Group Size Matters: Epistemic Network Analysis of GenAI's Impact on Collaborative Inquiry*

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Abstract

While collaborative inquiry offers opportunities for fostering higher-order thinking, its effectiveness is shaped by many factors, including group composition and external support. This study investigates how generative artificial intelligence (GenAI) influences collaborative inquiry discourse patterns across groups of different sizes. Within an 18-week undergraduate course on AI in education, 172 students from three classes, each assigned a different group size (small, medium, or large), participated in three collaborative inquiry sessions. In each class, half of the groups received GenAI support while the other half did not. Epistemic network analysis (ENA) was used to visualize and compare discourse patterns across conditions. Results revealed that GenAI-supported groups exhibited more task-oriented and cognitively structured discourse, while non-GenAI groups showed more open and socially emergent discourse. Notably, GenAI's influence varied by group size: compared with other group sizes, it is linked with more organization and cohesion in small groups, more cognitive reflection and integration in medium groups, and more socio-emotional support in large groups. GenAI also mitigated the negative impact of large group size on contribution frequency. These results suggest that group size moderates the impact of GenAI on collaborative inquiry, highlighting the need for instructional designs that align GenAI integration with group composition.

Keywords

Collaborative learning, Human computer interaction, Generative AI, Discourse Analysis, Community of Inquiry, Epistemic Network Analysis.

1. Introduction

Collaborative inquiry in online and blended environments engages learners in authentic problem-solving through questioning, elaboration, integration, and collective resolution [1,2,3]. Although it can foster deeper understanding and knowledge co-construction [4,5], its effectiveness depends on learners' ability to navigate both cognitive co-construction and complex social dynamics [2,6]. These demands often intensify as group size increases, making turn-taking more difficult, allowing dominant voices overshadow others, and weakening individual accountability [7,8,9].

Recently, educators and researchers have begun to explore generative artificial intelligence (GenAI) as a support mechanism for collaborative inquiry. GenAI tools can help clarify task requirements, generate scaffolds, offer real-time explanations, and help learners structure ideas [10,11]. Although early studies suggest that GenAI can enhance collaborative discourse processes [1,12,13], it remains unclear whether and how these effects differ by group size.

Community of Inquiry (CoI) framework provides a theoretical lens to investigate how GenAI shaping discourse patterns across different group conditions. The framework conceptualizes meaningful collaborative inquiry as the interplay of cognitive presence (CP), social presence (SP), and teaching presence (TP) [14]. Epistemic Network Analysis (ENA) are frequently used in studies based on CoI framework to map and visualize the connections among various collaborative

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activities [12,15,16,17]. This body of research positions the CoI framework not only as a classificatory lens for discourse, but also as a theoretical scaffold for revealing how particular configurations of cognitive, social, and teaching presence enable or constrain productive collaboration.

To address this gap, the present study examined how GenAI and group size jointly shape student discourse patterns during collaborative inquiry. Using a quasi-experimental design, we compared small, medium, and large groups under GenAI-supported and non-GenAI conditions. Guided by the CoI framework, we employed ENA to model and visualize the discourse structure, enabling fine-grained comparisons across conditions [18]. This study was guided by the following research questions (RQs):

RQ1: How does GenAI support influence collaborative inquiry discourse patterns?

RQ2: How does group size influence collaborative inquiry discourse patterns?

RQ3: How do GenAI support and group size jointly shape collaborative inquiry discourse patterns?

2. Related works

2.1. Challenges in Online Collaborative Inquiry

Collaborative inquiry encourages learners to pose questions, explore evidence, integrate ideas, and work toward resolution through group discourse [2]. Drawing on social constructivist perspectives, it has become a crucial instructional component in online and blended learning environments, both of which have gained prominence in mainstream education in the post-COVID era [3,19].

