Collaboration at Scale: Exploring Member Role Changing Patterns in Collaborative Science Problem-solving Tasks

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ABSTRACT

Our work-in-progress paper explores students' role-changing patterns while working on science tasks in small groups. Grounded on the Collaboration Conceptual Model, we examined how members in 15 middle school student groups changed their roles throughout the entire collaborative activities. We annotated students' role changes at a one-minute segment, as well as the overall group collaboration quality at the individual task level for each student group. Our analytical approach involved hierarchical cluster analysis and non-parametric statistical tests to identify the relationships between students' role-changing patterns and collaboration outcomes. Preliminary results identified two distinct group types that showed different patterns of role changes and manifested different group collaboration qualities and performances. We discuss how this work is of interest to the Learning@Scale community in promoting effective collaboration at scale in authentic classroom settings.

CCS CONCEPTS

• Applied computing → Collaborative learning.

KEYWORDS

collaborative patterns, collaboration quality, science education,K-12 education

ACM Reference Format:
Hui Yang, Nonye Alozie, and Arif Rachmatullah. 2022. Collaboration at Scale: Exploring Member Role Changing Patterns in Collaborative Science Problem-solving Tasks. In *Proceedings of the Ninth ACM Conference on Learning @ Scale (L@S '22), June 1–3, 2022, New York City, NY, USA.* ACM, New York, NY, USA, 4 pages. https://doi.org/10.1145/3491140.3528319

1 INTRODUCTION

Collaboration is considered as one of the twenty-first-century skills [10]. Broadly speaking, collaboration engages members working towards solving a problem together [16]. In contrast with individual attempts and autonomy, collaboration emphasizes teamwork and community [17]. Given its potential benefits to promoting students' motivations for STEM learning as well as to engage students in discussions and active interactions with course materials, many scholars and educational documents have emphasized the importance of fostering students' collaboration skillsets [15]. For instance, the Next Generation Science Standards (NGSS) suggest incorporating collaborative activities into science instructions such as when students design and conduct a scientific investigation [20]. Hence, understanding the dynamic nature of how students collaborate is imperative, especially to aid teachers with pedagogical practices that can support and reinforce students' learning in a collaborative environment [22].

A prior study has indicated that group members respond differently to the other members' behaviors and talks during collaborative activities [13]. Such interactions among group members, however, are complex because interactions can change from moment to moment as group members reshape their ideas together while assuming various roles in the process. For example, one group member may be guiding and leading others [5] in one moment then transition into a role of conflict solver in another moment. Therefore, understanding members' interactive behavioral patterns are crucial to understand a fuller picture and evaluate the collaboration process and outcomes [12, 14].

https://doi.org/10.1145/3491140.3528319

2 RELATED WORK AND RESEARCH QUESTIONS

2.1 The Collaboration Conceptual Model

Our work is grounded on the "interactions" paradigm which focuses on the characteristics and processes of interactions during collaboration [7]. We developed a multi-tiered collaboration conceptual model (CCM) and the CCM rubric which distilled the individual characteristics and collaborative interactions. The framework and rubric are based on studies that have attempted to parse out the complexity of collaboration through the use of constructs like teamwork and cooperative learning [3].

Teamwork highlights the structural and interpersonal interactions between group members [2]. In the CCM and CCM rubric, we referred to prior work studying teamwork to define the overall group collaboration quality. The overall group collaboration quality defines the cohesiveness of the interactions and the distribution of labor among group members, including the usage of communication strategies. The overall group collaboration quality locates in the highest order of the CCM and consists of five rankings from "1 (Need Improvement)" to "5 (Effective)".

Cooperative learning distinguishes specific individualized behaviors and interactions among group members during teamwork (e.g., [13]). The CCM and CCM rubric presents seven types of individual roles exhibited in collaboration based on cooperative learning literature, including "Contributor" and "Follower" (e.g., [5]). For instance, behavioral and verbal evidence for the role of "Contributor" is "solv[ing] problems interdependently by engaging with other students (behavioral)" and "expres[ing] difficulty with the problems, either by making errors or asking questions that indicate they are confused (verbal)".

