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# Exploring cognitive presence patterns in GenAI-integrated six-hat thinking technique scaffolded discussion: an epistemic network analysis

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## Abstract

Generative artificial intelligence (GenAI) has rapidly permeated educational settings, revolutionizing how university students approach learning and problem-solving. While its benefit to enhance personalized learning and academic performance is widely acknowledged, its impact on students' cognitive presence remains underexplored. This study attempted to investigate the influence of GenAI integrated six-hat thinking technique scaffolded discussions on cognitive presence patterns. In this 14-week study, 108 pre-service teachers used the six-hat thinking technique for scaffolded discussions in instructional design tasks. Of these, 54 incorporated GenAI tools for information retrieval and problem-solving, while the other 54 did not. Epistemic Network Analysis (ENA) was applied to examine differences in cognitive presence patterns between the two groups who used and did not use GenAI. The study further analyzed cognitive presence pattern differences between high-creativity and low-creativity pre-service teachers and found that GenAI contributed to enhancing the cognitive presence of pre-service teachers, with a notable benefit for those with high creativity levels. However, its influence on cognitive presence of pre-service teachers with low creativity levels appears to be more limited. The implications suggest that educators should use GenAI tools to enhance students' cognitive presence, but it is important to give more attention to creativity.

**Keywords:** GenAI, Cognitive presence, Creativity, Six-hat thinking, ENA, Pre-service teacher

## Introduction

Generative artificial intelligence (GenAI), such as ChatGPT, generates new content based on input and can performs tasks such as text generation, summarization, translation, question answering, and interactive dialogue (Cooper, 2023). In recent years, GenAI has had a significant impact on education. It provides students with real-time feedback, offers personalized learning experiences, and helps them understand complex concepts while increasing engagement and confidence (Adiguzel et al., 2023; Chaudhry et al., 2023). However, current research indicates that the impact of GenAI in education

remains somewhat controversial. Although GenAI facilitates easier information processing and problem-solving, it may lead to overreliance on its responses, potentially depriving students of higher-order thinking opportunities and hindering their ability to process information independently (Chan & Hu, 2023; Cooper, 2023). To mitigate these risks, structured guidance or scaffolding frameworks are necessary to ensure that students use GenAI to promote learning outcomes rather than hinder their cognitive development.

Six thinking hat is a thinking strategy tool used for effective collaboration across various fields (Chien, 2020; De Bono, 2017). It encourages students to analyze problems from different perspectives, helping them avoid fixed thinking patterns, promote the exchange of diverse viewpoints, and structure group discussions (Saariaho et al., 2015). Research has shown that the six-thinking hats can be applied to other fields and integrated with other tools (Mei et al., 2024). Therefore, it demonstrates potential as a scaffold for GenAI-supported discussions.

Cognitive presence is defined as the process of constructing and confirming meaning through sustained reflection and discourse (Lee, 2014). It reflects the cognitive levels of learners in knowledge construction and problem-solving, serving as a core element for achieving deep learning. As we expect GenAI to have a positive influence on the cognitive aspects of pre-service teachers, it is essential to explore the influence of GenAI on the cognitive presence of pre-service teachers, as it plays a pivotal role in reflecting cognitive levels and development.

Creativity, a critical component of higher-order thinking skills in Bloom's Taxonomy (Anderson & Krathwohl, 2001), significantly influences students' cognitive engagement and depth of interaction (Sibo et al., 2023). Previous studies have shown that highly creative students tend to demonstrate stronger reasoning skills and deeper interactions during knowledge construction, whereas less creative students often quickly reach a superficial consensus (Sibo et al., 2023). Therefore, in order to gain a comprehensive understanding of the role of GenAI in education, this study specifically examines differences in creativity levels among pre-service teachers.

This study integrates the six-thinking hats technique as scaffolding to facilitate structured discussions and examines the influence of GenAI on cognitive presence patterns among pre-service teachers. Furthermore, it investigates whether there are differences in cognitive presence patterns between high-creativity and low-creativity pre-service teachers who used and did not use GenAI. The study aims to provide evidence-based guidance for effectively integrating GenAI into the curriculum, offering a deeper understanding of how GenAI affects student learning and cognitive development.