Although collaborative inquiry holds strong potential for fostering critical thinking and knowledge co-construction [4,5], learners do not always fully benefit. Several constraints commonly arise. First, the dual demands of understanding new content and coordinating with peers can increase cognitive load [20]. Second, low confidence in contributing publicly, uneven engagement, and a fragile interpersonal climate can undermine open communication [21,22,23]. Third, groups often struggle to maintain clear structure and sustained focus on learning goals [23,24].

These challenges often intensify as group size increases. Empirical studies suggest that larger group sizes are associated with reduced information exchange, less diverse interactions, lower cohesion, and decreased individual performance [7,8,9,25]. These effects reflect structural constraints. Coordinating speaking turns becomes more difficult, a few outspoken participants may steer the conversation, and responsibility can diffuse across the group. As a result, learners may find it harder to connect to peers and sustain shared problem framing. Group size is therefore not a neutral design choice. It can shape who participates, how ideas circulate, and whether collective inquiry advances beyond exploratory talk.

2.2. Using GenAI to Facilitate Effective Online Collaborative Inquiry

In response to these challenges, educators and researchers have begun exploring GenAI as a support mechanism for collaborative inquiry. CoI model offers a foundational theoretical framework for describing how GenAI may scaffold learning process. Most directly, GenAI can provide cognitive support. Students who consult GenAI for clarifications, alternative explanations, or examples show consistent gains in subject knowledge and conceptual understanding. This can reduce cognitive load and help sustain attention to sense-making [10,11]. Secondly, GenAI may also strengthen social presence in direct or indirect ways. Individualized suggestions and feedback can embolden quieter members to participate and help distribute talk more evenly [26]. Emerging evidence also indicates that GenAI can broaden perspective-taking in diverse groups and improve mutual understanding [27,28]. Finally, by posing purposeful questions, proposing sequences, and maintaining topic focus, GenAI can support discussions to progress with greater coherence and fewer coordination snags [29,30].

However, the current evidence base remains limited in two important respects. Beyond studies that describe discourse qualitatively or rely on frequency counts [11,27,29], relatively few have examined the fine-grained process of how GenAI supported learning activities and learner interactions [1,30]. This gap limits our understanding of the process mechanisms through which GenAI influences collaborative efficiency. In addition, group size as a potential boundary condition remains underexamined. Since group size can greatly influence coordination demands and participation dynamics [7,25], GenAI's effects may also be contingent on group size. As group size grows, rising coordination costs may either heighten GenAI's facilitative value or constrain its influence on peer interaction. Yet existing findings are mixed. One study reported that smaller teams reported higher motivation and demonstrated higher collaborative problem-solving quality in an AI course [11]. Another found that larger groups generated better solutions when supported by AI [31]. Taken together, these inconsistencies underscore how little we know about whether, and how, the effect of group size differs between conditions with and without GenAI support.

2.3. Employing ENA to Trace Discourse Patterns in Collaborative Inquiry

To address these process-oriented questions, theory-informed analytics are needed, and ENA offers a promising upgrade for CoI-guided research. Comparing with conventional methods such as CoI self-report surveys and frequency-based content analysis [16,32], ENA visualizes how various components co-occur under different conditions, allowing researchers to compare process patterns rather than isolated ratings and frequencies. Some studies focus on the linkages among the sub types within a certain dimension of the framework [12,15,16], while others investigate how different presence interweave during online coursework, expanding our understanding of their reciprocal relations [17]. ENA has also been widely used to differentiate interaction structures across contrasting groups (e.g., high- versus low-achieving groups) in computer-supported collaborative learning (CSCL) studies, investigating underlying mechanism of collaboration success [33,34,35]. Together, these studies illustrate ENA's strength for modeling procedural dynamics that conventional analyses often miss.

As GenAI becomes rapidly and broadly integrated in educational settings, exploring its influence on collaborative processes beyond outcomes is increasingly essential. Based on the CoI framework, ENA may help unpack this "black box" by revealing how GenAI shapes discourse patterns across conditions, shedding light on pedagogical design and practical implementation.

