterns. All authors went through multiple rounds of discussion to develop higher-level themes that could capture how teams interpret ambiguity, negotiate meaning, and evaluate contribution. Once they reached to an agreement, two authors independently coded the discord discussion content. As per Cohen's kappa measure, there was a high level of agreement between the two coders, $\kappa = 0.86$, $p < .0005$. Following this assessment, the coders met to discuss and resolve disagreements through consensus. Peer evaluation comments were analyzed following the same process to identify how students articulate and justify their peers' perceptions, allowing comparison between observed interaction and perceived contribution.

Quantitative and qualitative findings were integrated to examine cases of alignment and mismatch between participation metrics and peer evaluations.

3.4 Ethical Considerations

This study received Institutional Review Board (IRB) exemption prior to data collection and analysis. All student identifiers were removed from the dataset before analysis, and data processing occurred only after final course grades were released. Participation in the research had no impact on students' grades or evaluation outcomes. The study used course-generated artifacts collected as part of normal instructional activities, and no additional interventions were introduced for research purposes. Students were informed that course data might be used for research and that participation was voluntary. All quoted excerpts were anonymized, and no demographic or personally sensitive information was collected or analyzed. Findings are reported at an aggregate level.

4 Results

We structured the result section around two research questions. To address RQ1, we performed mixed-method analyses of the Discord messages and identified four themes relevant to collaborative team work in the context of open-ended problems (section 4.1). For RQ2, we analyzed peer evaluation data and the findings are presented in section 4.2 and 4.3.

4.1 Navigating Open-Ended Problems in Collaborative Teams (RQ1)

To answer RQ1, we qualitatively analyzed Discord discussions from all eight teams throughout the semester and identified four recurring themes that explain how students approached open-ended problem solving in collaborative settings. Our analysis focused on how teams navigated ambiguity, managed disagreement, and coordinated work in the absence of a clearly defined solution path.

Decision Conflict Is Common in Open-Ended Team Projects: Across teams, decision conflict was a frequent part of collaborative work. Because project goals were open-ended and teams were encouraged to independently explore the trajectory of their projects, students often considered multiple possible directions simultaneously. During early stages, teams explored several visualization ideas in parallel, often without immediate agreement on which approach to pursue. Differences in interpretation, preferences, and perceived feasibility made disagreement a common and expected part of team discussions. These conflicts were not limited to the initial brainstorming phase. The teams revisited earlier decisions as their understanding of the problem evolved or as new constraints emerged. This suggests that the conflict was not a sign of breakdown or lack of coordination. It was a natural consequence of working on open-ended problems with multiple viable solutions.

Teams Resolve Conflict Through Resource Sharing and Comparison of Alternatives: To navigate disagreement and move toward consensus, teams frequently relied on sharing concrete resources. During brainstorming, students posted examples from a variety of online sources, including visualization inspirations, datasets, and external references, within their team channels. These shared materials helped students articulate their ideas more clearly and establish a stronger rationale for their preferred approaches. After teams reached agreement on a general topic or direction, they continued to draw on similar online resources to support further development and refinement of their designs. A common pattern involved proposing alternative ideas, sharing supporting resources for each option, and comparing those alternatives through discussion. This process allowed teams to weigh trade-offs and converge on decisions collaboratively.

Disagreement Triggers Sustained Engagement and Collaborative Sensemaking: Moments of disagreement often coincided with longer and more sustained discussion threads. As differences in interpretation occurred, students responded by explaining their reasoning, comparing alternatives, and asking follow-up questions. Instead of halting progress, these tensions frequently led to deeper engagement with the task and detailed discussion among team members. In several cases, conflict served as a catalyst for collaborative sensemaking, which prompted teams to clarify assumptions and refine their understanding of the problem space.

Again, student reflections illustrate how disagreement exposed gaps in shared awareness and then motivated changes in collaborative practices. For instance, in one conversation thread, team members acknowledged that their miscommunication stemmed not from opposing views, but from uneven attention to shared resources, which further led them to renegotiate their expectations for coordination and monitoring:

> *"Well, we honestly wouldn't have had any problems with communication if any of us had looked at the written requirements for phase 2, but in the future we should probably commit to looking at the Discord at least once on the Saturday and Sunday before the assignment is due to ensure that we haven't missed anything."*

This response reflects how moments of tension prompted teams to reflect on their coordination habits. Such approach indicates that disagreement played a productive role in supporting engagement and iterative refinement during open-ended problem solving.