## **Literature review**

### **GenAI in Education**

GenAI language models, based on the GPT architecture and trained on vast text datasets with billions of parameters, can understand, reason, associate, and generate creative content, while also handling emotions and facilitating human-computer interactions (Cooper, 2023). The interactive nature of GenAI language models makes them highly effective in educational settings. For example, feedback is a core feature of learning support and has proven highly effective in enhancing learning outcomes (Wisniewski et al., 2020). When students provide well-crafted prompts, GenAI models can offer immediate,

valuable feedback, acting as learning partners or teaching assistants (Lo, 2023; Sok & Heng, 2023). Specifically, GenAI models help students deepen their understanding and enhance critical thinking through dialogue (Essel et al., 2024). College students using GenAI produced higher-quality, more detailed, and creative problem-solving outcomes (Urban et al., 2024). Several studies have also shown that GenAI increased learning efficiency and supported personalized learning by providing immediate feedback and rich information (Stojanov, 2023; Wu et al., 2023).

Despite the potential benefits of GenAI in education, several challenges have emerged. A major concern is the risk of students becoming overly dependent on these tools, potentially weakening their critical thinking and problem-solving skills (Cooper, 2023; Sevnarayan, 2024). The ease of access to GenAI-generated information may reduce learners' motivation for deeper cognitive engagement and hinder the development of independent problem-solving abilities (Chan & Hu, 2023). Such reliance may also limit the depth and quality of educational experiences. While some studies suggest that GenAI can enhance student motivation and support higher-order thinking (Essel et al., 2024; H. Lee et al., 2024; Li, 2023), its deeper impact on cognitive development remains underexplored, highlighting the need for further investigation from a cognitive perspective.







### Six thinking hat technique

"Six-thinking Hats" is a thinking strategy tool introduced by Dr. Edward de Bono in 1985. It simplifies the thinking process by encouraging thinkers to focus on one perspective at a time. Each of the six hats is associated with a different color: blue, white, yellow, green, red, and black, each representing a unique way of thinking on a problem (Fig. 1).

The six-thinking hats method uses different colored hats to represent distinct logical thinking approaches to problem-solving. This multi-perspective thinking strategy not only fosters comprehensive analysis and reflection on the problem (De Bono, 2017; Göçmen & Coşkun, 2019), but also provides space for students to develop critical thinking and creativity (House et al., 2011; Marrapodi, 2003). Furthermore, the method allows students to seamlessly switch between different thinking roles, including black for criticism, yellow for optimism, and red for emotions (De Bono, 2017; Göçmen & Coşkun, 2019). These roles encourage students to think from multiple perspectives, prompting them to consciously evaluate and adjust their thinking processes and strategies during role transitions (Wei et al., 2018).

The six-thinking hats tool is widely used in education. Chien (2020) found it enhances pre-service teachers' reflective practices, fostering more effective thinking and innovation while solving practical problems. Chen et al. (2023) noted that it provides a structured framework for student design teams, enabling systematic thinking during design activities. The research also showed that teams often use the green hat (representing creativity) to generate numerous design proposals, fostering more options. Additionally, the tool helped to promote students' critical thinking skills and new ideas exploration (Kivunja, 2015; Morsy et al., 2021).

The six-thinking hats technique plays a significant role in providing a structured thinking framework and promoting the development of students' critical thinking. However, students often become overly reliant on GenAI, which can undermine their critical thinking abilities. While existing research suggests that the six-thinking hats can be

Type	Thinking Method	General definition
 Blue hat	Managerial	Directs and manages the overall process of discussion, ensuring focus and structure in the thinking approach.
 White hat	Neutral	Focuses on providing objective information and data, ensuring that the content discussed is neutral and fact-based.
 Red hat	Emotional	Allows the expression of personal feelings and intuitions without the need for logical justification.
 Green hat	Creative	Stimulates creativity and new ideas, exploring alternative options and perspectives to find solutions.
 Yellow hat	Positive	Encourages evaluating the plan optimistically, highlighting potential benefits and positive aspects.
 Black hat	Critical	Analyzes the plan critically, carefully identifying potential risks and problems to ensure safe and sound decision-making.