3. Methodology

3.1. Participants and Context

This study was conducted with 172 second-year undergraduate students (mean age = 20.20 years, range = 18 − 22 years; 24 male, 144 female, 5 unreported) enrolled in a compulsory teacher education course at a Chinese university. All participants were drawn from three intact classes with the same instructor. We have obtained informed consent from each participant, ensuring that their participation was voluntary and would not affect their grades.

The collaborative inquiry sessions took place in a computer classroom, ensuring each participant had individual access to a desktop. Students participated in collaborative inquiry via an online platform, with explicit instructions to refrain from face-to-face communication during the task. Both the instructor and a teaching assistant were present throughout the sessions to monitor and ensure that students remained focused.

3.2. Grouping and Experimental Conditions

To examine the effects of group size and GenAI support, we implemented one group-size condition per class: large (4 groups of 14 to15 students), medium (8 groups of 7 to 8 students), and small (16 groups of 3 to 4 students). Within each class (i.e., group-size condition), half of the groups were randomly assigned to use a GenAI chatbot for collaborative inquiry, while the remaining groups completed the same activities without GenAI support. Within each group, students were assigned rotating roles (Initiator, Supporter, Arguer) across sessions to promote balanced participation and comparable role exposure. For data integrity, we excluded the second-session activity of one GenAI-supported small group because one member was missing.

3.3. Libertinus fonts for Windows

During the 18-week undergraduate course on “Artificial Intelligence in Education”, three collaborative inquiry sessions were embedded in weeks 9, 12, and 15. Each session centered on an authentic course-related theme that required collaborative reasoning and problem-solving. Before the first session, the instructor introduced the study, obtained informed consent, and randomly assigned students into groups. Students also received training on using the GenAI tool (Chatbox) and sample prompts prepared by the research team. Each session lasted about 40 minutes, with all group discourse recorded for subsequent analysis.

In the GenAI-supported condition, each student could access Chatbox alongside QQ, a widely adopted instant messaging platform that supported group discussions via text, images, and files. Students could consult Chatbox for prompts or clarification, and then share relevant responses in the group chat. This setup kept the discussion centered on peer interaction while allowing students to incorporate GenAI input into the collaborative process. The switch between Chatbox and QQ was typically efficient, minimizing disruption to discussion flow. A teaching assistant was present to provide technical support and monitor adherence to the discussion format. At the end of each session, groups presented their findings in class. Students were instructed not use external GenAI tools, and they were informed that all interaction histories would be recorded for research purposes.

3.4. Data Collection and Analysis

Group discussion data were collected from QQ. All GenAI outputs that students shared during the discussions were incorporated into the main discussion dataset aligned by timestamp. This enabled us to examined machine-generated contributions as part of the collaborative inquiry process.

The collected data was annotated using the CoI framework, identifying indicators of cognitive, social, and teaching presence (see Table 1). Six trained coders worked in pairs and independently coded data from the three classes. Initial interrater reliability was satisfactory (Cohen’s kappa = 0.778, 0.869, and 0.889, respectively). All discrepancies were resolved through discussion before the remaining messages were divided for independent coding.

ENA was used to model and compare group discourse structures across conditions. We employed the rENA package in R to conduct ENA [36]. For the unit of analysis, we used unique combinations of “GenAI”, “theme”, “group size”, “group”, and “role”. Although the primary unit reflected role-assigned participants, we also aggregated networks at the group level to compare GenAI-supported and non-GenAI groups across different group-size conditions. Conversations were defined by unique combinations of “theme” and “group”. This definition assumed no cross-theme and cross-group interactions during discussions, which aligned with our design. Following prior studies, we used a moving stanza of seven lines to optimally balance sensitivity and specificity in detecting meaningful co-occurrences [18,37]. We further conducted Mann Whitney U test on the distribution of the ENA centroids to determine if the differences between the group activities of two different conditions were statistically significant.

