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An unobtrusive approach to modelling team cohesion and collaboration in ecological classroom settings

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ABSTRACT

Background: Cohesion and collaboration, particularly in K-12 settings, emerge as emergent phenomena, yet due to challenges in conducting classroom analytics studies in ecological settings, existing research mainly focuses on surveys. This calls for investigating cohesion in ecological settings to obtain insights directly applicable to students.
Aims: To derive ecologically valid insights into the emergent processes of cohesion and collaboration, this study analyses engagement, turn-taking, member influence and participation imbalance (using weighted eigenvector centrality) exhibited in audio of student conversations at both individual and group levels, which allows for inter-group and intra-group comparisons.
Sample: Participants were 16 school (K-12) students.
Methods: Participants were randomly divided into four groups. High-frequency communication exchanges were recorded for each group using an analog audio recorder. The audio was transcribed and analysed using an adaptation of Social Network Analysis with segmented nodes.
Results: Consistent with findings in educational and organisational psychology literature on teamwork, the results indicate that task cohesion relates to group performance in terms of task completion. We find that social cohesion patterns are dynamic and reflect evolving group dynamics through variations in turn-taking, influence, engagement and disengagement.
Conclusion: The study offers a conceptualisation of cohesion in ecological settings and demonstrates an approach to analysing cohesion and collaboration using audio data in authentic classrooms.

1. Introduction

Ongoing communication and active participation in collaborative work are essential traits of effective team members. Educational technology research (Ferguson & Buckingham Shum, 2012, pp. 23–33) has explored modelling learner interactions to equip learners with collaboration skills. In particular, there is growing interest and potential in developing analytics approaches to understand the relationships between learner interactions and performance (Bossche et al., 2011; Han et al., 2021) and, ultimately, support collaborative learning in face-to-face (co-located) classrooms (Dillenbourg, 2021).

A critical concept for studying and supporting collaborative learning processes is group cohesion. While cohesion is often studied in long-term or professional team contexts, we argue that it is equally critical in short-term K-12 collaborative settings, where students engage in the joint construction of knowledge. Cohesion is central to effective collaboration and plays a foundational role in developing skills essential for lifelong learning (Dascalu et al., 2015, pp. 350–354). Although research on cohesion as a holistic construct composed of task cohesion (group members' alignment with the group's common goal) and social cohesion (connectedness as a group) (Carron et al., 1985) is currently found mostly in higher education settings (Zamecnik et al., 2022, 2023), it is also relevant in K-12 contexts to enable co-construction of knowledge with their peers.

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Although cohesion has not been explored much in K-12 settings, evidence from higher education research suggests that cohesion in student design projects enhances knowledge sharing and better team performance (H.-H. Yang & Lin, 2022). In turn, knowledge sharing and team effectiveness have been associated with individual learning gains in team-based learning environments (Lin & Huang, 2020). The importance of investigating and supporting collaboration and teamwork is well established in both higher education and K-12 contexts (Thornhill-Miller et al., 2023). We posit that exploration of cohesion in K-12 contexts holds significant merit; given that, similar to collaboration, cohesion has been investigated widely in higher education (Grossman et al., 2022; Thornton et al., 2020; Zamecnik et al., 2023) and may apply similarly in K-12 environments. Cohesion is also one of the core constructs within the collaboration process (Bossche et al., 2006) and is therefore an essential construct when assessing and supporting collaboration in any setting.

Since student learning in schools comprises of terms composed of classes divided into several weeks short-term collaborative interactions in individual classes can promote student engagement (Yan et al., 2025), support equitable participation (Hogenkamp et al., 2021), and contribute to long term skill development in collaboration, and ultimately, overall student learning. Empirical evidence from classroom studies in higher education suggests that cohesion, characterised by balanced participation, clear communication, and mutual responsiveness, can emerge rapidly and is predictive of task performance even in activities lasting under 1 h (Hendry et al., 2016). These short term experiences, particularly social relations shaping social cohesion, accumulate over time and contribute to a positive social climate, which in turn links to students' sense of belonging and positive school outcomes (Veerman & Denessen, 2021), . Moreover, educators frequently utilise brief collaborative tasks to scaffold peer learning (X. Yang, 2023), which ultimately makes the formation of effective group dynamics within these limited timeframes essential for instructional effectiveness. Therefore, analysing and understanding the emergent dynamics of cohesion within short-duration K-12 collaborations is both pedagogically significant and practically imperative for enhancing classroom practices.

Group cohesion manifests in two ways: (1) the commitment of members to a common goal, known as task cohesion, and (2) their social connectedness as a group, referred to as social cohesion (Carron, 1982). Research has consistently shown a positive association between cohesion and group outcomes. While social cohesion plays an important role when outcomes are defined as behaviors, task cohesion consistently relates to behavioral and outcome-based performance measures (Beal et al., 2003; Chiocchio & Essiembre, 2009). Behavioral performance measures assess efficiency in terms of desirable behaviors, while outcome-based measures assess effectiveness characterised by outcomes (e.g. completion of tasks). A recent meta-analysis (Grossman et al., 2022) concludes that cohesion is a multidimensional construct with unique influences from individual facets (Grossman et al., 2022). Therefore, it is crucial to understand and analyse cohesion *as it develops* during student interactions to support collaboration in co-located classrooms.

However, analysis of collaboration and cohesion in classrooms remains a challenge and an open question in two ways. Firstly, self-report questionnaires alone remain the most popular approach to measuring collaboration and team cohesion (Salas et al., 2015). Such approaches are intrusive, time-consuming and rely solely on measuring attitudes, overlooking the importance of observable behaviors (Kovanovic et al., 2023). Particularly in collaborative learning classroom settings involving high-frequency communication and emerging interactions, such approaches do not allow investigation into the developing processes of collaboration and cohesion. Self-report measures of collaboration can also be inaccurate due to social desirability bias (Kormos & Gifford, 2014). Secondly, of the limited number of studies that use emergent and multimodal data to examine collaboration unobtrusively, most are conducted in lab settings (Cukurova et al., 2020) or involve non-student participants. This results in a lack of contextual and ecological relevance and limits the generalisability and applicability of research findings. To understand emerging collaboration, there is growing emphasis on the need for ecologically valid studies in authentic classroom settings using unobtrusive methods (Schneider et al., 2024).