**Fig. 1** The description of six-thinking hats (De Bono, 2017)

flexibly applied across various domains and combined with other tools (Mei et al., 2024), studies in this area remain limited. Therefore, when integrated with GenAI, the six-thinking hats hold significant potential to enhance critical thinking and reduce excessive reliance on GenAI.

### Cognitive presence

The Community of Inquiry (CoI) framework, as proposed by Garrison et al. (2001), is a teaching and learning model that describes the key elements of social interaction and cognitive construction in online and blended education (Garrison et al., 2001). The CoI framework functions through the interaction of three dynamically interdependent elements: cognitive presence, social presence, and teaching presence (Kanuka & Garrison, 2004). Among these, Cognitive presence, situated within online collaborative learning environments, is defined as the level of cognitive engagement and critical thinking exhibited by learners during collaborative meaning-making processes (Garrison et al., 2001). Specifically, it refers to learners' ability to collaboratively construct and validate meaning through sustained reflection and discourse within a learning community (Garrison et al., 2001). It is operationalized in the educational context into four phases: Triggering, Exploration, Integration, and Resolution

(Garrison et al., 1999). Triggering refers to a learner's inquiry sparked by an issue, dilemma, or divergence; this phase initiates curiosity and highlights what needs to be explored. Exploration entails gathering and discussing relevant information to understand the problem, often through brainstorming, questioning, and exchanging ideas from multiple sources. Integration is a reflective phase where learners interpret and synthesize the collected information, constructing meaning and proposing potential solutions through critical thinking and communication. Finally, resolution requires evaluating these solutions or hypotheses generated during integration, examining their feasibility or applying them in practice. If new issues arise during resolution, the cycle may begin again, thereby fostering deeper understanding through continuous reflection and discourse. To further support the understanding of cognitive presence, recent studies have investigated its application across diverse educational contexts. Research shows a strong link between cognitive presence and learning outcomes in online learning (Galikyan & Admiraal, 2019; Liu, Kong, Liu, et al., 2023a, 2023b). Galikyan and Admiraal (2019) identified the Integration as a key predictor of final outcomes. Liu, Kong, Liu and et al., (2023a, 2023b) showed that computer-based mind mapping promotes reflection, enhances cognitive presence, and improves learning outcomes.

Creativity, defined as the ability to generate novel and valuable ideas (Amabile, 1996), represents a higher-order cognitive skill in Bloom's taxonomy (Anderson & Krathwohl, 2001). According to Runco and Chand (1995), the cognitive components of creativity include divergent thinking, associative reasoning, and knowledge integration. These processes are closely associated with the mechanisms described by Garrison et al. (2001) as essential to cognitive presence, such as sustained critical inquiry and collaborative knowledge construction. Empirical studies further support this connection; For instance, Sibo et al. (2023) found that creative students use reasoning to build consensus, enhancing cognitive presence, while less creative students often reach consensus quickly with minimal engagement. Recent research also suggests that GenAI can scaffold critical thinking and reflective inquiry, which are key elements underpinning cognitive presence (Cooper, 2023; Essel et al., 2024). However, a significant gap remains in understanding how individual differences in creativity influence the development of cognitive presence, especially in GenAI-supported environments.

Existing research has mainly explored GenAI's impact on learning outcomes, with limited focus on its effect on cognitive presence. To address this gap, this study uses the six-thinking hats technique to scaffold structured discussions and examines differences in cognitive presence patterns between high-creativity and low-creativity pre-service teachers using GenAI. The aim is to deepen our understanding of how GenAI shapes students' cognitive processes and development. The research questions were as follows:

What were the differences on cognitive presence patterns of pre-service teachers who used and did not use GenAI during a six-hat thinking technique integrated discussion?