Table 1
Community of Inquiry coding scheme

Presence	Indicator	Description	Example (Translated from Chinese)
Cognitive Presence (CP)	Triggering Event (TE)	Raising initial questions or issues to spark meaningful discussion.	"Can AI help narrow educational resource inequalities, or will it instead exacerbate existing inequities?"
	Exploration (EX)	Investigating and sharing information, brainstorming ideas, and presenting different viewpoints.	"But I think algorithmic bias in AI may also constrain the scientific rigor of educational assessment, triggering a human–AI trust crisis."
	Integration (IN)	Synthesizing ideas, connecting different viewpoints, and forming coherent understandings.	"We have discussed the advantages of AI in personalized learning; now let us shift to the issue of technological access inequality and explore possible solutions."
	Resolution (RE)	Applying solutions, validating ideas, and reaching conclusions.	"Our group's view is that the application of GenAI in education brings more benefits than drawbacks."
Social Presence (SP)	Affective Expression (AE)	Sharing emotions, using humor, and expressing personal values.	"If AI ever develops emotions, I feel it might become like M3GAN [smile]"
	Open Communication (OC)	Engaging with others through replies, comments, and questions.	"Could you provide concrete evidence for this viewpoint and specify its scope of applicability? @Shirlyn"
	Group Cohesion (GC)	Building group cohesion, using group-specific language, and social interactions.	"Everyone's contributions have been very inspiring! Now, let me summarize the key points we've discussed."
Teaching Presence (TP)	Design & Organization (DO)	Designing, organizing, and setting up activities and course content.	"Maybe we can pick the speaking order by drawing lots."
	Facilitating Discourse (FD)	Guiding discussions, focusing on specific topics, and encouraging active participation.	"We mentioned that the level of economic development greatly affects the application of AI. So, do you think there are ways to overcome these barriers in less developed regions?"
	Direct Insruction (DI)	Providing content-related instruction, summarizing discussions, and offering feedback.	Quote content from an academic paper or other authoritative source.

4. Results

4.1. Overview of Discourse Patterns

The three collaborative inquiry sessions yielded a total of 9,649 codes based on 6,284 messages (see Table 2). Total code counts were comparable for GenAI-supported and non-GenAI groups (4,865 vs. 4,784). In both conditions, social presence (SP, 1,822 vs. 2,077) was most frequent, followed by cognitive presence (CP, 1,715 vs. 1,977) and teaching presence (TP, 1,328 vs. 730). Notably, TP in the GenAI condition was nearly twice that of the non-GenAI condition.

Sub-indicator distributions further clarified these differences. The lower overall CP in the GenAI condition was mainly due to fewer exploration (EX) codes (1,111 vs. 1,538). Regarding TP, GenAI-supported groups had more design & organization (DO) codes (927 vs. 419). For SP, GenAI-supported groups exhibited fewer affective expression (AE) and open communication (OC) codes, while group cohesion (GC) appeared more frequently.

Group size also shaped code distributions. Large groups produced the fewest codes (2,933), a pattern driven primarily by reduced TP. In small and medium conditions, GenAI-supported groups generated slightly fewer codes, including fewer CP and SP codes. In contrast, in large groups, GenAI support was associated with more TP and SP codes, particularly higher frequencies of TE, DO, and GC.

Table 2
The frequency of the three CoI elements across groups with and without GenAI support

Dimension	With GenAI				Without GenAI			
	Small	Medium	Large	Total	Small	Medium	Large	Total
Cognitive Presence	**546**	**569**	**600**	**1715**	**636**	**744**	**597**	**1977**
Triggering Event	81	87	141	309	59	42	59	160
Exploration	359	387	356	1102	456	638	444	1538
Integration	74	70	92	236	91	39	90	220
Resolution	32	25	11	68	30	25	4	59
Teaching Presence	**469**	**468**	**391**	**1328**	**316**	**292**	**122**	**730**
Design & Organization	333	343	241	917	177	180	62	419
Facilitate Discourse	120	116	130	366	107	101	57	265
Direct Instruction	16	9	20	45	32	11	3	46
Social Presence	**567**	**592**	**663**	**1822**	**692**	**825**	**560**	**2077**
Affective Expression	72	61	45	178	126	159	63	348
Open Communication	257	329	415	1001	332	502	393	1227
Group Cohesion	238	202	203	643	234	164	104	502
Summary	1582	1629	1654	4865	1644	1861	1279	4784