The CCM and CCM rubric presents the progression on how individual behaviors lead to the overall group quality based on a series of nuanced collaborative behaviors. Such behaviors include hands and body movements and positions, facial expressions, and utterances. These various types of collaborative behaviors are then aggregated and combined into explaining specific individual roles and the overall group quality [1].

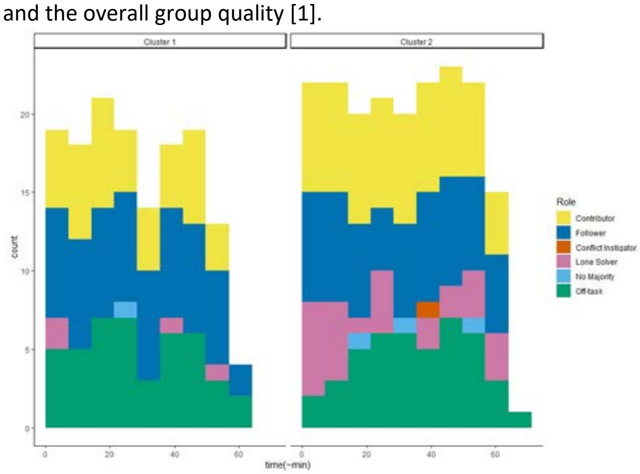

Figure 1: Histograms on Collaboration Duration and Role Frequencies for Both Clusters.

2.2 Studying Collaboration in Different Contexts

Emerging work focusing on assessing collaboration at scale has been situated in computer-supported or virtual/online settings [11]. For example, Liao and colleagues [18] studied 109 seventh-grade students' behavioral patterns in a digital game-based learning (DGBL) environment and found out that combining collaborative learning with instructional video supports students' learning outcomes in the DGBL context. Moreover, a recent study examined 116 triads who collaborated in a programming task in the online conferencing setting and analyzed participants' interactive patterns throughout the collaboration process [21]. The study found that certain behaviors influenced participants' task performance (e.g., limited speech without movement negatively related to task performance). In addition, some studies explored collaborative behaviors in classroom settings. For instance, Katuka and colleagues [14] examined middle school students' collaborative dialogue as they worked on block-based programming activities. The study first coded collaborative patterns extracted from collected data in order to understand how students interact with their peers and how such interactions affect their collaborative experience [14]. This study found that specific dialogue acts during the pair programming collaboration such as one student asked a question then their partners sought clarifications positively related to partner satisfaction [14].

To understand and promote effective collaboration at scale, this work-in-progress paper explores middle school students' interactive behaviors which are aggregated into different roles during collaboration in a controlled lab setting. We used our CCM rubric to categorize collaborative behaviors, hence, the current study is different from other reported studies on collaborative patterns which mostly have been grounded on an inductive process of detecting collaborative behaviors. Specifically, this paper answered two research questions:

1) What are the collaboration role patterns exhibited by 15 middle school student groups during collaborative science problem-solving activities?
2) To what extent do collaboration role clusters relate to the overall group collaboration quality, task completeness, and task accuracy?

3 METHODS

3.1 Context

This work was a part of a larger research project aiming to develop an automated assessment on collaboration quality so that teachers could use the information provided by our assessment technology to help students collaborate more effectively. At the early stage of this work, our team used the evidence-centered design framework [19] to develop a total of twelve independent tasks covering science contents aligned with the NGSS [20]. These multi-part science problem-solving tasks consisted of model building and open-ended discussion questions. We then recruited middle school students to complete our designed tasks and documented their collaboration behaviors in a lab setting after school.

3.2 Data Source and Analysis

Video and student artifact data used for this study came from 60 middle school students. Participant students were made up of 35% female and 65% male. On average, participating students reported that they were comfortable in working on the science topics (M = 2.7 out of 4) and collaborating with others (M = 3.4 out of 4). The students formed 15 groups of 3-5 participants. Each student group was video recorded while completing the task packet in a classroom after school for one hour. Each group was required to submit one packet with agreed-upon answers at the end of the collaboration session. Each group was asked to start from the first task and complete as many tasks as they could within the one-hour period.

Before analyzing the 15 groups of video and student artifact data, 3 trained education researchers scored each task packet for each group using a scoring rubric. Twelve education researchers independently observed and annotated video data using our CCM rubric in two ways: 1) students were assigned a role for every 1-minute segment, and 2) each group was assigned a group collaboration quality rating for each task.