What were the differences on the cognitive presence patterns of high-creativity and low-creativity pre-service teachers who used or did not use GenAI during a six-hat thinking technique integrated discussion?

How did the cognitive presence patterns of high-creativity and low-creativity pre-service teachers differ on who used GenAI during a six-hat thinking technique integrated discussion?

## Methodology

### Research context

This study was conducted within the context of a compulsory course Integrating Information Technology in Classroom for pre-service teachers at a large research university in central China. The course lasted for sixteen weeks and focused on teaching and learning in informationalized environments to develop students' skills in utilizing emerging technologies for education. During the course, students were required to engage in group discussions in project-based learning (PBL).

### Participants

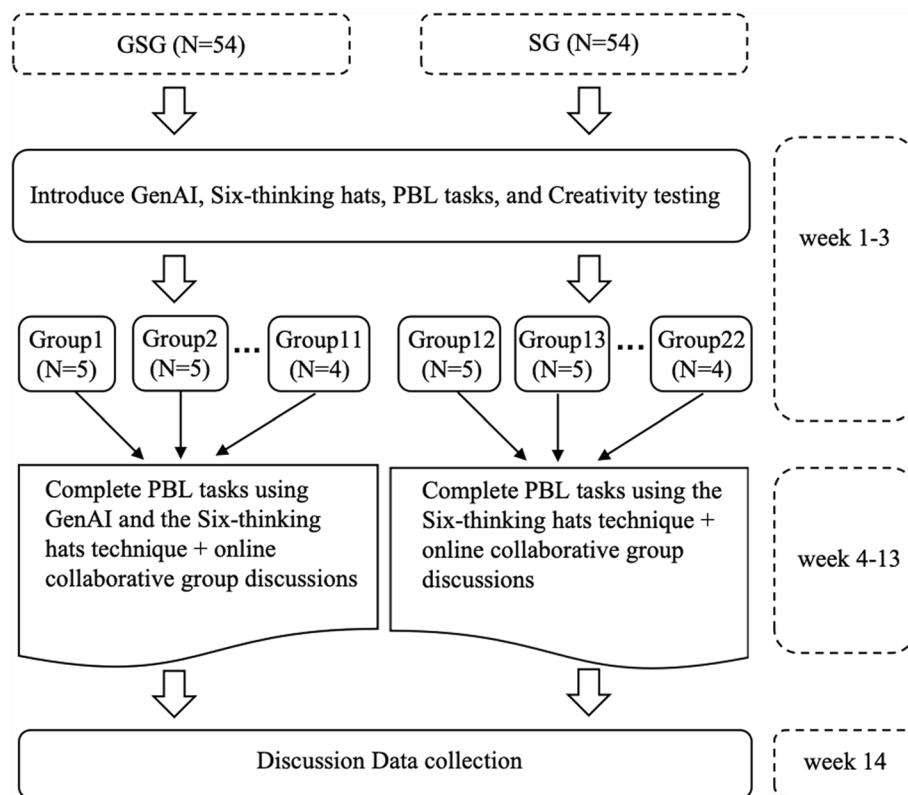
A total of 108 pre-service teachers voluntarily participated in the study. They were juniors majoring in geography (52.78%), English (23.15%), Mathematics (10.19%), Chinese literature (9.26%), Early childhood education (1.85%), History (1.85%), and Physics (0.93%). Some had teaching experience through volunteer work and tutoring, but they were unfamiliar with informationalized instructional design. None had experience with the six-thinking hats technique, and only a few had used GenAI for learning tasks prior to the course. They were randomly divided into groups that used six-thinking hats and GenAI (GSG for short,  $n = 54$ ) and groups that used six-thinking hats only (SG for short,  $n = 54$ ). There were 11 groups in GSG and 11 other groups in SG.