Innovations in technology, data collection, and analysis methodologies have enabled unobtrusive approaches to measure and support learning processes (Dawson, 2023), specifically cohesion (Kozlowski & Chao, 2018). Among others, interaction frequencies and information exchange (Kidwell et al., 1997), and dominance of members (Jayagopi et al., 2009) have been used as proxies to measure cohesion. For instance, Zhang et al. (2018) used sociometric badges to track the duration, frequency, and proximity of interactions, while Hung and Gatica-Perez (2010) measured cohesion through non-verbal cues, dialogue acts, turn-taking and interruptions by applying statistical, correlation and regression analyses. Social network analysis has also been applied to student interactions to identify engagement during collaboration. For example, Saqr et al. (2018) extracted individual and group-level insights on student engagement using Social Network Analysis (SNA) of online learner interactions to identify isolated and active students. However, these existing studies that unobtrusively analyse cohesion and collaboration mainly focus on online environments. Thus, investigating cohesion during face-to-face collaborative learning is still an open question.

In this paper, we conducted a collaborative activity in an authentic K-12 classroom to unobtrusively measure cohesion and collaboration by analysing student conversations, turn-taking and team member influence. Engagement, conceptualised as participation, is operationalised such that participation in on-task conversations represents on-task engagement, and participation in off-task conversations indicates off-task engagement. Most research on classroom collaboration relies on simulated settings or non-student participants. To address this gap, we analyse team member interactions using network graphs to measure cohesion and collaboration at both group and individual levels. Doing so enables intra-group and inter-group comparisons. We examine members' contributions to social and task cohesion by visualising separate networks for on-task and off-task conversations. Finally, we analyse cohesion over time by dividing the activity duration into four periods – two for building and two corresponding to iterative testing – and visualise network graphs for each period. We show that when task cohesion is operationalised as on-task conversations and social cohesion as off-task conversations, groups with high task cohesion achieve better task completion. Although social cohesion does not exhibit a clear relationship with performance, it may contribute to group dynamics and long-term sense of belonging. The resulting insights expand the theoretical understanding of cohesion and collaboration in small, co-located teams in ecological settings. The analytic approach also has the potential to help teachers understand the evolution of cohesion and collaboration and informs teaching strategies to support these emergent processes.

2. Background

2.1. Groups processes as socio-cognitive processes

Collaborative learning involves students working together towards a common goal, face-to-face or online (Dillenbourg et al., 1996). For this study, group processes are classified as task-related (cognitive) and non-task-related (social), adapted for conversational classroom data. Prior research (Olivera & Straus, 2004) has similarly established cognitive and social as two main perspectives on collaborative work. Further research (Bossche et al., 2006) highlights the role of interpersonal and socio-cognitive processes in fostering shared understanding and enhanced group performance. Bossche's findings (Bossche et al., 2006) highlighted the importance of both social interactions and thinking processes in enabling effective team learning and collaboration. Cognitive processes necessary for deeper learning occur in dialogues and often result from social processes (Van Der Linden and Renshaw, 2004). Early research stresses the importance of social interactions and the interplay of cognitive and social processes in building collective knowledge structures and promoting group productivity (Cohen, 1994).

Effective collaboration depends significantly on context-specific interactions, emphasising both cognitive and social elements that shape group communication and shared understanding. In classroom settings, collaborative work typically involves student discussions, focusing on task cohesion—the commitment to the group task (Mullen & Copper, 1994) – and social cohesion, characterised by interpersonal relationships (Festinger, 1950; Salas et al., 2015). Experimental and correlational research has previously conceptualised cohesion as task-related and non-task-related, interpersonal (Hirunyawipada et al., 2010; Susskind & Odom-Reed, 2016). Team interactions thus involve task-focused and social bonding elements, influencing cohesion. In such settings, engagement in on-task and off-task conversations serves as proxies for task and social cohesion, respectively.

2.2. Group cohesion

Cohesion emerges as an important construct during the socio-cognitive interactions of collaboration. Cohesion has been defined as shared task commitment and connectedness of group members to the group's goals (Mullen & Copper, 1994). In this paper, we adopt a multidimensional view of cohesion, focusing on two dimensions of cohesion (Salas et al., 2015), namely, task cohesion and social cohesion. Specifically, we define task cohesion as the shared commitment of group members to achieving the group's goals (Carron et al., 1985; Festinger, 1950). Similarly, social cohesion is defined as the closeness of group members based on social attraction towards other members (Carron et al., 1985; Seashore, 1954).

From early works on cohesion-performance relationships (Mullen & Copper, 1994) to more recent findings (Beal et al., 2003; Salas et al., 2015), cohesive groups perform better than non-cohesive groups. The relationship between cohesion and performance is bidirectional; not only does cohesion boost group success, but success also fosters cohesion (Forsyth, 2014). While task cohesion directly predicts performance, social cohesion contributes to system viability, albeit with a less direct impact on performance (Chang & Bordia, 2001; Gilbert & Moore, 1998). Despite this, the role of social cohesion in creating a conducive learning environment cannot be overlooked. Thus, measuring both dimensions of cohesion is essential to understanding cohesion as a whole and enhancing collaborative effectiveness.

2.3. Measuring Group cohesion

Cohesion has traditionally been measured across contexts using the Group Environment Questionnaire (GEQ) (Carron et al., 1985; Zamecnik et al., 2022). However, these self-report methods have limitations, particularly in scalability and providing an emergent, temporal insight into cohesion dynamics (Marks et al., 2001). Recent advancements advocate for unobtrusive approaches (Salas et al., 2015), multimodal analyses approaches (Chejara et al., 2024, pp. 800–806; Feng et al., 2024, pp. 587–597; Praharaj, Scheffel, Drachsler, & Specht, 2021), and audio analyses to extract verbal and non-verbal indicators (Kim et al., 2015, pp. 1645–1649; Praharaj, Scheffel, Schmitz, et al., 2021) to assess cohesion more holistically. For example, Social Network Analysis (SNA) has been effectively used to track cohesion in distance learning courses through communication patterns (Reffay & Chanier, 2003).