After scoring the student artifacts, we extracted the most frequently appearing individual roles in a one-minute segment to represent the dominant role for each group at that moment. Accordingly, each group had a representing collaboration role per minute across the entire collaboration process. For instance, the cumulative roles for a group during a 3-min task is as follows: “Follower, Follower, Contributor (“FFC”)...” meaning that most group members exhibited the “Follower” role in the first two minutes (“FF”) and “Contributor” role in the third minute of the task. The final dataset contains 15 role sequences to represent how the collaboration role changed over time.

We employed hierarchical cluster analysis to examine the sequential pattern clusters of collaboration roles among the 15 student groups [6, 9] . Subsequently, we ran non-parametric Mann-Whitney U tests [8] to further explore the relationship between the group level role-changed patterns (collaboration length and breadth) and the role proportions for each sequence. Collaboration length refers to the actual time that student groups worked on the tasks while collaboration breadth refers to the distribution of role changes from one minute to another [4, 12]. Finally, we compared the overall group quality and the collaboration outcomes on the task completeness and accuracy for the clustered groups.

4 PRELIMINARY RESULTS

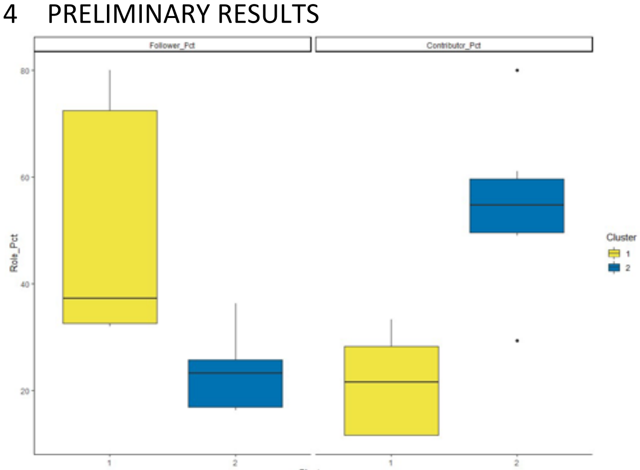

Figure 2: Boxplots on the “Follower” and “Contributor” Weights in Both Clusters.

4.1 RQ1. What are the collaboration role patterns exhibited by 15 middle school student groups during collaborative science problem-solving activities?

The hierarchical cluster analysis categorized two group-level collaboration role patterns based on 15 sequential data containing approximately 900 role change patterns. The first cluster contains 5 student groups, and the second cluster contains 10 student groups. Figure 1 shows the histograms for both clusters on the role changing frequencies during the entire collaboration process.

These two clusters showed different role-related patterns – collaboration length and breadth. The second cluster (n=10) exhibited a slightly higher median on the collaboration length (54.5 minutes versus 52 minutes) and a higher breadth on role changes (0.52 versus 0.40) compared with the first cluster group (n=5). These differences in collaboration length and breadth are not statistically significant based on the non-parametric Mann-Whitney U tests. The two clusters, however, showed differences in the weight of certain roles. As shown in Figure 1 and Figure 2, the first cluster contains significantly more “Follower” roles (37.3%) compared with the second cluster (23.3%) ($W = 48$, $p < .05$). The second cluster contains significantly more “Contributor” roles (54.7%) than the first cluster (21.6%) ($W=1$, $p < .05$). There were no significant differences in the other role proportions such as “Off-Task” between the two clusters.

4.2 RQ 2. To what extent do collaboration role clusters relate to the overall collaboration quality, task completeness, and task accuracy?

We detected two clusters based on the hierarchical cluster analysis: the first cluster with 5 student groups contained more “Follower” while the second cluster with 10 student groups consisted of more “Contributor”. We further explored how these two clusters (“Followers” versus “Contributors”) were distinct from each other on the overall group quality and task completeness and accuracy.

The “Followers” cluster (n=5) completed slightly statistically significant more tasks (9 versus 6) compared to the “Contributors” cluster (n=10) ($W = 41.5$. $p < .05$). However, there is not a statistically significant difference in task accuracy between these clusters. This shows that even though the “Followers” cluster completed more tasks in the same amount of time, the accuracy of their responses did not show a statistically significant difference.

