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Impacts of generative AI on student teachers' task performance and collaborative knowledge construction process in mind mapping-based collaborative environment

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ABSTRACT

Collaboration has long been recognized as an efficacious pedagogical strategy. With the visual pedagogical scaffold, for instance, mind maps, learners can externalize their comprehension and engage in meaning negotiation. However, given the limitations posed by the conventional collaborative environment such as the difficulty for groups to achieve deep discussions and generate group intelligence, the generative artificial intelligence (GAI) tool was introduced. The efficacy of the GAI tool in boosting task performance is still contested and its influence on collaborative knowledge construction remains unclear. Therefore, this study was conducted in an elective course at a university. A total of 30 student teachers were the participants, including 10 groups of 3 students. In the subsequent quasi-experimental study, 5 experimental groups employed the GAI tool and mind mapping based collaborative environment (GMMCE) and 5 control groups employed the conventional mind mapping based collaborative environment (MMCE). The results showed that the experimental groups outperformed the control groups on both collaborative tasks in the course. According to Ordered Network Analysis (ONA), the experimental groups developed a collaborative knowledge construction process in cognitive dimension, i.e., progressive interaction from individual to peer to group. On the contrary, the control groups were mainly reflected in the transition between learners' individual expression and peer interaction since they were more centered on the regulative dimension. We also supplemented students' perception of using the GAI tool from the interview data. Finally, we highlighted the implications for pedagogy and described the research limitations as well as future directions.

1. Introduction

As one of the terms commonly used in research to describe learners' cognitive processes during collaborative learning, Collaborative Knowledge Construction (CKC) mainly consists of externalization and integration of knowledge (e.g., Fischer et al., 2002). The rapid development of technology in the age of artificial intelligence has led to an accelerated rate of knowledge updating and the need

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0360-1315/© 2024 Elsevier Ltd. All rights are reserved, including those for text and data mining, AI training, and similar technologies.

for integration of interdisciplinary knowledge (e.g., Cress & Kimmerle, 2023). CKC is embodied in the process of learners interacting with classmates, teachers, and industry experts, which essentially facilitates the joint exploration of problems (e.g., Lin et al., 2013). Therefore, it requires group members to share information and resources, continuously improve ideas through peer interaction, and develop collective knowledge at the group level (e.g., Ouyang et al., 2023). However, recent research and educational practices have confirmed the difficulties and challenges associated with this process. It was found that collaborating as a team may reduce the quantity and quality of learning outcomes compared to working individually (e.g., Fischer et al., 2002; Paulus et al., 2010). For example, students might hesitate to share their ideas due to concerns about peer judgment. When group members are required to take turns presenting their thoughts, they might forget their ideas or choose not to voice them (e.g., Sun et al., 2022). Furthermore, this can impose a significant cognitive load, as individuals must simultaneously generate their own ideas and concentrate on the perspectives of others (e.g., Chen et al., 2019; Paulus et al., 2010). In these cases, the interaction and communication among learners remain confined to elementary stages, demonstrating the difficulty of reaching high levels of CKC.

To facilitate the expression of learners' individual perspectives and to minimize the cognitive load generated by the complex interweaving of perspectives within a group, it is necessary to incorporate pedagogical scaffolding as part of the instructional strategy (e.g., Chen & Hong, 2016; Fischer et al., 2002). Stone (1993) noted that the support given by the teacher during scaffolding depended greatly on the characteristics of the context. Learners can utilize scaffolding to reduce their cognitive load in complex tasks, thereby accomplishing tasks which they would not otherwise be able to do. Davis and Miyake (2004) described classroom scaffolding as a kind of help. For example, visualization tools allow learners to construct representations in the form of mind maps, diagrams, and texts (e.g., Stone, 1993; Van De Pol et al., 2010). Specifically, mind maps help group members better understand each other's perspectives and ideas by clearly demonstrating the relationships between information through hierarchical structures and connecting lines (e.g., Cendros Araujo and Gadanidis, 2020). When properly designed and embedded with appropriate pedagogy, mind maps can improve learning outcomes (e.g., Cendros Araujo and Gadanidis, 2020; Malycha & Maier, 2017; Suharto et al., 2023). Previous research has validated the effectiveness of using mind maps in math (e.g., Araujo & Gadanidis, 2020; Cendros Araujo and Gadanidis, 2020), language learning (e.g., Marriott & Torres, 2014), science teaching (e.g., Sun et al., 2022), and informal learning environments (e.g., Chen et al., 2019; Malycha & Maier, 2017). Meanwhile, students also maintained a positive view of mind mapping since they believed that the scaffolding helped them to save time and actively read the literary text (Suharto et al., 2023). In conventional mind mapping-based collaborative environments, the ideas generated by team members remain homogeneous and lack novelty. This phenomenon is particularly evident when creating shared mind maps, despite they can effectively facilitate information sharing and improve communication efficiency (Chang et al., 2018). Specifically, when group members edited and constructed mind maps together, they tended to imitate each other's ideas and expressions (Suharto et al., 2023). This tendency would undoubtedly limit the individual's self-reflection and creativity. As a result, the final output of group members tended to be similar and lacked diversity and novelty. Therefore, there is an urgent need to address this issue of how to break the convergence and promote diversified thinking among members in conventional mind mapping-based collaborative environments. On the other hand, mind maps are known for being highly concise, a feature that makes them effective in summarizing and presenting the ideas of individuals (e.g., Marriott & Torres, 2014). However, in the context of group collaboration it may prevent groups with differences in a priori knowledge levels from engaging in deep conversations (Fadillah, 2019). In particular, when group members utilized mind maps to organize their respective viewpoints during the consultation process, high-level students tended to be able to distill the key information more quickly and present it in a concise manner. By contrast, low-level students may find it difficult to formulate a clear viewpoint in a short period of time due to insufficient knowledge base. Furthermore, they were gradually placed in a passive position or even marginalized. Therefore, during the process of utilizing mind mapping as a highly effective tool to facilitate collaboration, we need to explore how to take into account the needs of students with different prior knowledge levels and ensure that each student can actively participate in the dialogues.

As a pioneering digital resource capable of bringing diversity, Generative Artificial Intelligence (GAI) shows great potential in addressing the challenges inherent in conventional mind mapping collaborative environments. GAI is equipped with an accessible interface facilitating human-like interactions and generating original text based on user prompts (e.g., Rudolph et al., 2023). Firstly, as an aggregator of wisdom, it provides group members with unprecedented perspectives and insights from its extensive knowledge base. By interacting with GAI, group members were able to broaden their sources of inspiration. Many research have demonstrated that this interactive process greatly enriched the diversity and novelty of their perspectives (e.g., Anantrasirichai & Bull, 2022; Wieland et al., 2022). For instance, Wieland et al. (2022) conducted a quasi-experimental study that asked participants to brainstorm with either a chatbot or a human as a partner. It was found that chatbot was more capable of allowing participants to generate more diverse ideas. Secondly, GAI shows great potential for balancing differences in ability among group members. In other words, it can serve as an effective bridge to narrow the knowledge gap among group members to a certain extent. Through precisely matching the needs of different learners, GAI provides customized learning resources and more specific practical solutions. Such process enables even learners with lower knowledge level to find suitable entry points and actively participate in group discussions and practices. For example, Habib et al. (2024) investigated the impact of GAI, namely ChatGPT-3 on the creativity of college students. The study found that the use of ChatGPT-3 promoted thinking fluency. Students enjoyed the brainstorming and idea generation, as GAI dynamically optimized its output based on user feedback and needs, enabling it to better meet the personalized needs of users. Meanwhile, they also noted the potential for GAI to negatively impact creative confidence as well.

To conclude, GAI holds the promise of solving many problems that currently exist in conventional mind mapping, such as convergence of viewpoints, low engagement, etc. Despite the increasing research on GAI tools applied to education in recent years, there is a dearth of practical explorations within the field of collaborative learning regarding the integration of GAI tools with collaborative environments supported by pedagogical scaffolds. Given that groups often exhibit varied learning behaviors contingent upon the support of diverse technological resources and instructional scaffolds, a meticulous analysis and comparison of these

behaviors during collaboration holds vital significance (e.g., Lin et al., 2013). Therefore, this study aims to analyze the specific effects of GAI integration into collaborative learning environments assisted by pedagogical scaffolding, especially its potential contribution to the collaborative knowledge construction process. It aims to not only enrich the theoretical implications of GAI tools in the field of educational applications, but also provide empirical evidence and strategic guidance for optimizing collaborative learning practices.

2. Literature review

2.1. Collaborative knowledge construction

To comprehend the process of knowledge construction that learners accomplish through online interactions, researchers have proposed a series of influential theories (e.g., Mayordomo & Onrubia, 2015). For example, in collaborative learning theory, CKC was considered to be an advanced stage of the collective cognitive process, i.e. intellectual convergence (e.g., Fischer & Mandl, 2005). Collaborative learning theory identified three stages that learners are required to go through as generating ideas, organizing ideas, and intellectual convergence. In addition, Mayordomo and Onrubia (2015) characterized the process of CKC in small groups as a four-stage process, i.e., "initiation", "exploration", "negotiation", and "co-construction". CKC at the elementary stage primarily involves learners engaging in the output of ideas and further developing a lower degree of interrelationship between peers. Getting to the advanced stage implies that learners are able to negotiate and reconstruct new meanings from each other's contributions (e.g., Araujo & Gadanidis, 2020). In other words, learners' expression of their perspectives is a necessary condition for collaborative knowledge construction, as the exchange of different viewpoints is the starting point for negotiation (e.g., Malmberg et al., 2022; Ouyang & Chang, 2018). Therefore, surpassing the mere division of tasks among team members, it emphasizes learners' sharing of ideas and information and continuous improvement through peer interaction, culminating in the development and construction of knowledge at the group level (e.g., Vygotsky, 1978). As a result, researchers have explored at the individual level how learners' self-learning behaviors are related to normative learning stages at the group level. For example, Malmberg et al. (2022) focused on the individual learning process as part of collaborative learning. They investigated how learners' individual monitoring evolved through phases of cyclic regulation in a collaborative learning context using temporal and sequential analysis. Lund (2019) proposed a multi-theoretical, interdisciplinary model that addressed how individuals and groups work together to construct knowledge in group interactions. As a key unit of analysis, the peer level is frequently used to reveal how groups realize the process of knowledge construction through peer-to-peer interactions and how they regulate and facilitate each other's learning process. For example, Zhang et al. (2017) revealed a diversity in teachers' behavioral patterns regarding social knowledge construction across various phases of activities. Notably, no statistically significant discrepancy was observed in the distribution of these behaviors, indicating that both actively engaged and less interactive teachers exhibited a range of strategies in facilitating knowledge construction. In contrast, Ouyang and Chang (2018) found that students who frequently interacted with their peers tended to make more cognitive contributions to the process of knowledge inquiry and construction. Prior researches have often delved into collaborative knowledge construction (CKC) with a tendency to focus on either singular or dual levels. However, the evolution of CKC across individual, peer, and group domains is not a linear progression but rather a complex interplay of interconnected dynamics (e.g., Lund, 2019; Ouyang et al., 2023). Therefore, it becomes imperative to examine the intricate features from multiple levels to gain a nuanced comprehension of the mechanisms underpinning knowledge construction within collaborative group settings.