Instructors Are Treated as Collaborative Resources: Teams regularly involved the course instructor during periods of uncertainty or disagreement, particularly when they struggled to evaluate competing options. However, instructor input was not treated as a definitive answer. Instead, students often framed the instructor's feedback as one of the perspectives among other options and compared it with their existing ideas.

Instructor feedback influenced planning decisions, especially during the later stages of the project, but teams retained ownership over final choices. For example, members of one of the teams drew on instructor guidance while they were in conflict among themselves about their next task and thus refined their collaborative plans:

> *"You know we don't have to do EVERYTHING the professor asks us to do? She even said that we don't have to, and that most of these are just suggestions. She said we could put something down like "will consider", that is a polite way of saying "we won't do it""*

This conversation shows that teams viewed instructors as collaborative resources who supported negotiation and progress. The role of the instructor as an authority was not the dominant perception in this context. Students did not expect the instructor to resolve all ambiguities on their behalf. As deadlines approached, students shared progress updates, solicited feedback from both peers and the instructor, and made iterative modifications based on that input.

Across teams, open-ended problem solving involved frequent decision conflict, iterative negotiation, and sustained discussion. Teams addressed disagreement by sharing resources, comparing alternatives, and refining ideas through collaboration, with conflict often coinciding with deeper engagement. Instructors acted as collaborative resources and avoided acting like an authority, and teams retained ownership of decisions. Together, these findings show that progress on open-ended tasks is shaped by ongoing negotiation and interaction, processes that are not always captured by final project outcome or grades.

4.2 Peer Evaluation and Perceptions of Contribution (RQ2)

To answer RQ2, we analyzed peer evaluation data collected across all four phases of the project. We used students' self-reported time investment, numerical ratings for their peers, and total number of messages sent on discord channel for quantitative analysis. In addition, we used text explanation of the peer evaluation for qualitative analysis. We used mixed-methods analysis to understand how students formed impressions of their peers' contributions.

Quantitative Analysis: We examined whether visible participation, measured by the number of messages sent and the amount of active time spent, was associated with peer evaluation outcomes. Across both measures, we observed a similar pattern: while greater participation was generally associated with higher peer feedback, the strength of this relationship was modest.

Figure 2(a) and Figure 2(b) show the relationship between message volume and peer evaluation score in four phases. Although several highly active participants (who sent higher number of messages) received strong evaluations, the relationship was not linear and the high volume of messages did not consistently correspond to higher ratings. Spearman's rank correlation revealed a moderate but weak positive association between messages sent and peer evaluation score ($\rho = 0.343$, $p = 0.0379$). This pattern is more

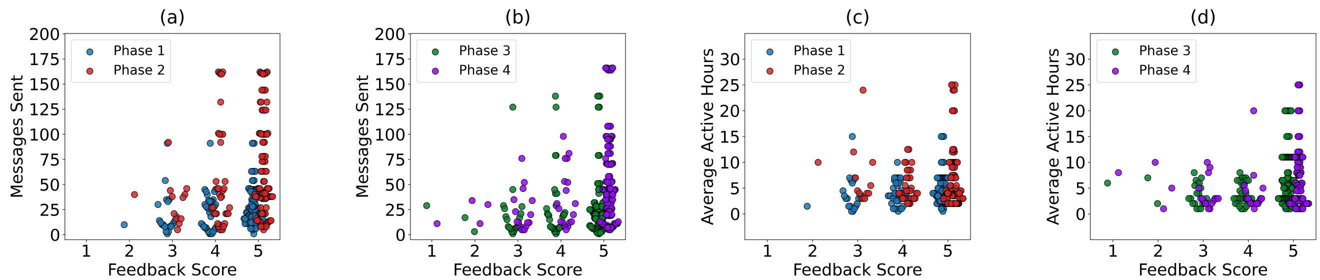

Figure 2: These figures compared the peer evaluation score against total number of messages sent (a and b) and total number of active hours spent (c and d) by each student through beeswarm plots. Each phase is represented using a unique color (blue for phase 1, red for phase 2, green for phase 3, and purple for phase 4). These plots indicate that there is moderately weak correlation between peer feedback and visible participation measures (total number of messages sent and total active time spent for the project).

prominently visible in the third and fourth phases of the project (Figure 2(b)).