As shown in Figure 3, the majority of group qualities in the “Contributors” cluster were ranked in the “progressive” stage or above. The “Followers” cluster group received more ranking on the “needs improvement” and “progressive” rank. In terms of the overall group collaboration quality, the “Contributors" cluster was found to have a higher overall collaboration quality compared to the “Followers” cluster group (W = 1178.5, $p < .05$).

5 DISCUSSION AND NEXT STEPS

In this study, we examined 15 groups of collaboration role change patterns in controlled lab settings. We focused on the aggregated interaction behaviors among group members and examined the differences in collaboration outcomes that resulted from the role patterns. Our findings showed that two clusters, the “Followers” and the “Contributors”, with different dominant participant roles had distinct collaboration quality. On average, the “Contributors” tended to have a higher collaboration quality but often spent more time on collaborating tasks with fewer completed tasks; the “Followers” tended to have a lower collaboration quality although the groups within this cluster were able to progress through the tasks more quickly. These two clusters had similar collaboration performance even though the “Contributors” cluster completed lesser tasks. Such patterns indicate that collaboration groups that may spend more time to complete a task and may also allow group members to contribute more or be in the role of a contributor more often. When the group shows equal distribution of intellectual and physical labor while completing the tasks, this may result in a higher collaboration

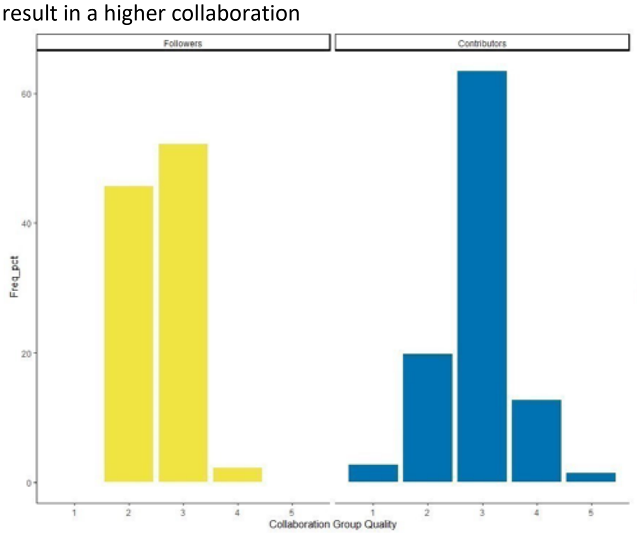

Figure 3: Bar Charts on Overall Group Collaboration Quality for Both Clusters.

quality for the entire group without diminishing the quality of the student artifacts produced as a group. On the contrary, we found that although a group may complete the tasks quickly, if students are mainly following along with little contributory engagement, they are likely to have a lower collaboration quality. This is consistent with teamwork and cooperative learning theories that advocate for group interdependence, individual accountability, and structural and interpersonal interactions [13]. We plan to continue examining individual role-related patterns’ effect on collaboration quality and performance as we collect more data.

Although prior work examining collaboration at scale has been situated in the technology-assisted learning environment, our work shows potential in analyzing collaborative behaviors in the everyday classroom using the CCM-based verbal and behavioral evidence to identify effective/ineffective collaboration. Our preliminary findings indicate that specific behavioral and verbal cues used to define specific roles, like “Follower” and “Contributor”, could become evidence to determine how well students are collaborating and how effective collaboration interactions exist within a group. Considering that substantial amounts of human efforts and resources were investigated in annotating all the 15 videos, future work, based on our CCM and rubric, could develop machine learning models which include specific individual roles along with other features in predicting the overall group collaboration quality so that human efforts could be reduced on assessing the group overall quality.

ACKNOWLEDGMENTS

We would like to thank our participants and to everyone who has been supporting the data collection process and the video annotation work for this project. We thank Dr. Shiyan Jiang for her valuable feedback on this paper. This material is based upon work supported by the National Science Foundation under Grant # 2016849 and an internal SRI International research and development grant. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the aforementioned funders.

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