### Procedures

The overall design is summarized in Fig. 2. During the first three weeks, participants were introduced to the PBL tasks and trained in using the six-thinking hats through micro-lectures, discussions, and Q&A sessions. Additional instruction on using GenAI was provided specifically to the GSG. At the end of the third week, a creativity test was conducted for both the GSG and SG to assess their creativity levels.

The PBL tasks involved creating an instructional design. Each group was required to create a QQ discussion group, a social media tool used for information sharing, communication, task planning, and assignment management in online collaborative learning. Over a thirteen-week period in the fourth and sixteenth weeks, each group discussed and selected the topic for their instructional design, then collaboratively worked on the design, including learner analysis, content analysis, selecting instructional strategies, designing teaching activities, assessment design, and developing multimedia courseware (such as courseware and micro-lesson).

Both GSG and SG were required to use the six-hat thinking technique for group discussions, following the sequence: red-white-yellow-black-green-black-green. While the blue hat is not explicitly included, it controls the process through the fixed sequence (De Bono, 2017). The sequence guides discussions on intuitive feelings (red hat), the current situation (white hat), advantages (yellow hat), shortcomings (black hat), and improvement suggestions (green hat). The group continues to discuss new shortcomings



**Fig. 2** Research procedure

(black hat) and improvement suggestions (green hat) until no new shortcomings arise. The blue hat's role is implicitly seen in the group's adherence to the sequence. Only the GSG uses the GenAI platform integrated with IFlytek Spark, a Chinese-developed tool effective for processing information in Chinese (Chen & Ye, 2024), to assist in completing learning tasks. Specifically, students in the GSG were instructed to consult GenAI during different "hats" to enhance their discussions. For example, during the white hat stage, they used GenAI to retrieve objective information and relevant data to support their instructional design ideas. In the green hat stage, they were encouraged to prompt GenAI for new perspectives, creative alternatives, or innovative instructional strategies. As they moved through each hat, the GSG integrated GenAI's suggestions into their evolving design plans, aligning the GenAI-generated content with the current focus of the discussion. Figure 3 illustrates an example of how the six-hat thinking technique was integrated into the actual discussion process. Each discussion group includes a teaching assistant who ensures that participants correctly applied the six-hat thinking technique during discussions without interfering with or interrupting the process, with the interface of Group 7 shown in Fig. 4.

#### Data collection

In this study, we collected and analyzed the discussion data on QQ from the GSG and SG groups over 13 weeks. The total number of posts is 15,678, with 9163 posts generated by GSG, 6515 posts generated by SG. All the participants were asked to complete

高中历史课堂有哪些学习评价方法？请分类回答

**White hat: What are the assessment methods used in high school history classes?**

高中历史课堂的学习评价方法多种多样，可以分为过程性评价、总结性评价。以下是具体的分类回答：

一、按评价时间节点分类

1. 诊断性评价

- 定义：在学期或单元教学开始时，为了解学生的学习准备情况而进行的评价。
- 目的：通过诊断性评价，教师可以了解学生对历史知识的掌握程度、学习兴趣和需求，以便制定针对性的教学计划。
- 方式：可以通过问卷调查、摸底测试、个别访谈等形式进行。

2. 形成性评价

- 定义：在教学过程中，为引导、促进学生学而进行的评价。
- 目的：通过形成性评价，教师可以及时了解学生的学习进展、存在的问题和困难，并给予及时的反馈和指导。
- 方式：包括课堂提问、小组讨论、作业批改、学习日志等多种形式。形成性评价注重对学生学习过程的监督和引导，旨在帮助学生及时发现问题、调整学习方法、提高学习效果。

3. 总结性评价

- 定义：在教学结束时，为判断学生学习成果的达成度而进行的评价。
- 目的：通过总结性评价，教师可以全面了解学生对历史知识的掌握情况和学习能力的发展水平，为后续教学提供参考。
- 方式：包括期末考试、历史论文、项目展示与汇报等。总结性评价注重对学生学习结果的衡量和判定，旨在为学生的学习成果提供一个全面的、客观的评价。