Previous research has used engagement as an indicator of cohesion. Members of a cohesive group feel connected and are likely to engage in frequent interactions and information exchanges (Kidwell et al., 1997). The engagement of groups with the tasks and their social engagement are workflow manifestations between individuals in learning (Gasevic et al., 2017; Joksimovic et al., 2019). Research by Mesmer-Magnus and DeChurch (2009) indicates strong associations between information sharing, cohesion, and performance outcomes. Cohesion can also be inferred unobtrusively through non-verbal cues, speaking time, turn-taking frequency, and dominance behaviors within group interactions (Hung & Gatica-Perez, 2010). Additionally, to measure cohesion, the dominant behavior of members could negatively impact social dynamics and cohesiveness in a group (Jayagopi et al., 2009). Overall, advancement in educational technologies, data collection, and processing methodologies has opened possibilities to provide collaboration analytics that enable timely feedback and interventions.

While CSCL research offers valuable insights, the specifics of face-to-face interactions warrant special consideration. In such settings, learners often form fully connected groups, where all members are directly linked, unlike in CSCL. Although network analysis has been applied to study collaboration in these settings, particularly through multimodal sensor data analysing movement and positioning (Echeverria et al., 2018, pp. 74–78; Martinez-Maldonado et al., 2020), group cohesion using audio data from live interactions has not been thoroughly explored. We address this gap by applying network analysis to unobtrusively assess emergent cohesion through levels of engagement in on-task and off-task interactions, member influence, and turn-taking. Member influence reflects dominance in interactions, while turn-taking indicates dialogue shifts from one speaker to the next. This study combines these indicators to provide a comprehensive view of cohesion and enables adoption into future real-time analytics systems to enhance collaborative effectiveness.

3. Research questions

Most learning in K-12 schools takes place in classrooms with frequent student interactions, yet research on face-to-face collaboration and cohesion in these settings is limited. Research often focuses on online learning or relies on surveys that capture attitudes alone without considering observable behaviors. Supporting cohesion in co-located classrooms requires modelling student interactions as they emerge. Secondly, due to the challenges of conducting research in authentic classroom settings, most research occurs in simulated environments which lack ecological validity. Conducting research in authentic settings using unobtrusive approaches can be challenging due to (i) the difficulty in aligning research activity design with the curriculum, (ii) the difficulty in scheduling and execution (data collection) and the frequent stakeholder communication needed, and (iii) logistical challenges including the need for specialised data collection equipment to capture interactions in noisy classrooms. To address this need, this exploratory study assesses collaboration, social cohesion, and task cohesion using interaction data obtained from student conversations. We investigate the following research questions.

1. How do observed patterns of individual and group-level task and social cohesion relate to group performance?

Research Question 1 examines overall patterns of task and social cohesion through network graphs visualising team interactions, turn-taking, individual member influence and disparities in influence in groups across the full activity duration. We assessed cohesion at both individual and group levels.

2. What patterns emerge in off-task versus on-task communication networks?

Research Question 2 analyses differences in task and social cohesion by distinguishing patterns in on-task versus off-task networks. It uncovers patterns specific to on-task and off-task networks that could otherwise not be identified.

3. What observations can be made regarding evolving temporal states of task and social cohesion at four intervals during 1 h of activity?

Research Question 3 examines how task and social cohesion evolve over time. We analysed temporal patterns by segmenting the activity into four intervals and creating network graphs. The first two networks corresponded to the building, and the last two to iterative testing.

4. Methods

4.1. Study context

The study took place at a private urban K-12 school in South Australia, where students participated in a Lego Mars Rover building challenge as part of their regular robotics lesson. The activity utilised Lego Mindstorms kits to build and program robots. Sixteen Year 9 students (11–14 years old) worked in four teams to build, program, and iteratively test robots to navigate increasingly difficult Mars terrains within 1 h.

4.2. Study data

Audio conversation data was collected to study communication and group dynamics during collaborative learning. An ethics clearance was obtained from the Research Ethics Committee to collect and analyse audio and video data. Additionally, the school granted clearance given the existing overarching parental consent for similar activities.

Audio data was recorded using ReSpeaker analog recorders placed at each table. Webcams aided speaker identification, and recordings were synchronised using Filmora[1] software. Three researchers oversaw data collection and validating observations for consistency. Professional transcription captured each utterance's start time, speaker, and content. Anonymity was maintained with generic speaker identifiers (Spk 1 to Spk 4). Utterances post-activity and indistinct speech were excluded, totaling approximately 130 out of over 5000 utterances.

Conversation content was coded for on-task and off-task interactions using a systematic approach (Strijbos et al., 2006). Each team's transcript was divided into segments of five utterances to retain contextual flow. Two coders independently coded an initial set of 30 segments per team, reaching inter-coder agreement above Cohen's Kappa >0.81. Discrepancies were resolved through discussion to ensure consistency. Once reliability was established, the remaining segments were split between the coders for independent coding. Utterances involving any conversations unrelated to the problem-solving robotics activity were coded as off-task. For instance, "Are you going to the school camp?", "Do you know the song …" and "I'm going shopping with mom" were classified as off-task conversations.

4.3. Analysis procedure

To analyse cohesion during collaborative learning activities, we employed bidirectional, weighted network graphs visualised using the Fruchterman-Reingold (Fruchterman & Reingold, 1991). The analysis was implemented using Python and the NetworkX library.[2] In these constructed network graphs, nodes represented individual team members, and edges represented turn-taking interactions between speakers. The size of each node represents the total number of utterances initiated by that node. The edge weight between two nodes represents the number of turns exchanged between the corresponding speakers. For example, when an utterance by Spk 1 is followed by Spk 2, it signifies a turn between Spk 1 and Spk 2; hence, the edge weight between Spk 1 and Spk 2 increases by 1. Additionally, since the turn was initiated by Spk 1, the node size for Spk 1 (the initiating speaker) increases by 1, and the edge width, representing turn-taking frequency, increases by a count of 1.