2.2. Mind mapping in collaborative learning

Reiser (2004) argued that scaffolding worked by reducing the complexity of the task. For example, tasks are organized in such a way that teachers direct students to focus on appropriate task components or guide them in problem solving (e.g., Davis & Miyake, 2004; Van De Pol et al., 2010). In addition, representations and thinking related to the co-construction of knowledge can be externalized in technology-rich learning environments by providing visualization tools (e.g., Fischer et al., 2007; Lu et al., 2010). For example, mind maps, which use a combination of text, graphics, color, and layout, have become an important tool in collaboration learning designed to enhance learners' knowledge organization and conceptual understanding (e.g., Malycha & Maier, 2017; Sun et al., 2022). Research studies have shown that the use of mind maps not only enhances individual learning, but also helps to promote peer interaction (e.g., Araujo & Gadanidis, 2020). During collaborative knowledge construction, mind mapping as a common reference point can help group members quickly understand and grasp the overall framework and details of existing knowledge. In the process of drawing mind maps, group members can add new ideas and perspectives liberally, which promotes knowledge innovation and expansion by continuously expanding and deepening the hierarchical structure of mind maps (e.g., Sun et al., 2022). Cendros and Gadanidis (2017) compared an online tool for group discussion, i.e., topic forums, with collaborative mind mapping. They argued that the hierarchical and structured nature of mind maps allowed for the smooth flow of ideas and a rapid visualization of key concepts in a more intuitive way. Furthermore, they incorporated collaborative mind mapping activities as an alternative to threaded forums into an elementary mathematics education curriculum (Cendros Araujo and Gadanidis, 2020). In this way, they explored how pre-service math teachers engaged in interaction and knowledge construction when participating in CKC. With the aid of mind maps, students no longer spent a great deal of effort describing or commenting on each detail of classroom activities, as they did in the threaded forums. Instead, they extracted the key topics or main ideas of the discussion and developed them (Cendros Araujo and Gadanidis, 2020). Overall, mind mapping can facilitate the clear presentation and exchange of ideas among peers through its visual features (e.g., Chen et al., 2019; Davis & Miyake, 2004). However, its inherent framework can also constrain students' creative thinking and lead to homogenized productions. This phenomenon may limit team creativity (Chang et al., 2018). In addition, mind maps are characterized

by simplicity and highly summarize the views and ideas of individual students. However, this high level of generalization sometimes becomes a stumbling block to deeper dialogue among group members (Chang et al., 2018). Specifically, a high degree of information condensation may make it difficult for low-level members to find entry points into the discussion, thus reducing their motivation to contribute ideas and ask questions. Meanwhile, high-level members tend to dominate the negotiation process, and in some cases even tend to complete the task alone (Fadillah, 2019). Thus, the simplicity of mind maps may exacerbate this imbalance when group members differ significantly in their knowledge base and professional backgrounds. Given the above, there is a need to incorporate more open and flexible digital resources along with the use of mind maps to promote diversity in the outcomes of the group's products and deeper dialogue among members (Chang et al., 2018).

2.3. Generative artificial intelligence

As a frontier product of technological development, GAI tools such as ChatGPT, Bing Chat, or ERNIE Bot, are gradually showing profound influence in multiple fields with their excellent learning and creation capabilities (e.g., Liu, Li, & Dong, 2024). A series of studies investigating the application of GAI tools in the field of education have presented complex and multifaceted results (e.g., Chen et al., 2023; Sun et al., 2024). It has proven to show promising results in improving the quality of programming education (e.g., Sun et al., 2024; Yılmaz & Yılmaz, 2023a). For example, Sun et al. (2024) employed a quasi-experimental design to explore the effects of a ChatGPT-based programming model on college students' programming behavior and academic performance. Upon examination, it was detected that the employment of a ChatGPT-based programming model elicited an enhancement in students' programming performance, albeit this improvement failed to attain statistical significance. Also utilizing a quasi-experimental design approach, Yılmaz and Yılmaz (2023a) found that generative artificial intelligence was beneficial for improving students' computational thinking skills and programming self-efficacy by comparing pre-test and post-test scale scores. In addition, GAI is also widely used to facilitate learners' language comprehension and writing skills (e.g., Liu, Zhang, & Biebricher, 2024). Liu, Zhang, and Biebricher (2024) compared students' cognitive processes of text generation in a GAI tool-assisted environment with a traditional writing environment. Furthermore, the study examined the behavioral patterns of creating images. It was found that the GAI tool was able to provide suggestions and guidance on textual elements for writing, thus facilitating students' language development, as well as helping learners to generate images as vivid examples. Moreover, the perception of students regarding the use of GAI tools are invaluable (Chiu, 2024). By delving into students' experiences, we can more accurately grasp the actual effects of these tools in facilitating knowledge acquisition and enhancing learning efficiency. For example, Chiu (2024) adopted a mixed deductive and inductive thematic analysis approach to analyze student questionnaire and interview data. In particular, the study focused on the three major themes of learning outcomes, pedagogy, and assessment to determine the changes that may be required in higher education following the implementation of GAI. Chan and Hu (2023) revealed that the students surveyed were generally optimistic about the incorporation of GAI in learning, with particular emphasis on its advantages in facilitating personalized learning.

While numerous researchers have hailed the potential positive impacts of GAI on task performance, a parallel strand of inquiry has surfaced, scrutinizing its accompanying limitations. Specifically, it has been observed to generate academic articles with spurious authorship and titles upon being tasked with producing cited articles (e.g., Liu, Zhang, & Biebricher, 2024). Furthermore, ethical dilemmas surrounding GAI-produced content have garnered attention (e.g., Sun et al., 2024). Yilmaz and Yilmaz (2023b) employed an open-ended question format to gather student feedback on the integration of ChatGPT in programming education. While ChatGPT can aid students in debugging their programs and boost their confidence, it may also provoke career-related anxiety due to concerns about its potential to replace human roles.

Up to now, research has mainly explored the impact of GAI on learning performance and learning behaviors across subject areas, while its application in mind mapping-based collaborative learning environments has not yet been discussed. In mind mapping based collaborative environments, several challenges arise, including convergence of viewpoints, low engagement, etc. (e.g., Chang et al., 2018; Suharto et al., 2023). To address these challenges, the introduction of generative artificial intelligence (GAI) presents a promising solution. Although there is a long tradition of using digital technologies and analytic tools to support knowledge construction (e.g., Chen & Hong, 2016), no previous work has integrated GAI tools into this context. In addition, the role of GAI tools in facilitating student learning performance is still controversial. Meanwhile, few studies have provided insights into how GAI tools specifically contribute to the knowledge construction process in teamwork (e.g., Cress & Kimmerle, 2023; Ouyang et al., 2023). Therefore, this study attempts to integrate the GAI tool into a mind mapping-based collaborative learning environment in order to explore its impact on task performance and the process of collaborative knowledge construction within groups. In the subsequent quasi-experimental study, the experimental groups employed the GAI tool and mind mapping based collaborative environment (GMMCE) and the control groups employed the conventional mind mapping based collaborative environment (MMCE). Based on the findings of previous studies (e.g., Sun et al., 2024; Chiu, 2024; Liu et al., 2024), we hypothesize that prudently integrating generative AI as an innovative digital resource into conventional mind mapping-based collaborative environments can positively impact student outcomes. Specifically, it can enhance task performance and promote deeper knowledge construction. The research questions are as follows.

1. What is the impact of integrating the GAI tool into mind mapping-based collaborative environment on students' task performance?
2. How does the collaborative knowledge construction process differ between GMMCE and MMCE groups at different stages of collaborative learning?
3. How meaningfully do student teachers in GMMCE perceive using the generative Al tool?

3. Methodology

3.1. Research context and participants

This study was conducted at a comprehensive university in central China during the autumn semester of 2023 in the course "Pedagogical Applications of Information Technology". As an elective course, the course lasted for eight weeks. Each week a 90 min session was conducted. Students enrolled in the course were student teachers in their sophomore and junior years who were actively seeking ways to integrate information technology into their subject matter. These student teachers have recognized the transformative potential of information technology in contemporary education. They actively explored and experimented with digital tools to enrich their instructional practices. Each student teacher was encouraged in our course of study to apply these theoretical concepts to their respective subject areas and to integrate technology in meaningful ways. Consequently, all student teachers were selected as participants in this study, including 13 males and 17 females. They majored in physics, history, mathematics, and many other disciplinary backgrounds respectively.

3.2. Experimental procedure

The experimental procedure is shown in Fig. 1. The study began with two questionnaire tests, which were completed by grouping the participants on the principle of homogeneity between groups. Moreover, five groups were randomly assigned as the control group and the other five as the experimental group. During the eight-week course study, all students worked collaboratively in groups to complete two tasks assigned in the course, namely, writing an instructional design (ID) and creating a multimedia courseware design (MD). It is worth noting that the MD task was completed on the basis of the ID task. The participants in the experimental group were interviewed at the end of the course study. The interviews focused on their experiences with the GAI tool. Finally, the products of all groups were evaluated using the Technological Pedagogical Content Knowledge (TPACK) gauge (Chen et al., 2021), which is primarily designed to assess technological, pedagogical, and content knowledge in educational settings.

3.3. Measuring tools

3.3.1. Two instruments for grouping

To ensure the robustness of the findings, we followed rigorous protocols for filtering and pairing procedures prior to the grouping stage. Firstly, a comprehensive assessment of students' relevant abilities and knowledge was conducted by distributing a test on problem solving ability and a questionnaire on subject pedagogy and technological knowledge. The first test instrument, adapted from PISA 2005, assesses problem-solving ability. Test items were translated into Chinese and validated through forward and backward translation to ensure reliability and validity. The second instrument, a questionnaire, focuses on pedagogical understanding, proficiency in information technology, and their collaborative endeavors, offering a comprehensive evaluation of students' educational competencies. The questionnaire has been used in previous studies (e.g., Zhang et al., 2022, 2023), and demonstrated strong reliability with Cronbach's alpha of 0.868. After that, the research assistant ensured inter-group consistency by precisely dividing the 30 student teachers into 10 groups of three students each based on their scores of two questionnaire tests (Refer to Table 1 for details). In addition, in order to verify the rationality of the grouping, this study also used the *Kruskal-Wallis test* to test the significance of the difference between the groups in terms of two tests. The results showed that there was no significant difference between the groups in either of these areas (*Kruskal-Wallis* $H = 9.000$, $df = 9$, $p = .437$ for two questionnaire tests). Therefore, five groups were randomly selected as control groups (named as groups 1, 2, 3, 4, and 5), and another five as experimental groups (named as groups 6, 7, 8, 9, and 10). The

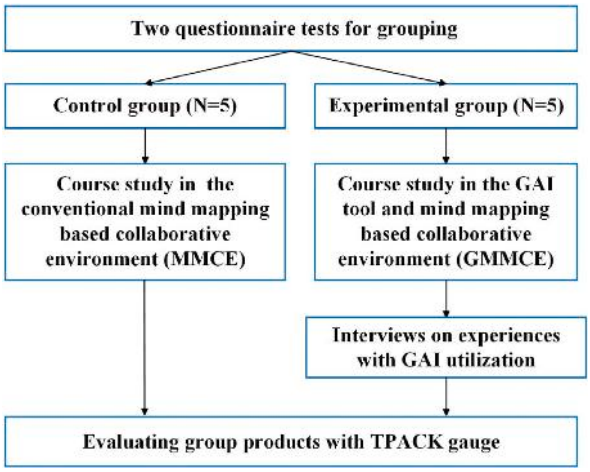


Fig. 1. The experimental procedure.

Table 1
The scores of two questionnaire tests.

Group	First questionnaire	Second questionnaire	Group	First questionnaire	Second questionnaire
1	250	179	6	250	173
2	245	182	7	249	186
3	248	173	8	253	179
4	250	182	9	250	177
5	245	187	10	251	181

former used the conventional mind mapping based collaborative environment (MMCE) and the latter used the GAI tool and mind mapping based collaborative environment (GMMCE).