二、按评价主体分类

1. 内部评价

- 定义：由学生自己、同伴或教师进行的评价。
- 方式：
  - 自我评价：学生对自己学习过程的反思和评价，如学习日志、自评问卷等。
  - 同伴评价：学生之间相互评价，如小组互评、全班讨论等。

在学习评价设计中，我们小组提出了两个方面的评价体系，一是学生成长记录卡，也就是教师评价；二是学生自我评价，多方面主题，能够比较全面地反映学生对“从局部抗战到全面抗战”的掌握水平，从而有利于教师进行下一步的教学计划；而学生也可以根据这个有针对性的进行复习。

采用这2种评价方式有什么弊端吗？为解决这些弊端你有什么创新的见解吗？用一段话回答，不要分点列述。

**Black hat and green hat: In our assessment design, we proposed two components: teacher evaluation via a student growth record card and student self-assessment. What potential drawbacks might these methods have, and what innovative ideas could address them?**

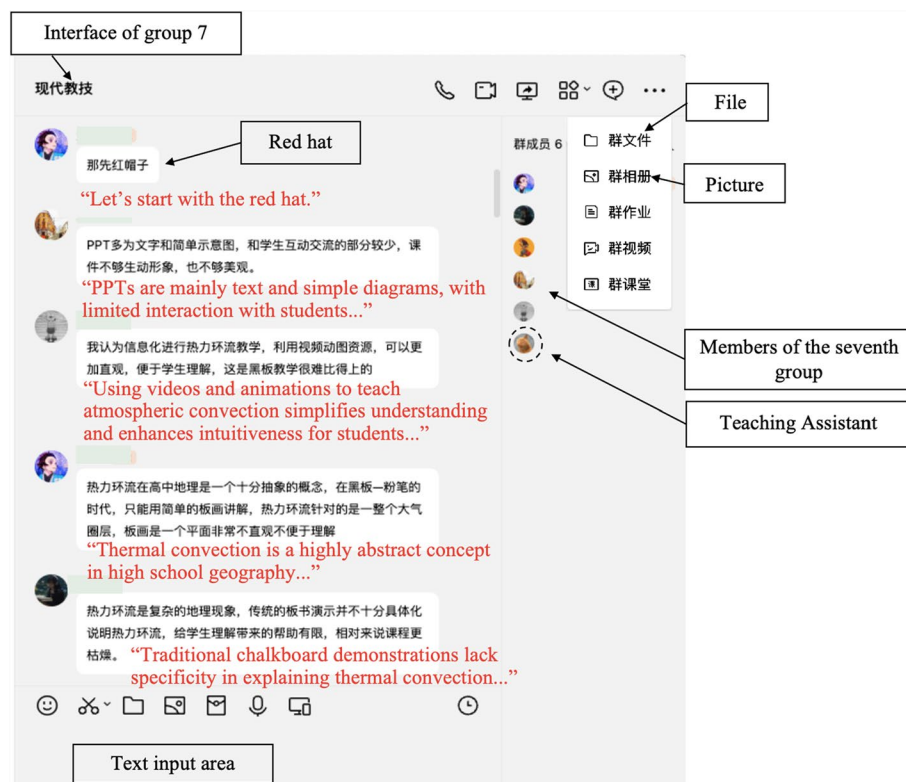
在学习评价设计中，采用学生成长记录卡（教师评价）和学生自我评价两种体系虽能全面反映学生对“从局部抗战到全面抗战”的掌握水平，但也存在一些弊端。教师评价可能带有主观性，难以完全客观地反映学生的学习情况；同时，学生自我评价可能缺乏自知之明，导致评价结果不够准确。为解决这些弊端，可以引入第三方评价，如同学互评或家长评价，以增加评价的客观性和准确性。同时，可以利用技术手段，如在线测试和数据分析，来辅助评价过程，提高评价的效率和准确性。此外，还可以定期组织学生进行自我反思和小组讨论，帮助他们更好地认识自己的学习情况，从而制定更有效的学习计划。