In our adapted Social Network Analysis (SNA), we retained the conventional edge representation, meaning edge weights continue to reflect the total number of turns between speakers irrespective of utterance type. However, we modified the node representation by categorising and counting speaker utterances explicitly into two types: on-task and off-task. Each node thus visually displays both the aggregate number of utterances initiated by each speaker and their proportional distribution into on-task versus off-task utterances (see Results section for visual illustration).

This adaptation did not structurally alter the underlying Fruchterman-Reingold algorithm for SNA. Rather, we refined the default representation of nodes (typically a single variable in NetworkX) by segmenting the speaker utterances into distinct categories (on-task and off-task). Consequently, our adapted approach provides a richer and more nuanced representation of individual contributions during collaborative interactions.

4.3.1. Network analysis for each team (RQ1)

For each team, we constructed an overall network graph to analyse on-task vs. off-task engagement and member influence, quantified using weighted eigenvector centrality. In our network analysis, weighted eigenvector centrality was used as a proxy for individual influence during collaborative conversations. Unlike simple degree centrality, which only counts the number of direct connections a node has, eigenvector centrality also accounts for the influence of connected nodes. Thus, a participant who interacts frequently with other well-connected members will have a higher centrality score. We calculated weighted eigenvector centrality using the weighted adjacency matrix of each group's network, using Python's NetworkX library, where edge weights reflect the frequency of turn-taking between participants. Node positioning in the network visualisations was derived using the Fruchterman-Reingold force-directed layout algorithm. Participants with higher eigenvector centrality tend to be drawn toward the visual center due to their dense and strong connections, whereas those with lower centrality are positioned toward the periphery. We do not manually manipulate node positions based on centrality; rather, centrality and positioning are often correlated in force-directed layouts due to the underlying network structure. We also report the coefficient of variation (CoV) of eigenvector centrality scores within each group to quantify disparities in influence. High CoV values signal dominant or free-riding behaviors, which can impact group dynamics and cohesion (Hall & Buzwell, 2013). Free-riding involves failure of one or more group members to contribute their fair share in group work (Aggarwal & O'Brien, 2008).

4.3.2. On-task vs off-task conversations (RQ2)

To address Research Question 2, we created separate network graphs for on-task and off-task utterances for each team. This allows a comparative analysis of task and social cohesion. The approach highlights differences in member participation, influence, and potential free-riding behaviors across on-task and off-task networks.

4.3.3. Temporal analysis of cohesion

We divided the activity into four segments to capture temporal patterns of cohesion. The first two segments represent building and the last two represent iterative testing stages. This segmentation allowed us to observe the temporal evolution of team networks.

4.3.4. Operational definitions

Group cohesion comprises task cohesion and social cohesion. In the current setting where the source of data is group conversations, similar to the conceptualisations in the past (Bettenhausen, 1991; Hirunyawipada et al., 2010; Susskind & Odom-Reed, 2016; Tan et al., 2022;

[1] https://filmora.wondershare.net/.
[2] https://networkx.org/.

Zijlstra et al., 2012), we conceptualise cohesion as task-related cohesion and non-task-related (interpersonal) cohesion. We operationalise task cohesion as on-task engagement represented by on-task utterances. Similarly, based on evidence from existing research acknowledging off-task behavior as a vehicle to promote trust and rapport building (Hendry et al., 2016), making classrooms a safe house for students (Pomerantz & Bell, 2011), we operationalise social cohesion in teams as off-task utterances. Node positioning in network graphs reflects the distribution of influence, derived from eigenvector centrality, while overall group engagement is visualised in horizontal bar charts distinguishing on-task (task cohesion) and off-task (social cohesion) utterances.

5. Results

Patterns of group cohesion were analysed in relation to the team performances. Team performance was measured as task completion, characterised by the number of terrains completed out of six terrains of increasing difficulties from terrain 1 to 6 (Fig. 1). As shown in Table 1, Group 1 completed their robot build and successfully tested it on 6 out of 6 terrains. Group 3 successfully tested their robot on 3 out of 6 terrains. Group 4 successfully tested on only the first terrain. Group 2, while attempting testing, was unsuccessful at completing any of the terrains/ boards.

5.1. RQ1: overall task cohesion and social cohesion relative to group performance

To analyse social and task cohesion patterns across groups, network graphs were constructed. Each node represents a speaker's on-task utterances in green and off-task utterances shown in red color. Node labels reflect the total count of utterances for each member. The edge thickness between two nodes represents frequency of turn-taking between the respective group members. Additionally, to visualise cohesion at the group level, on-task and off-task utterances and the percentages were visualised in horizontal bar charts. Member influence was quantified by using weighted eigenvector centrality, as illustrated in Table 2.

As shown in Fig. 2, Group 1 showed the highest overall engagement, followed by Group 3. Conversely, comparisons of the number of utterances revealed that Groups 2 and 4 showed significantly lower overall as well as lower on-task engagement than Groups 1 and 3. With over 95 % of utterances being on-task, Group 1 and Group 4 focused on task-related interactions relative to off-task interactions. In contrast, Groups 2 and 3 exhibited relatively higher proportions of off-task interactions, at 38 % and 43 %, respectively.

The analysis of member influence, measured by eigenvector centrality, revealed relatively balanced member influence within Groups 1 and 2. In contrast, Groups 3 and 4 showed higher disparities in member influence (unequal influence), with at least one dominant member

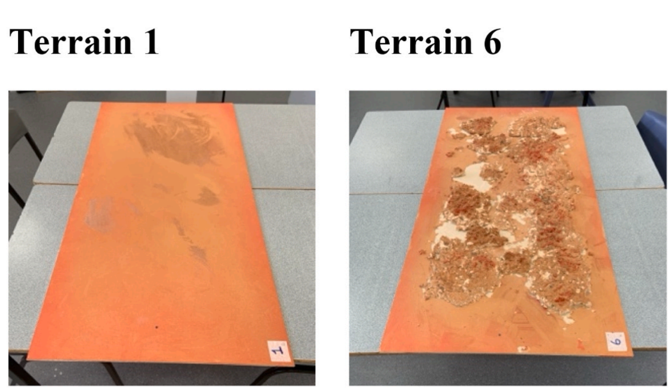

Fig. 1. Images of terrain 1 (least difficulty) and terrain 6 (high difficulty, rocky terrain).