3.3.2. *The coding framework for discourse data*

Each group completed the ID task and MD task during the course study by collaboration via a synchronous online discussion platform (i.e. Tencent QQ). Therefore, discourse data from the group's discussion were systematically gathered. Two research assistants conducted the coding process for all discourse data at the sentence level based on a coding framework adapted from Ouyang et al. (2023) (see Appendix 1). This coding framework was used to elucidate the relationship between the cognitive, regulative, and emotional dimensions of the knowledge construction process at the individual, peer, and group levels (Ouyang et al., 2023). Since the collaborative discourse data collected for this study rarely involved emotional expression, we focused primarily on the cognitive and regulative dimensions. The cognitive dimension included the individual level (e.g., students sharing their understanding), the peer level (e.g., peers negotiating their views), and the group level (e.g., forming a collective consensus). The regulative dimension stems from Hadwin et al. (2017, pp. 83–106), including self-regulation, co-regulation and the socially shared regulation. During the coding process, each utterance was given a code. The inter-rater reliability coefficient (Cohen's Kappa) was calculated to be 0.83, indicating strong consensus (Fleiss, 1981). It is worth noting that responses provided by the GAI in this study usually appeared as part of the student teachers' mind maps, with individual members negotiating the modules of the mind maps during the group discussion phase. Student teachers processed the content of the GAI and posted the content they consider appropriate to the QQ group for members to discuss. Therefore, we further provided two examples to illustrate how to assign codes to the content of the GAI and peer contributions (see Tables 4 and 5). Finally, a total of 6759 pieces of discourse data were obtained. Within the cognitive dimension, discussions at the individual, peer, and group levels were as follows: 1705 utterances (25.2%), 1407 utterances (20.8%), and 846 utterances (12.5%), respectively. Within the regulative dimension, there were 820 utterances (12.1%) at the individual level, 353 utterances (5.2%) at the peer level, and 1628 utterances (24.0%) at the group level.

3.3.3. *TPACK gauge*

Group products generated during both collaborative tasks were collected for assessment. Utilizing the Technological Pedagogical Content Knowledge (TPACK) gauge as an evaluation criterion, two research assistants independently scored the group products across

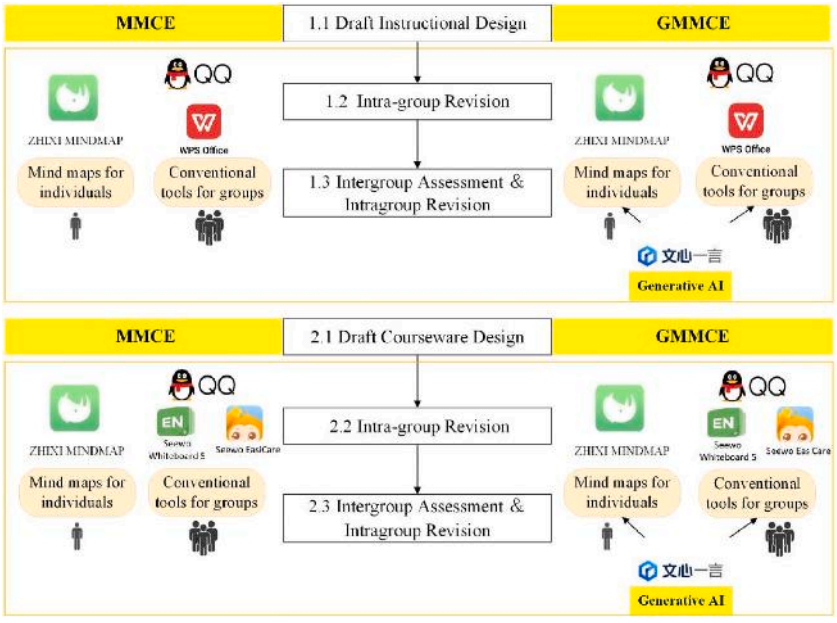


Fig. 2. Learning task completion process and the tools used.

7 dimensions of the TPACK gauge. Each dimension is rated on a scale ranging from 1 to 5, with a total score of 35. The Spearman's correlation coefficient returned a value of 0.908 ($p < .01$), indicating a high degree of correlation between the two research assistants and the reliability of the scores. The average score given by the two research assistants was taken as the final score for each group product.

3.4. The course study process within MMCE and GMMCE

As shown in Fig. 2, two tasks consist of three stages, namely, the first draft (stage 1.1 and stage 2.1), first round of intra-group revision (stage 1.2 and stage 2.2), and second round of intra-group revision (stage 1.3 and stage 2.3). Specifically, this study focused only on the two round of revision phase of the group's products, i.e., stage 1.2 and stage 2.2, stage 1.3 and stage 2.3. During the first round of intra-group revision, groups improved the products regarding the first draft through in-depth communication within the group. During the second round of intra-group revision, groups firstly evaluated the other groups' productions and then discussed the feedback within the group. To ensure fair evaluation, this study designed a mechanism for separate peer reviews between control and experimental groups. Specifically, the student teachers used ZHIXI MINDMAP as an individual to map their mind and clarify their ideas for revision before engaging in discussions and interactions within the group (See Fig. 2).

3.4.1. The first round of intra-group revision of ID

The control group utilized the ZHIXI MINDMAP for individual mind mapping. The creation of individual mind mapping helped with information visualization, allowed individuals to understand the ideas of team members, enhanced the efficiency of group discussions, and promoted the effective completion of learning tasks. As shown in Fig. 3, Student 1 suggested that the group's instructional design product could be modified in terms of both instructional method and instructional process. The other two students, i.e. Student 2 and Student 3, also suggested their own modifications from different aspects of the instructional design product.

While the control group mainly relied on conventional mind mapping, the experimental group additionally adopted a GAI tool - ERNIE Bot. Prior to the start of the course tasks, the research assistants provided the experimental groups with video tutorials and examples to share on the use of GAI, as shown in Table 2.

In addition, there is a need to learn how to identify potential problems with GAI outputs and select the valuable content. We have carefully crafted a series of video resources that vividly demonstrate how to critically embrace the content provided by the GAI. For example, possible sources of bias, limitations in data selection, and implicit assumptions in algorithm design. By sharing some examples of research failures that resulted from relying too heavily on GAI predictions, we have encouraged the group to remain cautious when utilizing GAI outputs. Student teachers firstly interacted with ERNIE Bot in depth by asking questions as an individual unit. In this process, they made full use of ERNIE Bot's intelligent analysis capabilities to obtain constructive comments and perspectives and completed individual mind maps prior to the group discussion. To ensure their peers gain a comprehensive understanding of the proposed modifications, the student teachers included links to the specific interactions with ERNIE Bot alongside each constructive suggestion for modification (see blue boxes in Fig. 4). The three student teachers in the Group 7 referred to three suggested modifications during their interactions with ERNIE Bot in their respective mind maps. The majority of them were about the design details of classroom interactions in instruction, such as the simulation game of "Tian Ji Racing", the role-playing session, the card game, or the rules of evaluation in the read-aloud part.

For example, by clicking on the links added by Student 2 in Fig. 4 we can see how he interacted with ERNIE Bot. Specifically, as illustrated in Fig. 5, a student teacher from group 7 selected the ID theme "Tian Ji Racing," a renowned tale from Chinese history.

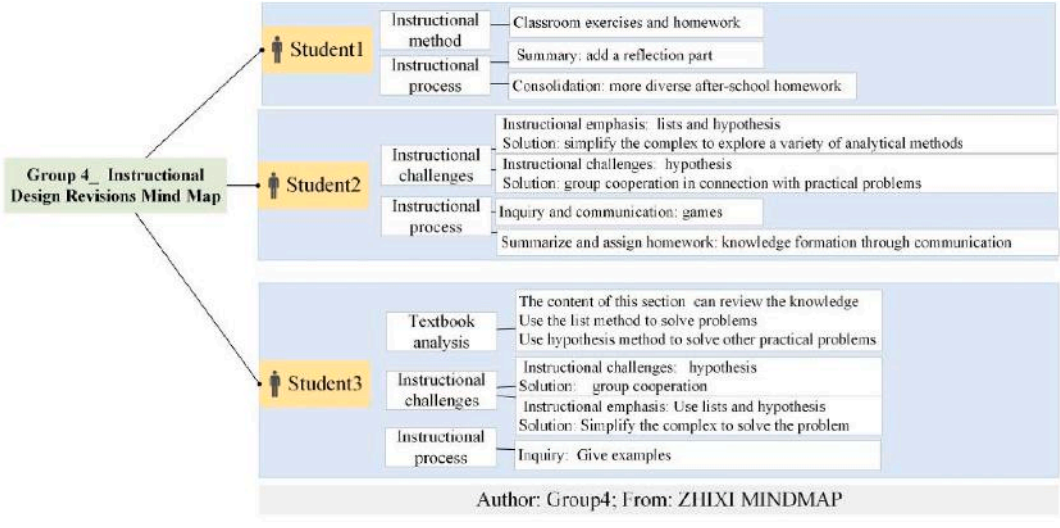


Fig. 3. Creating mind maps as individuals within the control group.

Table 2
Examples and tips on the use of ERNIE Bot.

Type	Content	Description
Examples	Creating a scenario for learning	How can information technology be used to create a conducive situation to stimulate students' interest in Chinese class? https://yiyan.baidu.com/share/zmdAaeEdEs
	Design of experimental exploration	How can information technology be used to design laboratory activities in conjunction with highlights of the physics curriculum? https://yiyan.baidu.com/share/boCXVszhKc
	Teaching strategies and methodologies	How can information technology be used to design review session in the maths lesson in order to enhance the interaction between teachers and students? https://yiyan.baidu.com/share/xSpBCjZeiG
	Learning assessment scale	How do I design an assessment gauge in a group presentation session? Please provide a detailed description of the dimensions and how the scores corresponding to each dimension performed. https://yiyan.baidu.com/share/tAszhyIKxt
Tips	Asking clear and specific questions	GAI can provide better answers if specific questions can be asked. Therefore, we need to avoid using vague language or asking multiple questions at the same time.
	Providing background information on the issue	Sharing relevant background information or details to help narrow down the question can help the AI better understand the question and provide a more accurate answer.
	Acknowledgement of understanding/ questioning	After receiving an answer, confirm that you understand the answer. Follow-up questions are asked as necessary, which can help clarify any confusion.
	How to write a good prompt?	Define roles + background information + task objectives + output requirements Important instructions can be placed at the end or repeated at the end. Add symbols to keywords for emphasis, such as [], "" for emphasis, " ….." for separation, etc.

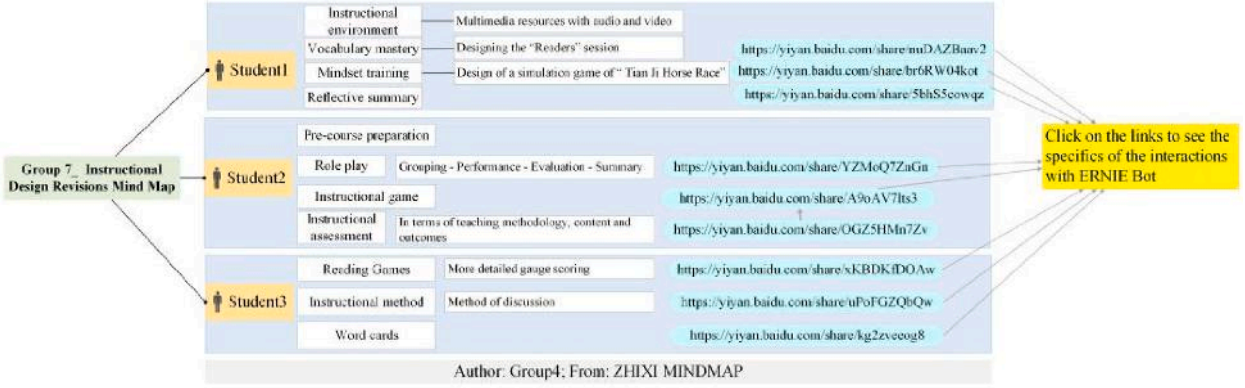


Fig. 4. Creating mind maps as individuals within the experimental group.