4.2. RQ1: Differences Between Groups with and without GenAI Support

Separate epistemic networks were generated for groups with (red) and without (blue) GenAI support, with a subtracted network constructed to highlight the differences between conditions (see Figure 1). In all network graphs, node size is proportional to the number of occurrences of that code as a response to others. The centroids, represented by round dots, indicate the central position of the network of each unit. While the means, represented by square dots, indicated the central position of each condition, with the surrounding crossline represents the confidence interval of centroids position. The edge thickness reflects the frequency of connections between nodes in separate networks, while in subtracted networks, it represents the magnitude of frequency differences between the two conditions, and the edge colors indicate which condition facilitates stronger connections.

The first and second dimensions, plotted on the X- and Y-axes in Figure 1, explained 38.5% and 9.9% of the variance in the network space, respectively. Interpretation of the X-axis suggests a spectrum from task-focused regulatory actions (left quadrants, e.g., DO) to open, exploratory communicative activity (right quadrants, e.g., EX, and OC). Central nodes (e.g., GC and TE) reflect a balance between regulation and interaction facilitation.

The mean of the GenAI condition (red) is more significantly left-shifted than that of the non-GenAI condition (blue) in X-axis (M_{GenAI} = -0.03, N_{GenAI} = 163, $M_{non\text{-}GenAI}$ = 0.03, $N_{non\text{-}GenAI}$ = 167, U = -1919, p = 0.013, r = .71). This result suggests that GenAI-supported groups engaged more frequently in exchanges centered on organization and facilitation (e.g., DO, GC), as evidenced by more and stronger connections among these nodes as well as with exploratory and open-communication nodes (EX, OC). In contrast, non-GenAI groups exhibited comparatively more frequent connections among nodes associated with affective and open communication (affective expression [AE], EX, OC), indicating a greater emphasis on socio-emotional and open-ended interactions.

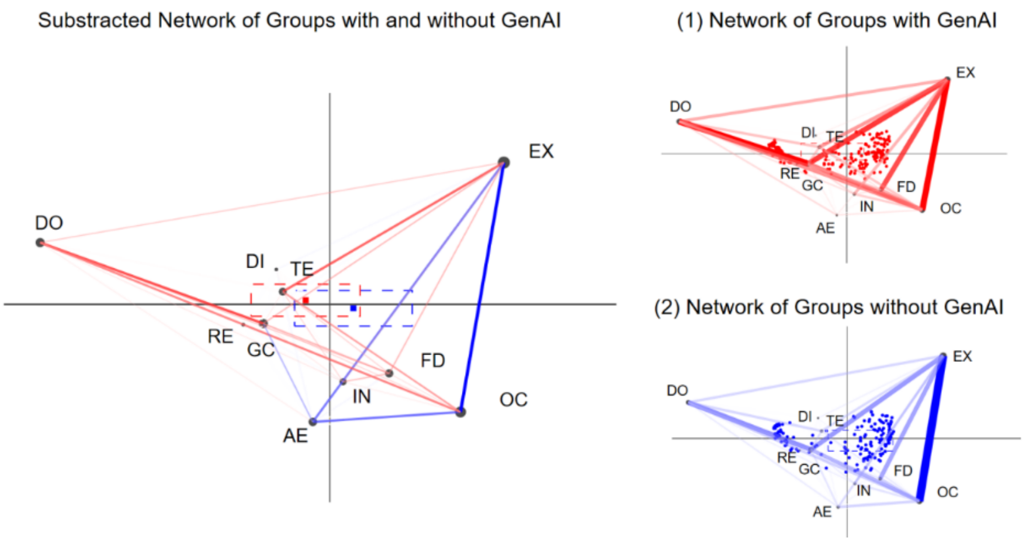

Figure 1: The separate and subtracted epistemic networks of groups with (red) and without GenAI (blue).
Note. DO = design & organization; RE = resolution; GC = group cohesion; DI = direct instruction; TE = triggering events; AE = affective expression; IN = integration; FD = facilitating discourse; OC = open communication; EX = exploration.