Table 1
Group performance represented by completion of terrains (boards).

Rank (Task Completion)	Group	Number of terrains completed
1st	Group 1	6
2nd	Group 3	3
3rd	Group 4	1
4th	Group 2	0

Table 2
Speaker Influence is measured by the weighted eigenvector centrality of team members. Disparity in influence (or inequality in influence) is measured by the Co-efficient of Variation (CoV).

Speaker	Group 1	Group 2	Group 3	Group 4
1	0.53	0.49	0.53	0.63
2	0.47	0.50	0.62	0.53
3	0.45	0.57	0.41	0.39
4	0.54	0.43	0.41	0.41
Disparity in influence (CoV)	8.69 %	11.77 %	21.15 %	23.14 %

within both groups. The coefficient of variation, displayed in Table 2, further quantifies the key differences by showing larger variations in member influence in Groups 3 and 4.

Finally, to answer Research Question 1, turn-taking patterns were also analysed to investigate interaction dynamics. Group 1 demonstrated collaborative participation through even distribution of turn-taking among all members. Group 2, however, showed distinct sub-groups between Members 1–2 and 3–4. While both Groups 3 and 4 showed a dominant member with high influence, turn-taking patterns in Group 3 showed strong relational connections with less influential members but greater off-task communication. Group 3's network also showed a dominant member with strong connections to peripheral members. The summarised results are also shown below in Table 3.

5.2. RQ2: patterns of task cohesion and social cohesion in on-task vs. off-task utterances

To answer Research Question 2, we created a network graph for off-task and another network for on-task interactions for each group, as shown in Fig. 3. The separate networks showed individual members' participation, member connections in turn-taking patterns, and inequality in member contribution or dominance of members in on-task vs off-task networks. Groups 1 and 3, with high task completion, both showed relatively higher on-task engagement. However, dominance behaviors and turn-taking patterns were different in both groups.

Group 2 showed low but relatively equal participation in the on-task network. However, the off-task conversations had a central dominating member. Group 2 also showed likely sub-group formation; turn-taking patterns showed member pairs with more frequent turns in the on-task and off-task networks. Subgroup formations corresponded to the patterns observed earlier in Fig. 2. The separate networks identify the member pairs focused on the on-task and off-task conversations. On the other hand, in Group 3, conversations in the on-task network were dominated by one member, while the group's off-task network showed relatively balanced participation.

5.3. RQ3: cohesion over time

Finally, to answer RQ3, we investigated cohesion over time by splitting the data for each group into four equal time intervals. Four networks are created for each group to show evolving networks over time. In network visualisations, node sizes can be scaled manually within the NetworkX library. For Figs. 2 and 3, which depict networks based on the entire activity duration, we used the default starting node size because the number of utterances was sufficient to ensure

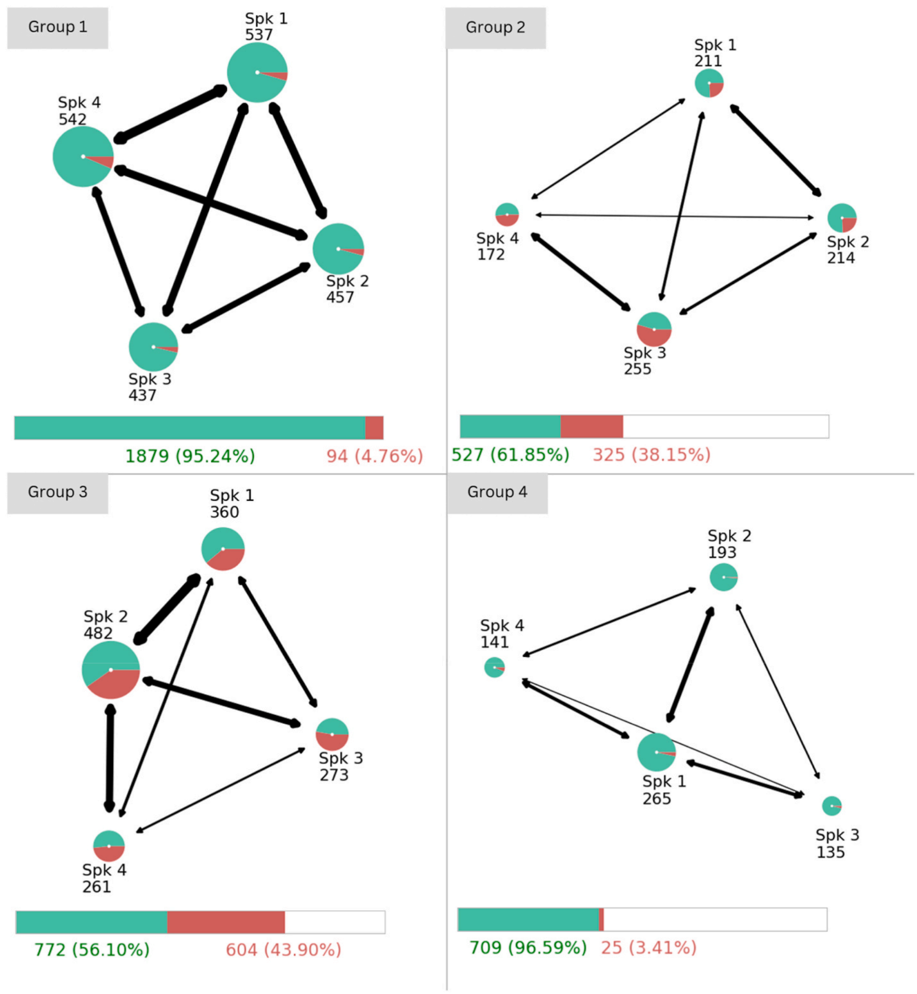

Fig. 2. Overall patterns of task cohesion and social cohesion for each group associated with group performances. To allow comparisons, the lengths of bars are relative to the length of the bar with the most utterances (i.e. Group 1).