A similar pattern emerged for time investment. As shown in Figure 2(c) and Figure 2(d), students who spent more active time on the project tended to receive higher peer evaluations, but with substantial variability. Some students received a higher peer evaluation despite a limited time investment, while others who invested more time did not always receive the highest scores. Spearman's rank correlation again showed a moderate but weak positive association ($\rho = 0.310$, $p = 0.0004$).

These findings suggest that while level of participation is related to peer evaluation, the effect is at the lower end of what is typically considered moderate. An increase in time spent or number of sent messages do not reliably translate into higher peer ratings, indicating diminishing returns to visible activity alone.

Qualitative Analysis: Qualitative analysis of peer evaluation justification helped us better explain this pattern. Rather than focusing on how often or how long someone participated, peers emphasized the impact of contributions on team coordination and decision-making. For example, one student received strong feedback because "He was proactive about keeping everyone on track and reminding us about deadlines." Another peer highlighted the value of clarity and evidence in communication, noting that "She explained her ideas clearly and with a lot of samples, which made it easier for the team to agree on a direction." These comments highlights that participation that supports coordination, clarification, and systematic progress was especially valued.

In contrast, lower peer evaluations were typically associated with specific gaps in contribution. Some comments mentioned lack of follow-through on assigned roles of their peers whereas others highlighted their peers' reduced involvement during critical phases of the project. For instance, one student noted about one of their team members, "As the team-lead, he did not consistently monitor progress or check in on task completion," while another commented that "Her contribution was limited during the final submission of the project." These examples suggest that peers evaluated contribution based on responsibility, timing, and perceived impact. The total time spent or the number of messages sent were not their priority when evaluating their peers.

In summary, these findings indicate that while time investment and visible activity are related to peer evaluation, their effects are relatively weak. Peer assessments appear to reflect judgments about the quality, relevance, and timeliness of contributions—particularly how those contributions supported coordination and collective progress than simply rewarding higher levels of activity.

4.3 Perception Mismatch in Peer Evaluation (RQ2)

To examine whether students' self-evaluations and peer evaluations were aligned, we extended our analysis for RQ2 and compared self-reported feedback scores with the average feedback students received from their teammates. Self- and peer evaluations showed a moderate association (Spearman's $\rho = 0.330$, $p = 0.0001$), indicating that students generally had some awareness of how their contributions were perceived. At the same time, the distribution of scores revealed substantial variation, indicating that alignment was far from uniform.

Qualitative analysis highlights these mismatches more clearly. In several cases, students rated themselves lower than what their peers did, because of their limited availability or perceived shortcomings in participation. For example, one student who rated himself 3.5 out of 5, cited:

> *"I did my work on time and got my vises in. I was communicative but felt I could do better, as I was busy with a hackathon. As a result, I didn't volunteer to help as much since I was managing other activities and had to delay meetings. Though, I did help review and check other team members' work before submission."*

Despite this moderate self-assessment, teammates rated the same student highly as 5 out of 5 on average, emphasizing the usefulness of his contributions. In contrast, there were also cases where students overestimated their own contribution but received comparatively lower scores from their peers . For instance, one student assessed himself as 5 out of 5 in all phases, but his teammates were critical and rated him 3 out of 5 on average. One teammate even explained why he didn't rate him higher:

> *"The only part of this phase he contributed to was the specific topic he had to answer questions on. He did not*

help with the visualization or the video. He also did not contribute to his role as project manager."

In summary, self- and peer evaluations were only partially aligned and that substantial perception mismatches were common. Some students underestimated their contributions due to high self-expectations, while others overestimated their impact compared to peer perceptions. Overall, peer evaluations appeared to reflect teammates' shared sense of dedication and meaningful contribution from teammates which is critical for effective collaborative efforts.