4.3. RQ2: Effects of Group Size on Collaborative Inquiry

Figure 2 presents the epistemic networks for groups with different sizes: small (red), medium (orange), and large (blue). As group size increases, the means shift from the top-left toward the bottom-right of the ENA space. Small groups demonstrate denser connections between DO and GC, highlighting a stronger organizational and cohesion focus. Medium-sized groups, in contrast, show more frequent connections between EX and OC, reflecting a greater emphasis on exploratory exchange. Compared with large groups, both small and medium groups exhibit stronger connections between DO and nodes including TE, GC, and EX. Large groups, however, stand out with stronger connections between TE and right-side nodes (EX, OC), as well as between DO and AE.

4.4. RQ3: Interaction Effects between Group Size and support of GenAI

Figure 3 presents the separate and subtracted epistemic networks contrasting groups with (red) and without (blue) GenAI support across different group sizes. In non-GenAI groups, there are stronger triangular connections among AE, EX and OC, which is a pattern most pronounced in medium and large groups, while the difference is relatively less evident in small groups. The influence of GenAI varies notably by group size. In small groups, GenAI-supported discussions show stronger connections between DO and GC, as well as between DO and more open nodes like EX and OC. In medium groups, in addition to DO–GC connections, there are also stronger associations between middle nodes (TE and integration [IN]) and open nodes (EX and OC). For large groups, more prominent connections appear between DO and two SP codes (AE and OC), and between facilitating discourse (FD) and other two SP codes (OC and GC). These network patterns offer a more nuanced explanation for the increased frequency of social and teaching presence codes observed in these conditions.