Table 3
Summary of results for Research Question 1.

Group	On-task utterances (rank)	Disparity in member influence (CoV)	Turn-taking (Relational connections between members)
1	1st	Low disparity	~ Equally connected
2	3rd	Low disparity	Subgroup formation
3	2nd	Member dominance. High disparity	Dominant member forms stronger connections with peripheral members
4	4th	Member dominance. High disparity	Dominant member forms weaker connections with peripheral members

readability. However, for Figs. 4 and 5, which display networks over four shorter time intervals, the number of utterances in each segment was significantly lower. To preserve visual clarity, we increased the base node size and edge thickness in these figures. As a result, node sizes and edge weights in Figs. 4 and 5 are not directly comparable to those in Figs. 2 and 3 (nor was it an objective of the analysis), and are intended for within-figure interpretation only.

As shown in Fig. 4, Group 1 consistently showed higher engagement over time. The second and third graphs showed slightly greater influence (or mild dominance) from a different member in each of the two networks. Group 2 showed diminishing conversations over time from the first to the fourth graph. Group 2 showed diminishing interactions over time, with pairs alternating between Members 1–2 (task-focused) and Members 3–4 (off-task-focused).

The temporal network graphs for Group 3 (in Fig. 5) showed higher overall member engagement over time. As the activity progressed, Member 2 continued to gain more influence and eventually became central to the network, pushing two group members slightly away from the center to the network periphery. Unlike Group 1, which had the highest task completion, the relatively high-performing Group 3 showed a sharper decline in member participation in the last two graphs.

Group 4 showed the lowest overall engagement over time. However, nearly all conversations were on task. The group started with high influence from a central member, but over time, the distribution of influence became more equal. The growing equality in influence did not emerge with increasing participation and influence from the less influential peripheral members but with the reduced participation and connections of the previously dominant central member.

6. Discussion

This paper presents an analysis of group cohesion using SNA of face-to-face collaborative small group discussions in a secondary school classroom. Cohesion was conceptualised as a socio-cognitive group process consisting of dimensions of task cohesion (cognitive) and social cohesion (social). Task cohesion was operationalised as on-task engagement, while social cohesion was operationalised as off-task engagement. As shown earlier in Table 2, Groups 1 and 3 performed

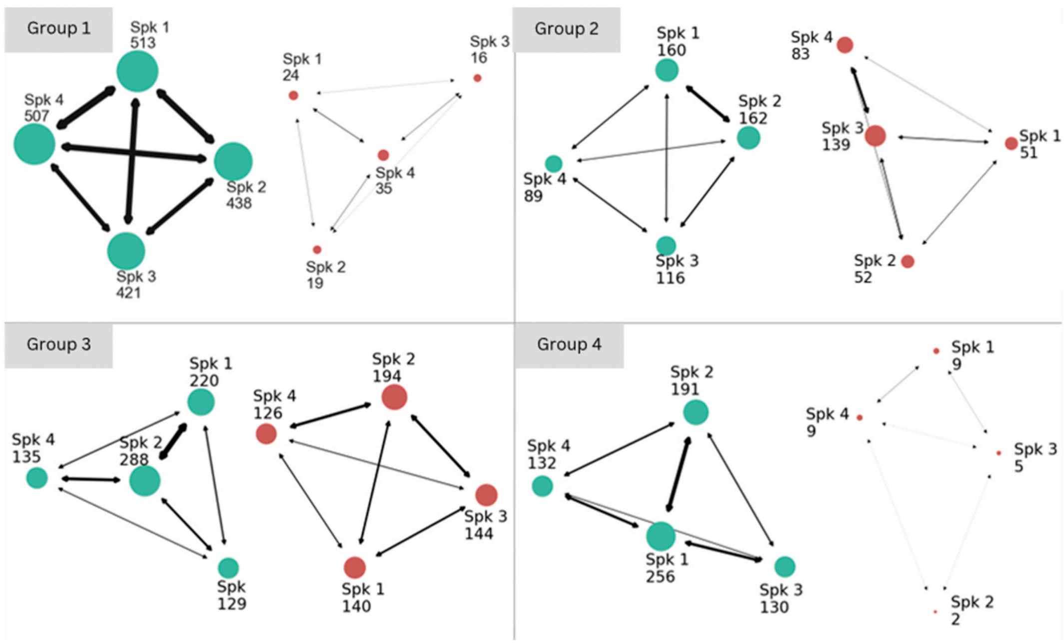

Fig. 3. Patterns of cohesion in off-task vs. on-task communication.