**Fig. 3** Integration of the six-hat thinking technique into discussion (example)

adapted versions of the Torrance Tests of Creative Thinking (TTCT) and the Southern California Creativity Test (SCCT) to assess their creativity levels. The TTCT (Torrance, 1966) is widely recognized for assessing core creative thinking abilities, including divergent thinking, fluency, originality, and elaboration, primarily through structured verbal and figural tasks. In contrast, the SCCT, developed by Guilford and colleagues within the framework of the Structure of Intellect model (Guilford, 1967), adopts a different yet theoretically related approach, emphasizing specific cognitive operations such as ideational fluency and flexibility through a series of divergent production tasks. While both instruments assess creativity, they emphasize distinct but partially overlapping dimensions, thereby enabling a more comprehensive and differentiated evaluation of participants' creative potential. Participants' creativity levels were derived from aggregated scores across items adapted from both instruments. Based on these scores, the top 20% in both GSG and SG were classified as high-creativity groups, and the bottom 20% as low-creativity groups (Zhang et al., 2022).

### Data coding

The online discussion transcripts served as the primary data source for analyzing cognitive presence (Anderson et al., 2001). In this study, we evaluated the discussion



**Fig. 4** The Tencent QQ interface (group 7)

data by combining quantitative content analysis with the cognitive presence coding scheme proposed by Garrison et al. (2001). All posts related to cognitive presence were coded into four levels: (1) Triggering; (2) Exploration; (3) Integration; and (4) Resolution. Table 1 shows the details of the coding rules. These stages represent different levels of cognitive presence, ranging from the lowest level of Triggering to the highest level of Resolution (Garrison et al., 1999).

For the subsequent analysis, we used a fine-tuned MOOC-BERT model proposed by Liu et al. (2024) to categorize each post into cognitive presence stages. The MOOC-BERT model, a specialized adaptation of BERT-Base-Chinese, was developed by Liu et al., (2023a, 2023b). The proposed model exhibited robust reliability across evaluation metrics, achieving accuracy = 0.881, precision = 0.858, recall = 0.861, and F1 = 0.859 on Dataset-AstrTalk (all values > 0.85), while maintaining comparable performance on Dataset-IntroPsy with corresponding scores of 0.782, 0.790, 0.782, and 0.786 (all > 0.78). The fine-tuned BERT model used in our study was further trained on a large-scale, expert-annotated dataset containing approximately 20,000 samples, achieving high classification reliability with F1 scores between 0.779 and 0.965 across four cognitive presence categories. These results validate the robustness and appropriateness of the model for our cognitive presence analysis (Kong et al., 2024; Liu et al., 2024). A total of 15,678 discussion texts were encoded, including 2536 Triggering, 8548 Exploration, 3751 Integration, and 843 Resolution.

**Table 1** Coding scheme cognitive presence

Category	Description	Example
Triggering	Recognizing the problem	Why do earthquakes typically occur in Turkey rather than in Russia?
Exploration	Divergence of ideas	I totally disagree with what he just said
	Exchanging ideas	I would like to share the study methods I know here
	Suggestions for consideration	The cost of AR devices is relatively high, and it is difficult to achieve nationwide widespread adoption
	Leaps to conclusions	With the continuous advancement of AR technology, AR globes are likely to be applied in more disciplines
Integration	Convergence within the group	I have the same opinion as the previous students on this issue
	Convergence in a single message	In the digital age, the integration of AR and VR technologies highlights the significant applications of globes in education, research, and other fields, achieving a seamless blend of technology and application
	Connecting ideas, synthesis	After checking a lot of information, there is no accurate term for quasars so far
	Creating solutions	Therefore, educators need to rethink and make substantive and innovative changes to teaching evaluation
Resolution	Application and solutions	This method uses virtual environments and augmented reality to help students explore and understand geographical landscapes

### Data analysis

To address RQ1, RQ2, and RQ3, descriptive statistics and chi-square tests were employed to analyze differences in the frequency of cognitive presence across various comparisons: between GSG and SG (RQ1), between GSG and SG within both high-creativity and low-creativity pre-service teachers (RQ2), and between high-creativity and low-creativity pre-service teachers within the GSG (RQ3). ENA was then used to visualize and explore their respective cognitive presence patterns.