Fig. 5. Interaction with the ERNIE Bot of experimental group during stage 1.2.

Consequently, she posed queries regarding the integration of information technology tools to assess student comprehension, simulating the role of a primary school Chinese instructor guiding students through the lesson. Afterwards, ERNIE Bot provided a detailed response to the question. It suggested that the group could design an interactive game for evaluation at the end of lesson. Furthermore, it outlined a systematic approach comprising five key steps: creating an interactive game, making word cards, organizing group competitions, using speech recognition and providing real-time feedback. Therefore, following their interaction with ERNIE Bot, each student teacher within experimental groups proceeded to create an individual mind map. Within this mind map, they also incorporated selected suggestions provided by ERNIE Bot, among other pertinent details.

Then, a heated discussion within the group centered on the individual mind maps drawn by the student teachers. There was no difference in the learning platforms used by the experimental and control groups at this stage. As shown on the left side of Fig. 6, group members expressed their views and shared information on a synchronised online discussion platform (i.e. Tencent QQ). Meanwhile, they also synchronised the revision of their instructional design productions using WPS Office platform (see right side of Fig. 6).

3.4.2. The second round of intra-group revision of ID

Groups were firstly required to evaluate the products of other groups during the second round of the revision. Scoring and modification suggestions are included within the evaluation task. Notably, a TPACK gauge was used as the evaluation scale. For example, Group 6 first scored Group 7's products based on the seven dimensions of the TPACK gauge, followed by a detailed explanation of each score and suggestions for modification. Therefore, the research assistant explained in detail the specific meaning of each dimension regarding the TPACK gauge and the level of productions corresponding to each score. This not only helped the groups to complete the evaluation task, but also helped them to improve themselves according to the criteria of the gauge. In addition, the course resource website was posted by the research assistants for viewing and submitting comments. As depicted in Fig. 7, there was a catalogue of resources provided by the research assistants on the left, which included task descriptions, evaluation scales, and evaluation reference cases. There were details of the evaluation comments submitted by each group on the right. During this stage, student teachers can not only communicate with their peers in the group, but also interact with other groups by logging on to the course website.

The control group completed the evaluation tasks primarily based on guidance from the research assistants. In other words, they started by drafting their ideas as an individual unit and then discussed them as such within the group. Finally, a consensus was reached among the members on the grading and revisions and then uploaded to the course website. The experimental group, on the other hand, additionally relied on the support by the ERNIE Bot. Firstly, the experimental groups were allowed to upload the instructional design products that needed to be evaluated and the TPACK gauge to the ERNIE Bot. Second, the experimental group needed to write a suitable prompt to instruct ERNIE Bot to evaluate according to the gauge. As depicted in Fig. 8, the research assistant provided a prompt example at this stage. "The school is holding a competition for instructional design products, and the scoring for this competition is given from the 7 dimensions of the TPACK gauge and each dimension was given a score on a scale of 1–5. 1 represents very little elaboration, 2 represents not much elaboration, 3 represents some elaboration, 4 represents elaboration in relative detail, and 5 represents detailed elaboration. Now, as a judge, please rate the following instructional design documents according to the TPACK gauge and give suggestions for revision". Therefore, student teachers in the experimental group had preliminary scores and



Fig. 6. Learning platforms used in the group discussion stage of the ID task.

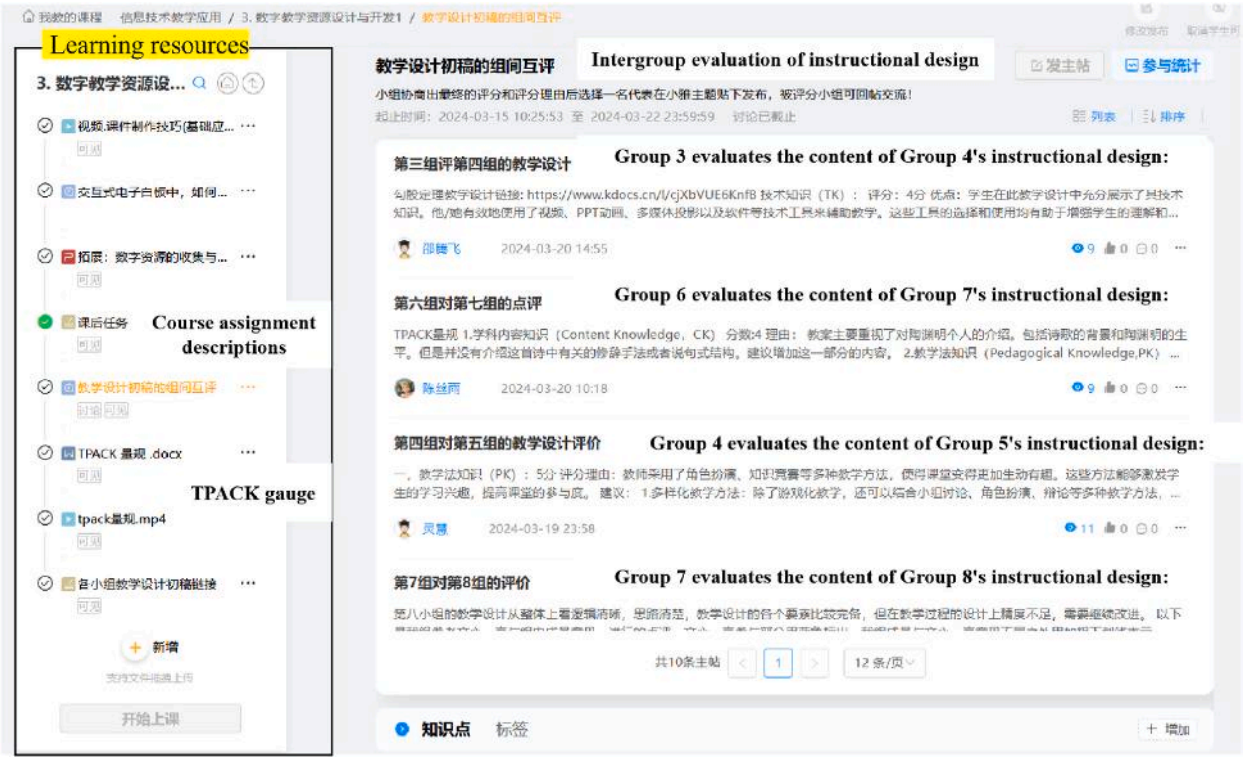


Fig. 7. Inter-group evaluation of ID document on the course website.

modification suggestions after interacting with ERNIE Bot, which were used as a basis for discussion and consensus within the group. Next, student teachers in the experimental group formulated the final scores and modification suggestions after point-by-point discussions on the synchronised online discussion platform (i.e. Tencent QQ). These scores and modification suggestions were sent to the evaluated groups. Finally, each evaluated group discussed the scores and modification suggestions and refined their own group's instructional design product.

3.4.3. The first round of intra-group revision of MD

Similar to the ID task, student teachers continued to complete their individual mind maps before the group discussion during MD task. Group members expressed their views and shared information on a synchronised online discussion platform (i.e. Tencent QQ). Unlike the ID document, multimedia courseware not only requires the integration of multimedia elements such as pictures, video and audio, but also known for its interactivity, dynamics and high visualization. These characteristics make the courseware content more colourful and can effectively enhance the effective learning. Therefore, Seewo Whiteboard 5 online platform and Seewo EasiCare online platform were provided in this study with the aim of supporting the groups in completing the production and presentation of the courseware content. As illustrated in Fig. 9, such instruments greatly facilitate the smooth process of courseware production with their powerful editing functions and convenient interfaces.

Student teachers in experimental groups were also given additional opportunities to interact with the ERNIE Bot. After the previous stage of the task, the student teachers had mastered the skills of dialogue with ERNIE Bot. Therefore, the research assistants did not provide any operational guidance during the MD task. During this task stage, student teachers were not able to upload courseware design documents directly to ERNIE Bot. Therefore, they often interacted with ERNIE Bot by uploading screenshots of the courseware design documents. As illustrated in Fig. 10, a student teacher uploaded a screenshot of his own mind mapping to the ERNIE Bot, seeking feedback and insights. ERNIE Bot, in turn, provided a detailed summary of the screenshot content. Subsequent dialogue ensued, with the student teacher elaborating on their understanding of the content of the MD, while seeking ERNIE Bot's guidance on enhancing technological utilization. ERNIE Bot responded by suggesting improvements focused on enhancing interactivity, diversifying presentation formats, personalizing learning experiences, integrating additional learning tools, and optimizing technological utilization. Through iterative interactions with the ERNIE Bot, student teachers received targeted guidance and advice that improved the quality and effectiveness of the MD.

3.4.4. The second round of intra-group revision of MD

As the final task stage of the course, the second round of courseware revision required groups to firstly evaluate each other and then improve based on the comments received. Similar to the process for the second round of ID revisions, the groups were graded on the



"Now the whole school is holding a competition for ID products, and the scoring for this competition is given from 7dimensions of TPACK and each dimension was given a score on a scale of 1 to 5.
1 represents little elaboration, 2 represents little elaboration, 3 represents elaboration, 4 represents more elaboration, and 5 represents full elaboration.
Now, as a judge, please rate the following instructional design documents according to the TPACK gauge and give suggestions for revision" :

Based on the above material texts and user requirements, I will grade the instructional design document on seven dimensions of TPACK:

Content Knowledge (CK): 4
.....
Pedagogical Knowledge (PK): 4
.....
Technological Knowledge (TK): 4
... ...
Technological Pedagogical Knowledge (TPK): 3
.....
Technological Content knowledge (TCK): 5
.....
Pedagogical content knowledge (PCK): 4
.....
Technological pedagogical content knowledge (TPACK): 4
.....

Fig. 8. Interactions with the ERNIE Bot of experimental group during stage 1.3.

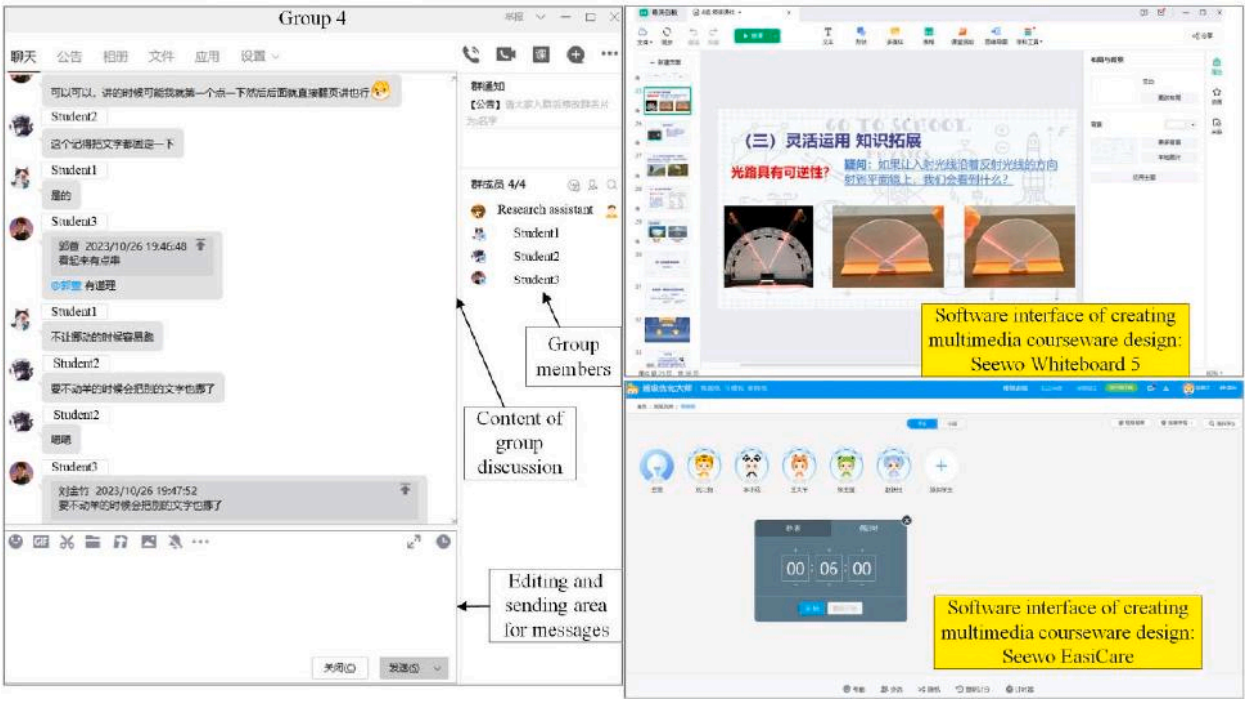


Fig. 9. Learning platforms used in the group discussion stage of the MD task.