5 Discussion and Design Implications

Conflict as a Feature of Collaborative Sensemaking in Computing Education: Computing courses are often criticized for emphasizing highly structured, instructor-led problem solving, with limited opportunities for collaborative sensemaking [19, 30]. Such one-directional instructional models can constrain students' agency and sense of belonging, factors linked to self-efficacy and persistence in computing. Our findings offer a contrasting view of collaboration in open-ended computing contexts. Across teams, decision conflict was common and closely tied to sustained discussion and negotiated understanding. Disagreement did not indicate breakdown; instead, it frequently prompted students to articulate assumptions, compare alternatives, and refine ideas collectively. These patterns suggest that open-ended team projects create forms of collaboration that are less visible in directive computing instruction by foregrounding interaction and shared decision-making. In this context, conflict becomes a mechanism through which students participate more fully in the learning process, potentially supporting confidence, agency, and belonging.

Interpreting Peer Evaluation in Collaborative Open-Ended Work: Our findings indicate that peer evaluation in open-ended team projects reflects more than visible participation or time investment. Although quantitative associations between activity measures and peer ratings were weak, qualitative feedback showed that peers emphasized the relevance, timing, and impact of contributions. Students valued actions that supported coordination, clarified decisions, and helped teams make progress, beyond simple activity levels. Differences between self- and peer evaluations further suggest that peer judgments were shaped by shared team experiences. These mismatches indicate that peer evaluation captured socially situated judgments about contribution quality and impact that were not fully explained by participation metrics alone. This perspective shifts attention from how much students contributed to how their contributions were experienced within collaborative work.

Instructor Role in Open-Ended Team Work: Our findings show that students treated instructors as facilitators instead of authorities align with principles from inquiry-based learning, which emphasize learner-driven exploration and sensemaking [37]. Prior work suggests that such approaches support deeper understanding by making learning driven by curiosity instead of prescribed solution paths. In this study, students sought instructor input during moments of uncertainty, but engaged with it as one of the perspectives among several other options. Teams compared instructor suggestions with their own ideas, weighed trade-offs, and retained ownership over final decisions. This pattern suggests that open-ended team projects can position instructors as facilitators who support inquiry and reflection without resolving ambiguity, highlighting how inquiry-oriented instructional roles can be enacted through collaborative negotiation.

Design Implications: Our findings suggest several implications for designing, supporting, and evaluating collaborative open-ended work in computing education. **First,** decision conflict across teams indicates that disagreement is a natural part of open-ended problem solving and not a sign of ineffective collaboration. Students navigated ambiguity through discussion, comparison of alternatives, and negotiated decision-making, often treating instructors as collaborative resources instead of final authorities. This points to an instructional role centered on facilitating negotiation and supporting sensemaking. Instructors can encourage this process by prompting teams to justify alternatives, articulate assumptions, or explain decisions made after disagreement, while preserving student ownership. **Second,** peer evaluation functioned as a socially grounded assessment mechanism, reflecting how contributions were valued within teams beyond visible activity alone. Differences between self- and peer evaluations suggest that peers drew on situated knowledge of team interactions when forming judgments. In addition to serving as a scoring tool, peer evaluation can provide instructors with insight to guide formative feedback, such as identifying perception mismatches or highlighting contributions that supported coordination and decision-making. For researchers, peer evaluation offers an analytic lens into collaborative sensemaking that complements interaction-based analyses.

6 Limitations

This study is based on a single project-based visualization course at one institution, which may limit the generalizability of the findings. Future work can examine similar collaborative dynamics across multiple courses and institutional contexts. In addition, our analysis relied on interaction logs, participation metrics, and peer evaluations, which did not capture informal or unrecorded interactions or students' internal reasoning. Future studies could combine log data with interviews or reflective methods to provide a more complete account of collaborative sensemaking. Finally, this work is exploratory, aiming to characterize collaborative processes without establishing causal relationships. Future research can extend this work through longitudinal designs to examine how instructional choices shape collaboration and peer evaluation over time.

7 Conclusion

This study examined how students in a project-based visualization course navigated open-ended problems, managed disagreement, and resolved internal conflicts, as well as how these behaviors shaped peer perceptions. By analyzing sustained team discussions on an online platform alongside peer evaluations across multiple project phases, our findings highlight the limitations of relying solely on simple participation counts. Instead, the results underscore the importance of considering the substance of students' contributions, their impact on group decision-making, and the broader collaborative context in which those contributions occur. These insights offer implications for researchers and system designers working on collaborative learning environments.

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