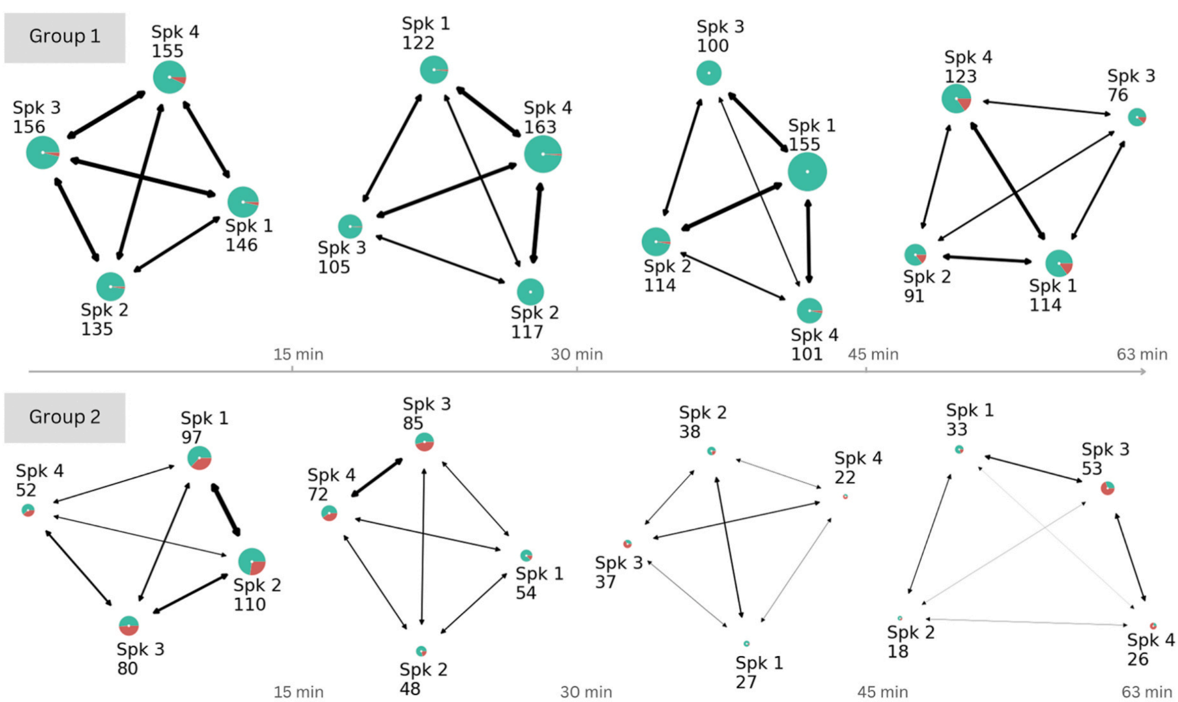

Fig. 4. Emergent patterns of cohesion over time (0–63 min) for Group 1 and Group 2.

highly, while Groups 2 and 4 showed low performance on task completion.

6.1. Research question 1

6.1.1. Groups with higher task cohesion show high task completion

Frequent information exchanges among participants in a group can support cohesion and enhance collaborative learning (Peterson, 2012). Our findings at the group level suggest that the teams with higher task cohesion, determined by high engagement in on-task conversations, performed highly on task completion, regardless of the relative proportion of task cohesion to social cohesion. For example, Group 3, despite lower proportional task cohesion, still exhibited sufficient task engagement, ranking second in performance. A similar inference could not be made about social cohesion determined by off-task conversations. Consistent with prior research (Bossche et al., 2006; Chang & Bordia, 2001; Grossman et al., 2015), task cohesion showed a stronger link with performance compared to social cohesion. We reach a similar conclusion regarding cohesion and performance relationships using spoken interactions in a face-to-face ecological classroom setting.

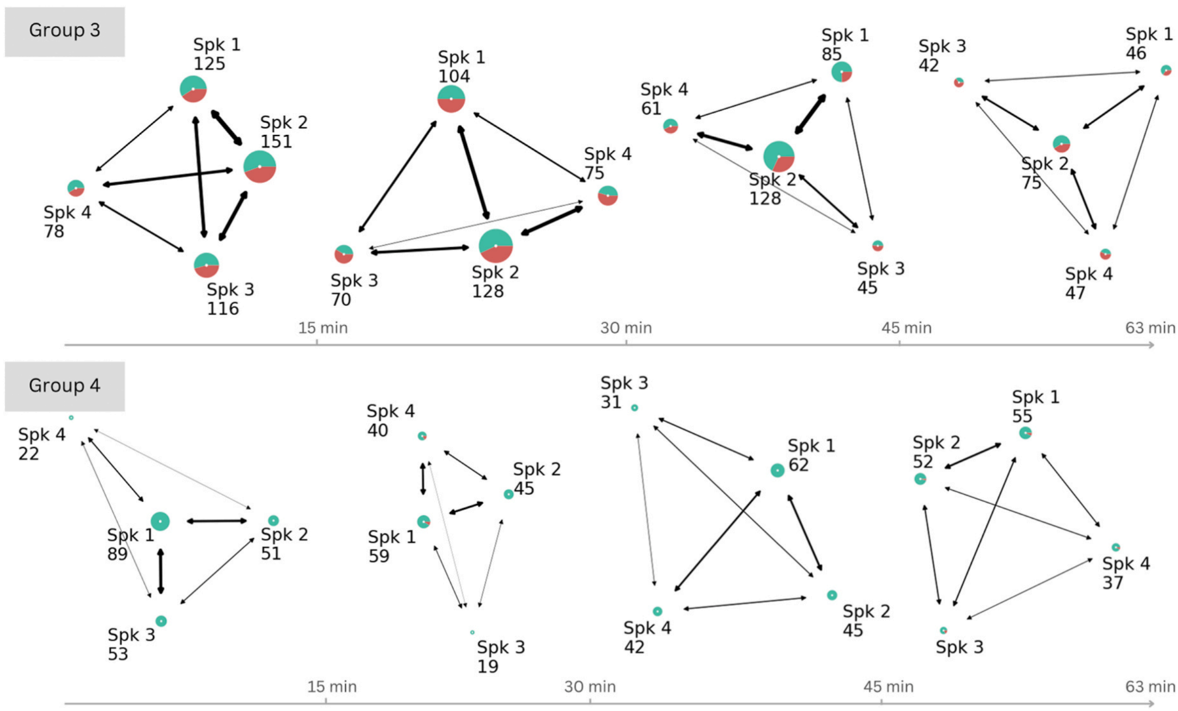

Fig. 5. Emergent patterns of cohesion over time (0–63 min) for Group 3 and Group 4.

6.1.2. Balanced participation and turn-taking patterns as proxy indicators of cohesion

The member engagement and turn-taking patterns in network graphs suggest that the relatively equal participation in Group 2 reflects balanced opportunities for members to contribute. Equality in member contributions and influence can be associated with group cohesiveness. However, the turn-taking patterns in Group 2 (shown in Fig. 2) reveal the formation of subgroups, which complicates this interpretation. Despite equal participation, the formation of task-focused and socially-focused subgroups in Group 2 suggests reduced overall cohesion (Paxton & Moody, 2003). Group 2's subgroup formation into task and social pairs highlights potential barriers to collective group cohesion. Thus, while equal participation might suggest cohesion and collaboration (Fischer et al., 2013), subgroup formation and Group 2's low task cohesion indicate otherwise. The group did, however, show second highest task cohesion, which has not been observed to have a direct link with performance (Grossman et al., 2015).