Fig. 10. Interactions with ERNIE Bot during the first round of intra-group revision of MD.

dimensions of the TPACK gauge and subsequent revisions were written. The research assistant provided the appropriate course website so that the group could upload and download resources. The group conducted another round of consultation based on the content of the other group's evaluation and individual in-depth reflections. During this stage, student teachers can not only communicate with their peers in the group, but also interact with other groups by logging on to the course website (see Fig. 7) through posting messages. In addition, if there were irreconcilable conflicts and disagreements among members regarding the revision of the group's productions, they could seek help from the research assistants at any time. Meanwhile, the research assistants uploaded more excellent works in the learning resources for reference. For the experimental group, they were already proficient in interacting with ERNIE Bot. By uploading images and sending text, ERNIE Bot was able to give appropriate feedback. Finally, after receiving the evaluation comments, the group could complete the final draft of the courseware with the help of the various learning platforms in Fig. 9.

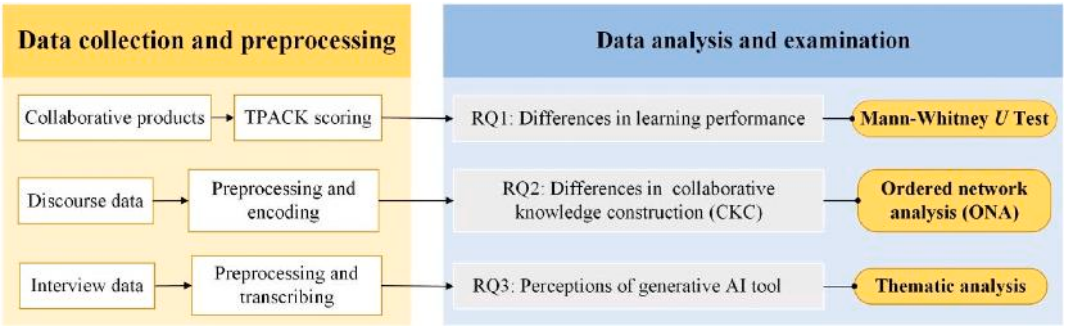


Fig. 11. Procedure of data collection and analysis.

3.5. Data collection and analysis

Fig. 11 illustrates the systematic procedure adopted for the data collection and subsequent data analysis. To address research question 1, we conducted the Mann-Whitney *U* test to determine whether a statistically significant difference existed between the scores of the experimental and control groups. To address research question 2, we visualized the ordered network model of the experimental and control groups using R package, i.e., ona (Tan et al., 2023). Built upon the foundation of the Epistemic Network Analysis (ENA) method, ONA quantifies and visualizes the transition frequencies between coded events within the datasets (e.g., Tan et al., 2023). The ONA algorithm first uses the coded and segmented data to accumulate connections for each unit of analysis. In the application of the ONA algorithm to each unit, a sliding window methodology is employed to discern the connections instantiated by the instant data row. Drawing upon a review of prior literature, we have determined an optimal sliding window length of seven for the analysis of the current datasets (e.g., Li et al., 2023). Notably, a comprehensive technical elaboration of the ONA methodology transcends the boundaries of the present research. The seminal study conducted by Tan et al. (2023) offers a profound expansion on the technical principles underlying ONA.

To address research question 3, semi-structured interview data from experimental groups (GMMCE) were collected using an online conference system (Tencent Conference system). Before recording interviews, we ensured students knew about and agreed to the recording. In addition, we conducted a pre-interview to test the applicability of the protocol. Subsequently, we refined the interview process to delve deeply into student teachers' perceptions and experiences with GAI tools (refer to Appendix 2 for the interview protocol). The interview data collection ranged from 40 to 60 min, averaging around 55 min per recording. A rigorous thematic analysis approach, as outlined by Braun and Clarke (2006), was employed to scrutinize the interview data. Firstly, two research assistants transcribed the audio data while achieving familiarity of the interview data through checking and rereading. Secondly, develop initial codes based on the data. Thirdly, identify themes based on initial codes. The different codes were categorized into potential themes at a broader, thematic level and organized all relevant coded data within the identified themes. Fourth, revise and refine themes. Fifth, define and elaborate themes. The essence of each theme was further defined considering the themes themselves and the relationship of each theme to the others. After developing a complete set of themes, the final analysis and report was conducted.

4. Results

4.1. What is the impact of integrating the GAI tool into mind mapping-based collaborative environment on students' task performance?

We collected the scores of each group's products under the TPACK gauge. As shown in Table 3, during the ID task stage, the MMCE groups' product scores ranged from a high of 31 to a low of 16 ($M = 21.8$, $SD = 5.7$). The GMMCE groups' product scores ranged from a high of 33 to a low of 24 ($M = 28.8$, $SD = 3.8$). During the MD task stage, the MMCE groups' product scores ranged from a high of 32 to a low of 19 ($M = 24.6$, $SD = 4.7$). The GMMCE groups' product scores ranged from a high of 33 to a low of 27 ($M = 29.4$, $SD = 2.3$). Furthermore, we explored the statistical significance of differences in the above scores using the Mann-Whitney *U* test. The results found a significant difference between the MMCE and GMMCE groups in the ID product scores ($U = 3.000$, $z = -1.984$, $p < .05$). However, the significant difference between the groups of MMCE and GMMCE was not observed in the scores of the MD ($U = 4.000$, $z = -1.776$, $p = .076$).

4.2. How does the collaborative knowledge construction process differ between GMMCE and MMCE groups at different stages of collaborative learning?

Regarding research question 2, we used Ordered Network Analysis (ONA) to model the group discussion process in different settings and visualized the ONA networks. As depicted in Figs. 12 and 13, the augmentation in node size mirrors an escalation in the frequency of occurrence. Furthermore, the intensity of color within each node is commensurate with the quantity of self-loops associated with that node's code, where saturation signify a heightened number of self-connections. The edge thickness and colour saturation represent transitions between codes, with thicker and more saturated edges representing a higher frequency of transitions. Notably, the chevron between two edges represents the direction of the transition between codes.

First, we created ONA networks in the ID task stage for the MMCE and GMMCE groups to gain a detailed understanding of node connectivity and network structure. In addition, we also created subtraction ONA networks to account for differences in the different collaborative environments. Red edges represent more frequent transitions for MMCE groups, while blue edges indicate more frequent

Table 3
The results of non-parametric tests between experimental and control groups.

Group	N	Mean	SD	Max	Min	*U*	*z*	*p*
Experimental (ID task)	5	28.8	3.8	33	24	3.000	−1.984	0.047*
Control (ID task)	5	21.8	5.7	31	16			
Experimental (MD task)	5	29.4	2.3	33	27	4.000	−1.776	0.076
Control (MD task)	5	24.6	4.7	32	19			

Note: *$p < .05$.

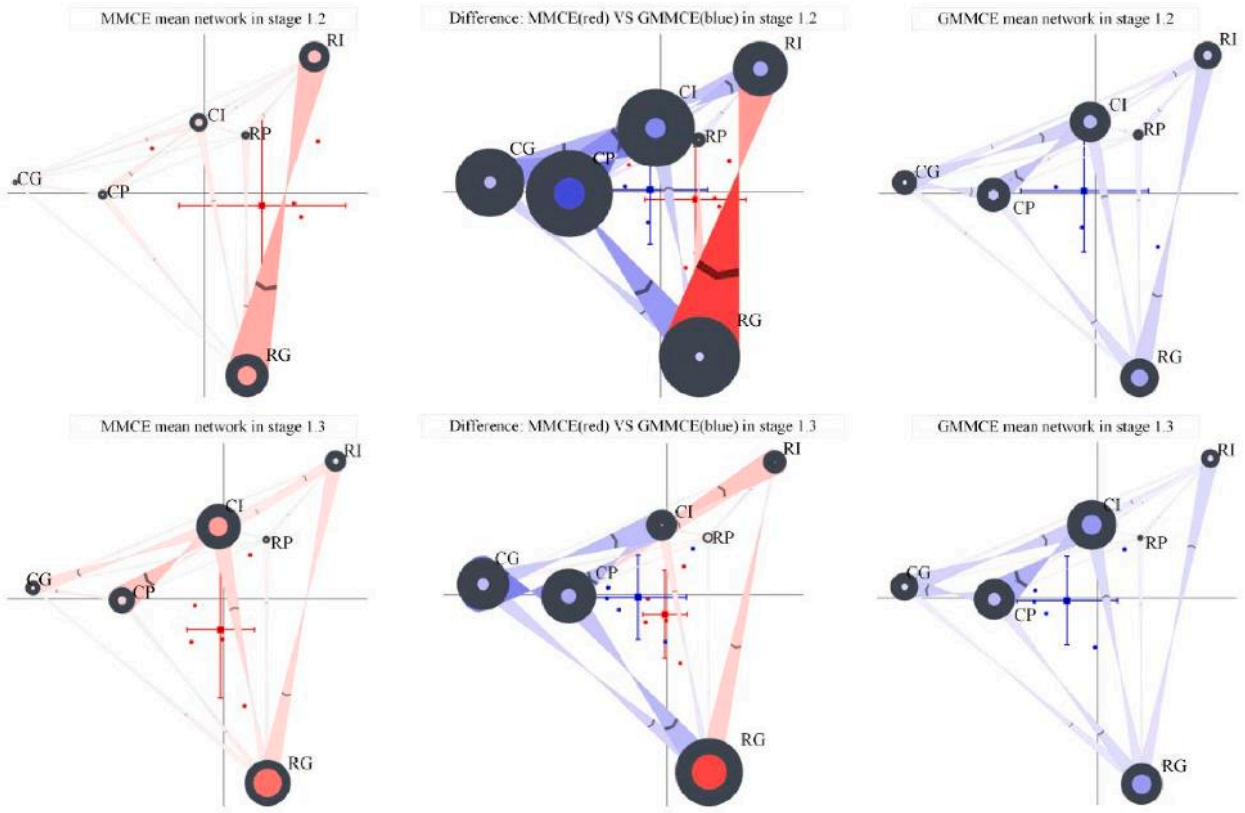


Fig. 12. ONA networks in the ID task stage.
Note. CI is short for "Cognitive dimension_Individual level", CP is short for "Cognitive dimension_Peer level", CG is short for "Cognitive dimension_Group level"; RI is short for "Regulative dimension_Individual level", RP is short for "Regulative dimension_Peer level", RG is short for "Regulative dimension_Group level".

transitions for GMMCE groups. As shown in the first row of Fig. 12, during stage 1.2, student teachers in the MMCE groups used skills in the regulation dimension more frequently, such as planning, monitoring, and reflecting. Their transitions occurred more frequently from the individual to the group level (RI to RG), with a prevalence of self-transitions at both levels of collaborative knowledge construction. In contrast, student teachers in the GMMCE groups were more inclined to collaborate through the use of cognitive dimensions of skills such as presenting ideas, consensus building, critiquing and summarizing during the collaborative process. Specifically, GMMCE groups made strong transitions from CG to CI and from CI to CP. In addition, GMMCE groups' transitions from CP to RG and from CI to RI are also strong.