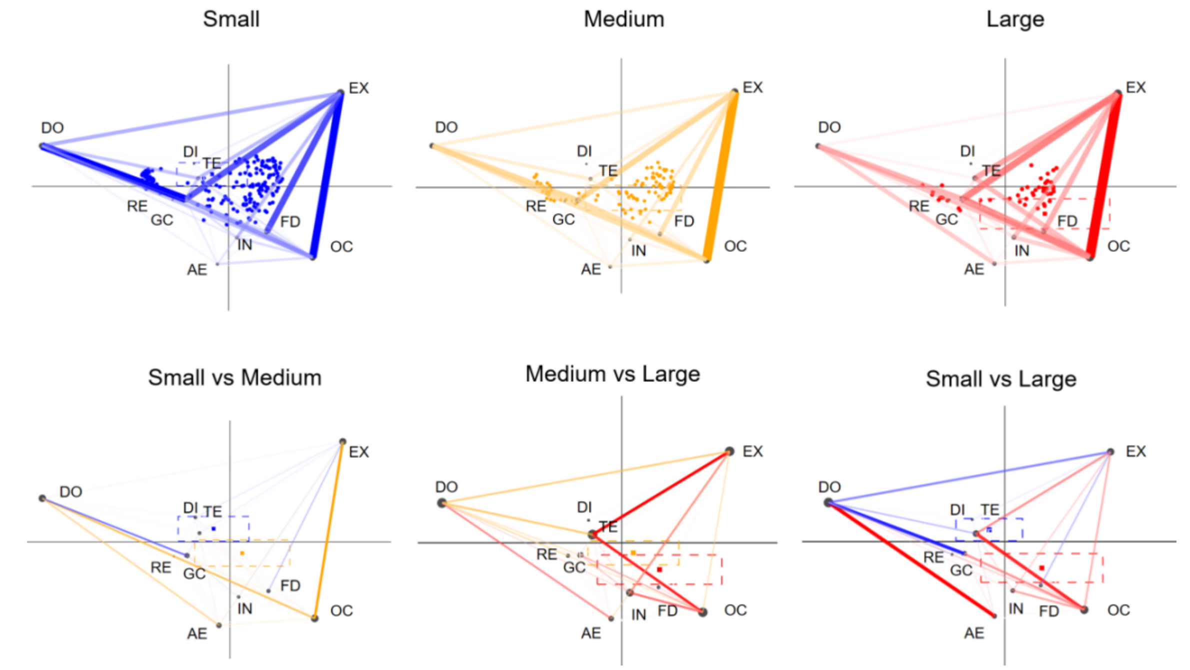

Figure 2: The separate and subtracted networks of small (blue), medium (orange) and large (red) groups.
Note. DO = design & organization; RE = resolution; GC = group cohesion; DI = direct instruction; TE = triggering events; AE = affective expression; IN = integration; FD = facilitating discourse; OC = open communication; EX = exploration.

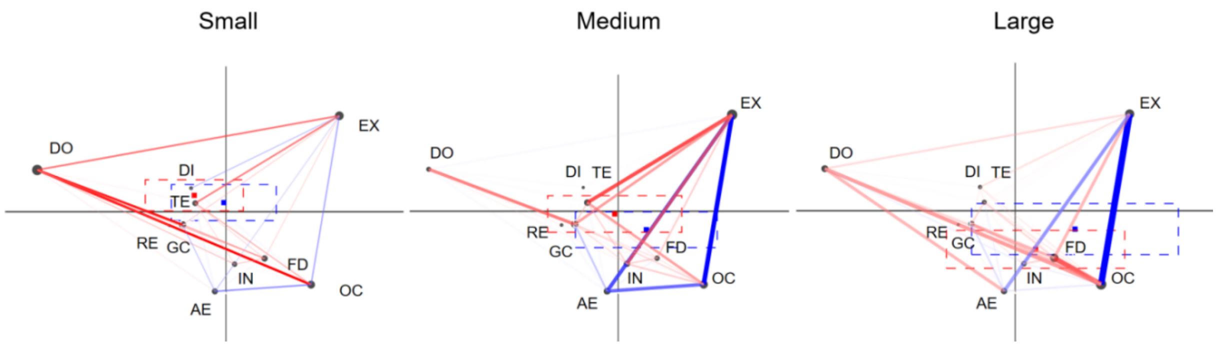

Figure 3: The subtracted networks contrasting groups with (red) or without (blue) GenAI across different group sizes.
Note. DO = design & organization; RE = resolution; GC = group cohesion; DI = direct instruction; TE = triggering events; AE = affective expression; IN = integration; FD = facilitating discourse; OC = open communication; EX = exploration.

5. Discussion

5.1. RQ2: Effects of Group Size on Collaborative Inquiry

The observed leftward positioning of the means of GenAI-supported groups in the ENA space (Figure 1) suggests a greater emphasis on task-focused regulation and structured facilitation. Specifically, these groups exhibited stronger co-occurrence between facilitating nodes and exploratory moves. In this context, GenAI likely served as a form of pre-scaffolding, helping participants clarify goals, organize ideas, or rehearse responses before open discussion with peers [10,11]. In contrast, non-GenAI groups showed more connections among affective expression (AE) and exploratory codes. This right-leaning triangular pattern reflects more socially emergent interactions, possibly due to less external structure and a heavier reliance on peer-initiated regulation [21,23,24].

Notably, GenAI-supported groups exhibited fewer exploratory (e.g., EX and OC) and affective codes overall. This pattern suggests a possible trade-off: students may become more tightly aligned with structured task progression, potentially at the expense of intellectual risk-taking, conversational openness, and autonomy in self-directed exploration. Accordingly, when incorporating GenAI, instructors may need to intentionally preserve space for cognitive openness and peer bonding—especially in contexts where affective engagement is essential for sustaining participation and collaboration [22].