6.2. Research question 2

6.2.1. Influential group members direct the group's focus

In terms of the second research question (RQ2), Fig. 3 provided additional insights regarding the patterns of task and social cohesion in separate networks. Dominance can positively influence group performance if task-focused, but may hinder performance if primarily socially oriented (Stasser & Abele, 2020). The dominance of socially-focused members, as observed in Group 2, likely constrained task performance. The imbalance suggests that Group 2 was not positioned for members to perform at their best.

In contrast, balanced task and social dominance in Group 3's influential member likely enhanced group cohesion and performance. In groups with unbalanced participation or a highly influential member, the influential member is likely to shape the group's focus. Prior research suggests that task-focused groups perform better on task completion (Bossche et al., 2006). Therefore, predominantly task-focused behavior from the influential member is likely to be conducive to good task-completion outcomes.

6.3. Research question 3

6.3.1. Emergent patterns of cohesion over time

For the third research question, we examined patterns of group cohesion over time (Figs. 4 and 5). Group 3 and Group 4 demonstrated key differences in their network structures. In Group 4, Member 1 initially held a central role but relinquished influence over time, decentralising the network. This shift likely reflects information saturation, where centralisation becomes less efficient for complex tasks (Forsyth, 2014). While decentralisation could increase engagement from other members, it is only effective when those members can match the central member's competence, which was not observed in Group 4.

In contrast, Group 3 maintained a centralised network, with Member 2 consistently at the center across all intervals. This stability in sustained leading behavior suggests that the dominant member may have been successful in effectively managing the group's growing informational complexity. Due to this, the group likely avoided disengagement typically associated with centralisation in complex tasks.

Finally, Group 1 presented shifts in leadership roles over time, which suggests the presence of shared leadership. Although shared leadership has not been directly linked to improved performance, it is positively associated with group cohesion (Mathieu et al., 2015). These findings demonstrate that network analysis, using metrics like eigenvector centrality, can provide deep insights into group cohesion by revealing how engagement, influence, and leadership dynamics evolve over time.

The analytical approach presented here provides educators with insights into cohesion dynamics. However, for educators to adopt such methods in practice, clear translation from analytic insights into actionable strategies is necessary. Below (see Table 4), we provide a concise reference guide demonstrating how educators can practically utilise these insights. The table identifies relevant questions of interest, visual indicators used in our analytic approach, and questions educators might ask to inform their interventions and improve collaborative learning in ecological classroom settings.

Table 4
Reference guide for educators to interpret analytics to inform classroom interventions.

RQ	Analytic component	Information	Questions for Interventions
RQ1 in Fig. 2	Node size = number of utterances. Node pie-slice = green (on-task) vs. red (off-task). Edge thickness = turn-taking frequency. Bar below = total on-task (green) vs. off-task (red) counts + %.	Task-to-social talk ratio. Who spoke most/least. Whether influence is balanced or concentrated. Sub-groups (thick edges only within certain pairs).	Is on-task talk significantly low in some groups? Are one or two students overly dominant (very large central node)? Do I see "cliques" (dense edges only between two nodes)?
RQ2 in Fig. 3	Left: on-task network (all green nodes). Right: off-task network (all red nodes).	Who leads cognitively vs. socially? Whether social talk is evenly shared or driven by a single member.	Is the academic leader *also* social glue? If not, could I buddy them? Are off-task moments inclusive (many red nodes) or exclusive (one red hub)?
RQ3 in Figs. 4 and 5	Four miniature networks per group in chronological order.	Growth or fade in total talk (node sizes). Shifts in who leads (node size & centrality move). Whether a group stalls (edges thin out) or rallies late. Member dominance. High disparity	Does talk crash sooner in some groups? Does a new speaker step up mid-task (shared leadership)? Is one group silent while another is lively. Why? Is the active member influential (well-connected) or dominant (weakly connected with most members)?

6.4. Limitations

This exploratory, descriptive study is limited by its small sample size (16 students across four teams), which, while consistent with prior ecological classroom studies (Nanninga et al., 2017, pp. 206–215; Zhang et al., 2018), constrains generalisability. Our study was also based on one classroom activity. Future research should conduct longitudinal data collection over the course of a school term, despite that data collection in in-situ K-12 classroom settings is a well-known challenge and a developing research area(Cukurova et al., 2020; Schneider et al., 2024). As our goal was to validate a new analytic approach, we prioritised accuracy through manual transcription and coding of on-task and off-task utterances. Although this ensured data quality amid complex classroom discourse, it limits scalability. Future research should explore automated approaches (Suraworachet et al., 2024, pp. 473–485) to enable broader deployment, examine the temporal nature of interactions more deeply, and integrate behavioral with attitudinal data. Investigating the bidirectional relationship between task and social cohesion also presents a promising direction for future research.

6.5. Implications and conclusion

Our study has several implications for research and practice. Our findings demonstrate the value of unobtrusive methods in authentic classroom research, utilising audio to capture high-frequency communication and interactions, thereby understanding the evolution of collaboration. Such a developing understanding of classroom learning processes is not possible with the widely used self-report approaches.

The contextual relevance of our findings is a step forward towards ecologically relevant exploration of classroom collaboration. We highlight that to make sense of these high-frequency data sources, appropriate analytic approaches and indicators are needed. Our study presents a conceptualisation of cohesion as a socio-cognitive group process and links it to behavioral indicators in the context of conversational audio data in K-12 classrooms. Researchers and practitioners can draw inter-group and intra-group comparisons of group cohesion using the proposed conceptualisation, indicators, and the analytic approach. With the use of unobtrusive methods to observe and support cohesion in its early stages, there exist opportunities to assess the applicability of existing collaborative learning theories as well as to develop theories on emerging group dynamics in classrooms.

CRediT authorship contribution statement

Arslan Azad: Writing – original draft, Visualization, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Vitomir Kovanovic:** Writing – review & editing, Supervision, Methodology, Funding acquisition, Conceptualization. **Malgorzata Korolkiewicz:** Writing – review & editing, Visualization, Supervision. **Andrew Zamecnik:** Writing – review & editing, Supervision. **Srecko Joksimovic:** Writing – review & editing, Supervision. **Mutlu Cukurova:** Writing – review & editing, Conceptualization.

Data availability

The authors do not have permission to share data.

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