The second row of Fig. 12 shows that the MMCE and GMMCE groups had similar ONA network structures during stage 1.3. For example, both produced frequent self-transitions in the CI and RG. There was a strong tendency for both to transition from CI to CP in the cognitive dimension. MMCE groups exhibited a robust transition from CI to CP, whereas the transition from CP to CG appeared weaker. In contrast, GMMCE groups demonstrated a strong transition from CP to CG and from CG to CI, indicating a developmental trajectory of collaborative knowledge construction.

Group 6's transcribed example of the ID task provided more compelling evidence of this research finding. Table 4 illustrates a transcribed example from group 6. The discourse interaction among group members Zhu, Zhou, and Ji centered on refining an instructional assessment generated by ERNIE Bot for their instructional design. As shown in Table 4, we coded each student utterance excluding ERNIE Bot's answers. Firstly, Zhu introduced the initial version of the assessment, which Zhou critiqued for its overly generalized content, particularly in the final two paragraphs. In response, Zhu defended the relevance of the assessment, arguing that its specificity aligns with the group's unique instructional design. After interaction with a peer, Zhu suggested modifications to the instructional assessment section, relying on ERNIE Bot's answers. Ji and Zhou subsequently acknowledged the improvements in Zhu's revised version of the assessment. With ERNIE Bot's help, consensus at the group level was eventually reached after two rounds of discussion within the group. This collective dialogue exemplifies a collaborative effort aimed at refining the instructional assessment to better align with the group's specific instructional design objectives.

In addition, Group 1's transcribed example for the ID task offered more persuasive evidence. Table 5 illustrates a transcribed example from group 1. The discourse interaction among group members Zhang, Huang, and Li centered on refining their instructional design. As shown in Table 5, we coded each student utterance. Firstly, through regulation at the group level, Zhang identified the resources needed for the task. Following this, Zhang started a new topic by articulating his views in the cognitive dimension and

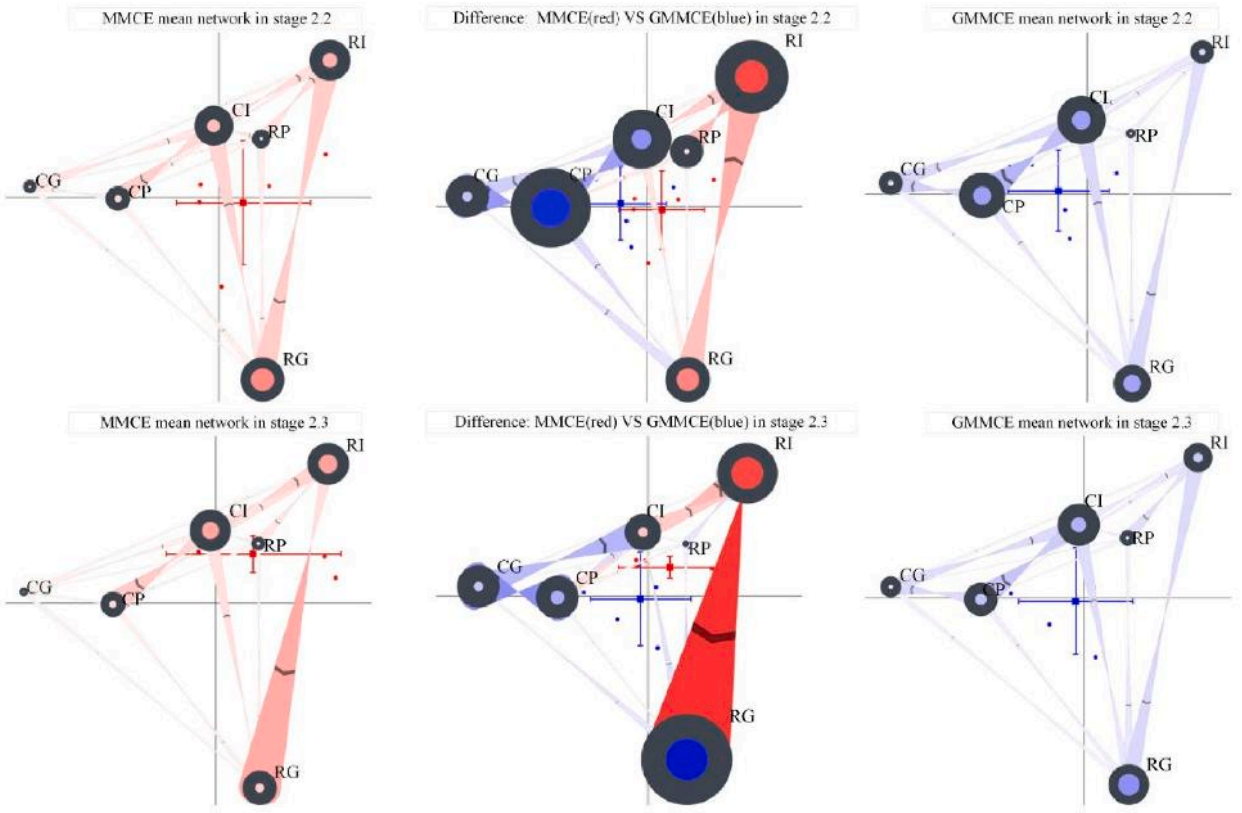


Fig. 13. ONA networks in the MD stage.
Note. CI is short for "Cognitive dimension_Individual level", CP is short for "Cognitive dimension_Peer level", CG is short for "Cognitive dimension_Group level"; RI is short for "Regulative dimension_Individual level", RP is short for "Regulative dimension_Peer level", RG is short for "Regulative dimension_Group level".

established a consensus with Huang at the peer level. Zhang then clarified the next steps for the group and reported on what he had accomplished while Huang also monitored his own completed work. Finally, Li regulated at the group level, clarifying what the group had accomplished and the next steps to be taken.

As illustrated in the first row of Fig. 13, student teachers in the MMCE groups persisted in employing the skills of the regulation dimension to navigate through the collaborative task during the stage 2.2. For example, MMCE groups made a stronger transition from RI to RG. Similarly, we observed this feature in the network diagram of the GMMCE groups (right side of the first row). However, the subtracted network diagram reveals that compared to GMMCE groups, MMCE groups also displayed more frequent transitions from the group level to the individual level (middle of the first row). Similar to the previous stage, both the MMCE and GMMCE groups realized

Table 4
Transcribed example from group 6 (GMMCE) during the ID task.

Turns	Transcript	Code
1	Zhu: ERNIE Bot's answer.	/
2	Zhu: This is the instructional assessment I used ERNIE Bot to import our instructional design.	CI
3	Zhou: The last two paragraphs of this are too general.	CP
4	Zhou: Can we just delete the last paragraph?	CP
5	Zhu: Why? Our instructional assessment is specific to our instructional design, so surely the overall instructional assessment should also be specific to our overall instructional design.	CP
6	Zhu: ERNIE Bot's answer.	/
7	Zhu: Or maybe some of these could be added?	CP
8	Ji: We can build on this foundation.	CP
9	Zhu: Integrate our three instructional assessments?	CP
10	Zhou: The second version you posted is better.	CP
11	Zhu: Instructional assessment should include the following key points …...	CG
12	Ji: I think it's pretty complete, too!	CG

Note. CI is short for "Cognitive dimension_Individual level", CP is short for "Cognitive dimension_Peer level", CG is short for "Cognitive dimension_Group level".

a collaborative knowledge construction process that transitioned from CI to CP. In addition, they demonstrated a strong transition from CI to CG, indicating that individual contributions were absorbed by the group's shared understanding.

During stage 2.3, MMCE groups continued to manifest a strong transition from RI to RG. On the cognitive dimension, they still had a strong transition from CI to CP while the transition from CP to CG diminished. In addition, we observed that MMCE groups made strong transitions from CI to RI and from CP to RI. On the contrary, student teachers in the GMMCE groups not only demonstrated a strong transition from CI to CP and from CP to CG but also exhibited a strong transition from CG to CI. In other words, the GMMCE group maintained the developmental trajectory of collaboratively constructed knowledge presented in the previous task phase.

Table 7 shows a transcribed example from group 7. The group engaged in a discussion on how to design the presentation segment of MD task. Prior to the group discussion, Chi cited the answers given by ERNIE Bot in her mind map and included a link to the interaction with ERNIE Bot. In particular, ERNIE Bot provided suggestions from two perspectives: visual presentation and technical support. In response to this section of the mind map, Li firstly inquired whether the preview products had been collected prior to class. Next, she offered her perspective on this specific issue. Chi proposed rewarding students who performed well in the preview task, cautioning that presenting sub-optimal work could undermine the intended effect. Mei expressed a preference for showcasing excellent work to motivate students. After the peer level exchanges and interactions, Li agreed with the points made by the other two members. Therefore, the group reached a group level of agreement on how to select student products for presentation section.

Table 8 shows a transcribed example from group 4. The group engaged in a discussion on how to revise their multimedia courseware design. Liu and Wang initially identified the elements of the work to be accomplished through group-level regulation. Liu elaborated his views on a specific knowledge point and reached a consensus with Wang. Next, Liu and Wang regulated at the individual level by articulating what they wanted to accomplish and what they had accomplished. Finally, Liu again used group-level regulation to clarify the division of labor and reach a consensus with Chen.

Finally, we utilized ONA to illustrate the centroids of collaborative knowledge construction between MMCE and GMMCE groups in the ONA space across various task stages (refer to Fig. 14). As depicted in Fig. 14, red squares visually emphasize the centroids corresponding to MMCE, whereas blue squares visually emphasize the centroids corresponding to GMMCE. We focused on explaining the first dimension (x-axis) because it accounts for a large part of the explained variance. This dimension clearly distinguishes the connections associated with two dimensions: the cognitive dimension and the regulative dimension. In particular, GMMCE groups' centroids are predominantly positioned towards left part of the ONA network domain, indicating a stronger association with cognitive dimension. These centroids exhibit relatively stable positions during the different task stages. In contrast, MMCE groups' centroids are predominantly positioned towards right part of the ONA network domain, suggesting that they are more connected to skills related to the regulative dimension. There were large variations and fluctuations in the centroids of the MMCE groups across task stages. In the ID task, the ONA network centroids are closer to the RG. During the MD task, the ONA network centroids gradually move upward, indicating that the centroids of MMCE groups is closer to the RP and RI.

4.3. How meaningfully do student teachers in GMMCE perceive using the generative Al tool?

To address research question 3, we conducted semi-structured interviews with the student teachers in the experimental groups (GMMCE condition) at the end of the course. Table 6 shows the student teachers' perceptions on the experience of using the generative Al tool.