5.2. RQ2: Effects of Group Size on Collaborative Inquiry

Group size appeared to shape how collaborative inquiry unfolds. In small and medium groups with fewer turn-taking constraints and lower coordination costs [7, 8, 9], brief organizational cues (e.g., structuring tasks, sequencing turns) might efficiently unlock cognitive exploration and facilitate coordination. By contrast, larger groups tended to rely more on distributed cognitive triggers (e.g., problems, questions, or conflicts) rather than centralized organizational directives, encouraging broader and more parallel participation [20, 38, 39]. Organizational moves might serve as socio-emotional regulation to maintain positive climate, rather than directly driving exploration [20, 40].

These findings imply that facilitation should be tailored to group size. In small and medium groups, brief organizational scaffolds are sufficient to reduce coordination costs while preserving space for open-ended inquiry and relationship building. In large groups, facilitation should rely less on orchestration and more on well-timed cognitive prompts that allow many participants to contribute in parallel. At the same time, structural guidance may work best when paired with affective interactions, helping maintain a constructive climate and sustain engagement as coordination demands rise.

5.3. Interaction Effects of GenAI and Group Size

The effects of GenAI support interacted dynamically according to group size, moving from structural support to cognitive mediation and, eventually, to socio-emotional regulation. In small groups, where coordination was naturally more manageable, GenAI acted as a structural catalyst that amplify open discussion by clarifying task goals and sequencing contributions [29]. In medium groups, learners might draw on GenAI to articulate cognitive triggers, explore alternative perspectives and integrate various contributions, enabling groups to benefit from diverse inputs [20,41].

In large groups, prominent TP–SP connections suggests that GenAI promoted groups remain socially workable at scale. When group size raises coordination costs, GenAI might cultivate a more supportive and inclusive discourse environment by clarifying group focus, appreciating members' ideas, and inviting various contributions [7, 30, 46]. This helps explain why large non-GenAI groups showed a sharp participation drop, consistent with prior studies [7,8,9,25], whereas GenAI-supported groups maintained higher contribution frequency. The finding also provides a complementary perspective to studies reporting no significant effect of GenAI on communication volume [42,43].

Taken together, these patterns suggest that instructional design of collaborative inquiry should strategically align GenAI's role with group size. GenAI can be used to enhance structural clarity by reinforcing task framing in small groups, and support idea generation by offering cognitive scaffolding in medium groups. In large groups, GenAI can be positioned as a resource for fostering constructive climate and emotional stability amid the increased coordination challenges of large-scale collaboration.

5.4. Limitations and Future Work

This study has three limitations that should be acknowledged, each of which points to future research directions. First, the sample was limited to university students from a single institution, which may restrict the generalizability of the findings. Future studies should include more diverse populations across different educational contexts to validate and extend these results. Second, due to the undirected nature of ENA, the analysis does not capture the actual directionality of interactions. While our interpretations draw on prior literature, future work should incorporate sequential methods to better infer temporal dynamics. Third, this study employed an on-demand GenAI tool under controlled conditions. Participants' engagement with GenAI may differ in more naturalistic or less structured settings, potentially affecting the transferability of results to other learning environments.

6. Conclusion

This study demonstrates that GenAI support and group size jointly shape the dynamics of online collaborative inquiry. Using epistemic network analysis, we found that GenAI can function as a flexible, consultative resource across different group size conditions—supporting task structuring and cognitive scaffolding in small and medium groups, while helping sustain socio-emotional engagement in large groups despite the negative effects of group sizes. At the same time, GenAI support may also narrow students' exploration and conversational openness.

Our findings highlight that GenAI integration in collaborative learning should be context-sensitive rather than uniform. Educators and instructional designers should consider group composition and task demands when deploying GenAI, aiming to preserve open inquiry while strengthening coordination and engagement. This work also contributes to the emerging literature on AI in computer-supported collaborative learning by underscoring the importance of adaptive, responsive design in building effective technology-enhanced learning environments.

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Declaration on Generative AI

During the preparation of this work the authors used Gemini 3 in order to improve the readability and language of the manuscript. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

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