Concerning the first theme i.e. frequency of interaction with ERNIE Bot, Group 6 reported more frequent interactions during the ID task phase compared to the MD task phase. The second theme explored what student teachers discussed and interacted with ERNIE Bot about. Specifically, student teachers in Group 6 indicated that ERNIE Bot was able to provide ideas for the introduction and classroom activities during the ID task phase. The student teachers in Group 8 found that ERNIE Bot provided an explanation of the basic functions of the Seewo Whiteboard 5 software before they familiarized themselves with the software. Most student teachers agreed that ERNIE Bot enhanced the creativity of the group's products by providing a variety of examples to stimulate new ideas and thoughts, such as designing game activities based on the learning context. In addition, ERNIE Bot also assisted the student teachers in

Table 5
Transcribed example from group 1 (MMCE) during the ID task.

Turns	Transcript	Code
1	Zhang: Let's all take a look at this instructional design idea on this course website.	RG
2	Zhang: I asked another group and confirmed that our assignment was to convert this instructional design mind map into an instructional design document.	RG
3	Zhang: Therefore, I think our document can contain the following elements: instructional objectives, instructional content, learner characteristics, and instructional emphasis, etc.	CI
4	Huang: I think it's about the same, and it can be refined on this basis.	CP
5	Zhang: I'll start tonight with the overall instructional design. Then tomorrow at 4:00 p.m., we'll discuss how to refine it.	RG
6	Huang: OK.	RG
7	Zhang: (Sending a document) These are the parts I write about in addition to the instructional process.	RI
8	Li: OK.	RP
9	Zhang: Let's see if there's anything that's not quite right and needs to be changed.	RG
10	Huang: I also have a section on instructional design.	RI
11	Zhang: The main point is that I'm not sure if there is a strict definition of what the teacher means by instructional design.	RG
12	Li: We'll just follow your module and then add in a slight modification of what we both changed.	RG

Table 6
Student teachers' perceptions on the experience of using the generative AI tool.

Themes	Codes	Group
Frequency of interaction with ERNIE Bot	High frequency of interactions during the ID task phase	Group 6
	Low frequency of interaction during the MD task phase	Group 6
	The revision process for both tasks involved interaction with ERNIE Bot	Group 8
		Group 10
Content of interaction with ERNIE Bot	Formulate classroom activities within the ID task phase	Group 6
	Craft introduction session within the ID task phase	Group 6
	Introduce the basic functions of the Seewo Whiteboard 5 within the MD task phase	Group 8
	Modify and refine ID elements such as the instructional process, instructional objectives, and learner assessment	Group 8 Group 9
	Provide many examples to develop new ideas and thoughts within the both collaborative task phases	Group 6
		Group 7
		Group 8
		Group 9
	Summarize ID products by uploading documents	Group 6
Approaches of interaction with ERNIE Bot	Refer to the questioning format, examples and videos provided by the research assistants	Group 6 Group 7
		Group 8
		Group 9
		Group 10
	A further question and answer session is more likely to result in the desired answer	Group 10
	The interaction during the ID task phase involved asking ERNIE Bot questions by uploading documents	Group 9 Group 10
	The interaction during the MD task phase involved asking ERNIE Bot questions by uploading pictures	Group 9 Group 10
Effect of interaction with ERNIE Bot	Help us to a great extent to revise our ID products	Group 9
		Group 10
	Help us to a lesser extent with MD revisions	Group 9
		Group 10
	ERNIE Bot is able to contribute to the enhancement of the production	Group 6
		Group 8
		Group 10
	ERNIE Bot is largely unfamiliar with the functions on Seewo Whiteboard 5 and therefore does not have any substantive suggestions	Group 7 Group 8
		Group 9
	ERNIE Bot makes it easy to find information and modify content	Group 8

Table 7
Transcribed example from group 7 (GMMCE) during the MD task.

Turns	Transcript	Code
1	Li: ERNIE Bot's answer in Chi's mind map.	/
2	Li: Is this one collecting the previews already?	CP
3	Li: Can we also give a reward if the students do a better job of previews?	CI
4	Li: Or are we showing the better student work?	CI
5	Chi: If sub-optimal work is presented, it may fail to achieve the intended demonstrative effect.	CP
6	Mei: I prefer to show excellent work to motivate students.	CP
7	Li: That's fine.	CG

Table 8
Transcribed example from group 4 (MMCE) during the MD task.

Turns	Transcript	Code
1	Liu: I've reviewed the mind maps and the things that need to be changed are: instructional process, group work, instructional reflection, and so on.	RG
2	Liu: And is there anything else you'd like to change?	RG
3	Wang: OK, I think it's great!	RG
4	Liu: How about instructional reflection? We don't have that in our original presentation thoughts.	CI
5	Wang: I think instructional reflection could really be weakened out of the equation, as the other sessions actually do cover this.	CP
6	Liu: I added the learner profiling with the rotating animation and then supplemented it with a group work session.	RI
7	Wang: Let me try how to add a hyperlink.	RI
8	Liu: Why don't we split up the work? Two people will do the technical support, and one people will do the multimedia courseware.	RG
9	Chen: So I'm in charge of presenting the last two sections of the lesson?	RI
10	Liu: Yes.	RP

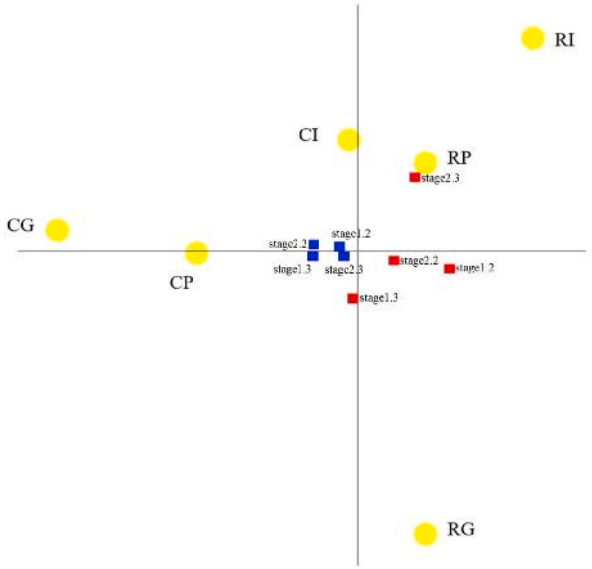


Fig. 14. ONA network centroids of MMCE (red) and GMMCE (blue) groups across different task stages. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)
Note. CI is short for "Cognitive dimension_Individual level", CP is short for "Cognitive dimension_Peer level", CG is short for "Cognitive dimension_Group level"; RI is short for "Regulative dimension_Individual level", RP is short for "Regulative dimension_Peer level", RG is short for "Regulative dimension_Group level".

summarizing and organizing their IDs by receiving documents. The third theme explored how student teachers interacted with ERNIE Bot. The interview data found that all student teachers referred to materials such as videos, cases and questioning styles provided by the research assistants. Group 10 carried out further question and answer sessions based on this, with longer questioning chains yielding more relevant answers. In addition, student teachers tended to ask questions about the ID tasks by uploading documents. Due to current technological limitations, student teachers were more likely to upload screenshots to ask questions about the MD. Finally, regarding the interactive effects of ERNIE Bot, Groups 9 and 10 reported significant contributions to ID revision but limited impact on MD. While some praised ERNIE Bot's convenience for information retrieval, others noted challenges in obtaining practical advice and accurately describing MD difficulties through textual descriptions. Since ERNIE Bot's familiarity with the advanced functionalities of the Seewo Whiteboard 5 was limited, which hindered its ability to provide practical advice. Consequently, its guidance was more general in nature, focusing on technical operations rather than offering constructive advice at a detailed level. Additionally, the interactive exchange primarily involved uploading images, which posed challenges in accurately conveying the interactive aspects of MD. This method struggled to capture the characteristics of developing MD, making it difficult for student teachers to articulate their design challenges through textual descriptions alone.

5. Discussion

In this study, a generative artificial intelligence tool was introduced into mind mapping-based collaborative environment. The experimental design and findings of this study demonstrate a new possibility for the application of GAI tools in collaborative learning.

5.1. Differences of task performance between GMMCE and MMCE groups

GMMCE groups outperformed MMCE groups on both collaborative tasks in the course. In particular, the experimental group significantly outperformed the control group on ID task. This result is consistent with Liu, Zhang, and Biebricher (2024) that the application of GAI tools in the collaborative learning field enhances learners' achievement in a certain way. Furthermore, in the context of text-based content creation, GAI tools prove valuable as a supplement. They help students enhance the quality of their work by improving relevance, logic, and educational value through powerful text-processing capabilities and intelligent recommendations (Chan & Hu, 2023). However, no statistically significant difference was found between the experimental and control groups in scoring group work on multimedia courseware design tasks. This may be due to the nature of the task itself. Creating multimedia courseware relies heavily on integrating images, sounds, and videos to boost interactivity and engagement. Current GAI tools lack the capability to generate such complex content, limiting their effectiveness in this area. This finding underscores the need to consider task types when evaluating digital resources and tools in education, to better identify appropriate applications and optimize tool design (Chang et al., 2018). Accordingly, Chang et al. (2018) innovatively incorporated mobile online resources on the basis of conventional mind mapping functions. This initiative not only broadens the information sources of mind maps, but also greatly facilitates the process of information retrieval and data storage for users. In conclusion, GAI tools combined with effective pedagogical scaffolding (e.g., mind mapping) in

collaborative environments in higher education would facilitate deep learning by assisting students in exploring and relating knowledge in depth (e.g., Chen & Hong, 2016).

5.2. Differences of CKC process from three levels between GMMCE and MMCE groups

The student teachers' discourse data were analyzed in depth using ONA to explore the groups' knowledge construction process. The results showed that the experimental and control groups demonstrated various characteristics across the different task phases. Specifically, the experimental group's (GMMCE condition) preliminary discussion of collaborative tasks focused primarily on cognitive dimensions, such as the transition from the individual level to the peer level. They developed a more coherent process of knowledge construction in the cognitive dimension by the later stages, i.e., shared understanding and collective wisdom at the group level (e.g., Fischer et al., 2002). However, this strength was weaker in the control group (MMCE condition) once they entered the transition from the peer level to the group level. Not to mention the fact that on this basis individuals are able to internalize and form their own unique and systematic knowledge structures. This may be due to the fact that the experimental group was given the opportunity to develop further with the help of the GAI. Although the advice given by the GAI was often rather general, it was to some extent able to promote more detailed and in-depth discussion on a certain topic among the group members (Suharto et al., 2023). This phenomenon suggests that GAI's involvement in complex tasks can positively contribute to the dynamics of group discussion and further accelerate the formation of collective wisdom (Yilmaz & Yilmaz, 2023b). On the contrary, Yilmaz and Yilmaz (2023b) found that using GAI for relatively simple tasks had a negative impact on students' thinking skills. This occurred because students tended to stop developing their thinking skills after obtaining the desired answers from tools like ChatGPT. Referring to the four phases of collaborative knowledge construction proposed by Mayordomo and Onrubia (2015), i.e., "initiation", "exploration", "negotiation", and "co-construction", we found that GAI's answer was seen as the starting point easing the challenges in the initial stages of project, thereby contributing to a steady improvement in the quality of the group's work. As Ouyang and Chang (2018) posited, the process of individual knowledge inquiry, peer interaction, and group construction unfolds in a gradual and developmental manner. To foster greater peer interaction, students are encouraged to engage in elaborate construction of their own arguments. On the other hand, with the assistance of GAI, the initial task obstacles within the group are alleviated, allowing for more focus and energy to be directed toward the construction of collective intelligence (e.g., Chen et al., 2019; Paulus et al., 2010). As Chang et al. (2018) argued, the innovative integration of mind mapping with digital resources within a conventional educational framework not only significantly stimulated students' interest, but also effectively facilitated the networked construction of their knowledge systems. Meanwhile, it provided strong support for students to deepen their understanding and expand their learning boundaries. We also observed that control groups tended to shift to focusing on individual task comprehension, planning, and completion progress after articulating their personal views and engaging in peer interactions, which may also account for the inability of group discussions to further develop into collective intelligence. Specifically, they were conducted by highly motivated group members who often led the discussions. The main focus is on regulating and clarifying the tasks that need to be accomplished within the group and the progress of the various tasks. Low-motivated or low-performing participants tend to be marginalized in this process. They were involved in the group discussion mainly through monitoring their own task completion. Compared to the control groups, the experimental groups developed more divergent thinking with the support of the GAI tool. As a core indicator of the creative potential, divergent thinking plays a crucial role in stimulating novel ideas and promoting diversity in problem solving (Runco & Acar, 2012). As a result, the GAI tool expanded students' divergent thinking and significantly increased the heterogeneity and inventiveness of group productions (Habib et al., 2024).

5.3. Perception of using GAI tools in GMMCE groups

Thematic analysis of the interview data revealed four major themes: frequency of interaction with ERNIE Bot, content of interaction with ERNIE Bot, approaches of interaction with ERNIE Bot, and effect of interaction with ERNIE Bot. According to content of interaction with ERNIE Bot, the majority of student teachers agreed that the multiple examples provided by ERNIE Bot developed new ideas and thoughts within the both collaborative task phases. Concordant findings were reported by Habib et al. (2024) and Wieland et al. (2022), showing that GAI was expected to be effective in combining with pedagogical methods to promote creative thinking development. Habib et al. (2024) revealed that university students increasingly preferred to utilize GAI technology when seeking brainstorming and creativity stimulation. This technology can quickly and comprehensively provide multiple answers, greatly assisting students in the depth and breadth of their elaboration processes. According to effect of interaction with ERNIE Bot, it is a platform that allows student teachers to ask questions, explore and learn more about the basic and advanced features of multimedia courseware development software. It not only responds to these questions instantly, but also provides personalized guidance and advice based on the student teachers' specific needs. This result is consistent with the findings of previous studies (e.g., Sun et al., 2024; Yılmaz & Yılmaz, 2023a). Sun et al. (2024) found that GAI facilitates students to efficiently share their raw code or complete error information, which greatly improves the efficiency of students in receiving personalized feedback from multiple sources. Furthermore, Yılmaz and Yılmaz (2023a) provided a comprehensive summary of the versatility of GAI in programming education. For example, it not only facilitates personalized learning, but also provides clear explanations and programming examples to help students better understand programming concepts and techniques. Biggs (1999) suggested that students' perceptions of the learning environment and instructional strategies can greatly influence their learning outcomes. Specifically, positive attitudes and tendencies are likely to drive learners to explore knowledge in depth and reach higher levels of knowledge construction. On the other hand, negative attitudes tend to lead to superficial learning (Mayordomo & Onrubia, 2015). The current study revealed that students showed a more positive acceptance of the GAI tool, which explained the previous two questions. In particular, students were generally able to follow the

research assistant's guidance to complete the interactive sessions successfully, demonstrating promising learning engagement and adaptability. Accordingly, the interview results also explained in part why the experimental group obtained a better task performance and achieved a deeper knowledge construction.

6. Pedagogical implications

Based on the findings of this study, GAI tools have demonstrated significant benefits in enhancing task performance, especially in document composition assignments (e.g., Liu, Zhang, & Biebricher, 2024). This implication emphasizes the need to incorporate such tools in the field of higher education. In addition, there were challenges in realizing in-depth discussions associated with the themes of tasks in the collaborative process. It was reflected in the fact that group members tended to focus excessively on the completion of the task without engaging in the construction of collective intelligence during the collaboration process (e.g., Cress & Kimmerle, 2023). Confronted with this challenge, GAI presented a potential solution in its own unique way. Specifically, this tool effectively stimulated students' perspectives and ideas through its powerful content generation and intelligent interaction capabilities, which in turn spawns richer and deeper discussions within the group (Wieland et al., 2022). Furthermore, it not only had the ability to respond instantly to students' queries, but it was also able to provide guidance and advice based on learners' individual needs (Yılmaz & Yılmaz, 2023a). This feature greatly facilitated the efficiency of students' information retrieval and collection, shortening the period of knowledge acquisition. However, the generalized large language model (LLM) confronts challenges in in-depth pedagogical practice, especially in the integration of multidisciplinary knowledge and diversified media resources (e.g., text, images, video), which makes it difficult to output constructive and practical pedagogical suggestions. Therefore, teachers and instructional designers should firstly design instructional activities by setting open-ended questions, role-playing, and case studies to guide students to have in-depth discussions related to the topic of the task. Based on this, teachers and instructional designers may skillfully conceive and design a personalized intelligent agent (PIA) application program driven by generative artificial intelligence as the core technology. With the deepening of instruction, PIA will automatically adjust instructional strategies and resource allocation by accumulating data on students' learning behaviors, thus promoting the overall development of each student in an optimal way. Given the nature of collaborative learning activities, which are highly complex and dynamic, GAI tools must be properly integrated with well-designed collaborative scaffolds. Specifically, with abundant case studies and opportunities for hands-on practice, teachers and instructional designers can help students gradually acquire the skills to create and apply effective prompts based on learning tasks and their own needs, laying a solid foundation for their learning in the age of artificial intelligence (Rudolph et al., 2023).

7. Conclusions, limitations and future studies

This study conducted a quasi-experimental design to explore the impact of GAI on the task performance and collaborative process in higher education. The instructor of the course provided student teachers with mind maps to scaffold during various stages of the collaborative task. The student teachers first mapped their thinking maps individually, and then engaged in refined discussion and negotiation within their groups. Prior research has found that the application of mind maps in collaborative learning processes can effectively address difficulties and challenges encountered (e.g., Fischer et al., 2002). Our research further designed a collaborative environment combining a GAI tool and mind maps, validating its effectiveness in enhancing group task performance. The control group (MMCE condition) primarily relied on conventional information technology tools to complete group tasks, while the experimental group (GMMCE condition) brought in the application of a GAI tool. Moreover, this study collected discourse data from group discussions and analyzed the collaborative knowledge construction process across different task stages using ONA. Relying on an existing coding framework, we investigated the sequence and frequency of connections between different behaviors from two dimensions and three levels. In contrast to the task performance of the group, the analysis of process data revealed transitional patterns among student teachers during collaboration, providing an in-depth understanding of group interactions and dynamics. The experimental group (GMMCE condition) focused on discussions in the cognitive dimension throughout the collaborative tasks, and developed a process of collaborative knowledge construction that primarily reflected a progressive collaboration and interaction from individual to peer to group. It emphasized the initiative and independence of individual student teachers, as well as the negotiation and interaction among peers and the joint exploration and construction at the group level. Empirical analysis revealed that the integration of Generative AI (GAI) in complex task significantly enhanced group dynamics and accelerated the development of collective intelligence. GAI effectively mitigated initial task barriers, enabling group members to concentrate more on the deeper construction of collective knowledge. In contrast, discussions in the control group (MMCE condition) focused primarily on moderation, facilitating task completion. Some knowledge construction was achieved in the cognitive dimension, as seen in the interplay between individual expression and peer interaction. Therefore, the innovative use of mind mapping and digital resources can significantly boost students' exploratory interest and foster a networked construction of knowledge. This enriched learning environment strongly supports deeper understanding and broader learning horizons.

The current study encounters several constraints, firstly stemming from the sampling composition, which comprises exclusively of student teachers from a central Chinese university. We conducted the research in authentic educational settings, observing and recording real-world occurrences. This approach ensures that our research has strong practical implications, but it also suggests that the findings may not generalize well to significantly different research contexts. Future research has the potential to apply collaborative environments based on GAI tools to a wider range of educational contexts and participants. Another key limitation of this study is that the traditional collaboration tools and GAI tools adopted are rooted in the Chinese language environment. This specific cultural context may limit their multilingual applicability and functionality in a global perspective. Therefore, future research can effectively

supplement or replace the traditional collaboration tools and GAI tools to support their educational applications. For example, ERNIE Bot corresponds to ChatGPT, and Tencent QQ, as a mainstream instant messaging software, is similar to Facebook and Instagram in terms of the functions and usage scenarios provided. In addition, future research should endeavor to implement a more refined coding strategy at the data preprocessing stage to clearly differentiate between GAI information and group members' own ideas. Through this differentiated coding, we can not only clearly outline the embedded trajectory of GAI content in group discussions, but also further analyze the sequential transition characteristics of group members' statements immediately following the delivery of GAI information. Lastly, we primarily focused on group product scores as an indicator of task performance and collected discourse data from group discussions for in-depth analysis. While these data provide valuable insights into the learning process and collaborative outcomes, the study has some notable limitations. Specifically, we were unable to collect behavioral data such as click streams, which could offer a more intuitive reflection of students' engagement and interaction during learning. Future research should explore the use of more advanced technologies and methods to collect and analyze multi-modal data. For instance, eye-tracking technology and electroencephalography (EEG) devices can be utilized to gather eye-movement and brain activity data from students during collaborative learning.

CRediT authorship contribution statement

Shuowen An: Writing – original draft, Investigation, Data curation. **Si Zhang:** Writing – original draft, Supervision, Conceptualization. **Tongyu Guo:** Investigation, Data curation. **Shuang Lu:** Validation, Software. **Wenying Zhang:** Software, Investigation. **Zhihui Cai:** Validation, Software, Methodology.

Availability of data and materials

Data will be made available on request.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix 1. Coding framework

Dimension	Level	Code	Description
Cognitive dimension	Individual (CI)	New ideas generation	Stating one's viewpoints or initiating a new topic
		Ideas further elaboration	Providing further explanations or summaries of one's viewpoints
	Peer (CP)	Question presentation	Requesting a peer to clarify or further explain his/her viewpoints
		Consensus building	Simply endorsing a peer's viewpoints without disputing them in order to reach a consensus
		Countering viewpoints	Presenting viewpoints that are contrary to those of peers, with additional justification and evidence
		Agreement and summary	Endorsing peer's viewpoints and further concluding with own observations
	Group (CG)	Question presentation	Seeking clarification and explanation of existing viewpoints of the group
		Consensus building	Simply endorsing existing viewpoints within the group in order to reach a consensus
		Agreement and summary	Endorsing existing viewpoints within the group and further concluding with own observations
Regulative dimension	Individual (RI)	Goals and plans	Identifying resource requirements and planning next steps for oneself
		Monitoring and reflection	Monitoring and evaluating own progress and schedule to meet standards established for the task
	Peer (RP)	Task understanding	Clarifying the details of the assignment or answering questions about the objectives of the tasks in an appropriate manner
		Goals and plans	Identifying resource requirements and planning next steps for peer

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(*continued*)

Dimension	Level	Code	Description
		Monitoring and reflection	Monitoring and evaluating progress and schedule of peer to meet standards established for the task
	Group (RG)	Task Understanding	Asking the group for details of the task or answering questions to all group members about the purpose or requirements of the task
		Goals and plans	Identifying resource requirements and planning next steps for group
		Monitoring and reflection	Monitoring and evaluating progress and schedule of group to meet standards established for the task

Appendix 2. Interview protocol

(1) Have you used ERNIE Bot in the revision process of two tasks? How often was ERNIE Bot used? Please talk specifically about how ERNIE Bot was used.
(2) Do you think ERNIE Bot has been helpful in improving your production? If not, why do you think it didn't help? Please specifically talk about how you felt about using it in this process.
(3) Have you watched any of the case videos provided by the research assistants or referenced any of the examples provided by the research assistants while using ERNIE Bot?
(4) What other information do you think should be provided to help you better interact with ERNIE Bot?

Data availability

Data will be made available on request.

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