ENA constructs an epistemic network model by analyzing the co-occurrence of cognitive elements in discussion texts to reveal the interactions of cognitive engagement across different dimensions. It uses a sliding window mechanism to calculate co-occurrences within specific segments, then transforms the data into an adjacency matrix, which is processed through normalization, dimension reduction, and singular value decomposition to visualize relationships between cognitive elements in a two-dimensional space (Swiecki et al., 2020). In the cognitive network, nodes represent cognitive elements, and the thickness of connections indicates the frequency of their co-occurrence. ENA has proven effective in analyzing cognitive presence (Liu, Kong, Liu, et al., 2023a, 2023b). In this study, ENA Webkit (<http://app.epistemicnetwork.org>) was used to analyze the coded discussion data (Shaffer et al., 2016). Nodes in the ENA network represent cognitive presence codes, and edges reflect the frequency of connections between them.

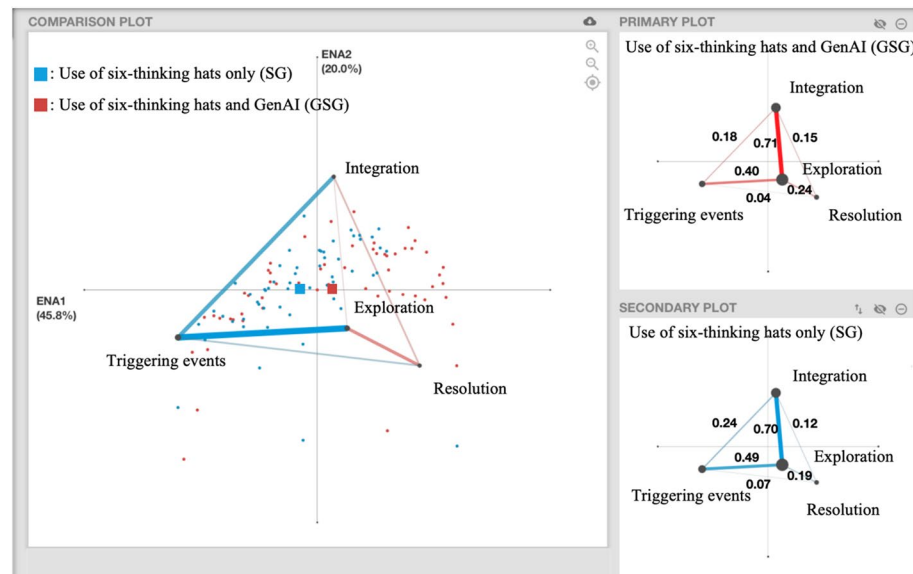
### Results

**What were the differences on cognitive presence patterns of pre-service teachers who used and did not use GenAI during a six-hat thinking technique integrated discussion?**

To explore differences in cognitive presence patterns between pre-service teachers using or not using GenAI, we compared the frequency distribution of cognitive

**Table 2** Frequencies and distributions of cognitive presence levels of in the GSG and SG

	Triggering	Exploration	Integration	Resolution	Total
SG	1053 (16.16%)	3566 (54.74%)	1577 (24.21%)	319 (4.90%)	6515
GSG	1483 (16.18%)	4982 (54.37%)	2174 (23.73%)	524 (5.72%)	9163
Total	2536 (16.18%)	8548 (54.52%)	3751 (23.93%)	843 (5.38%)	15,678

**Fig. 5** ENA networks of cognitive presence for the GSG (red) and SG (blue)

presence in the GSG and SG (Table 2). A Chi-square test showed no statistically significant difference between the two groups ( $\chi^2 = 5.282$ ,  $df = 3$ ,  $p = 0.152$ ). As shown in Table 2, Exploration ( $n = 8548$ ) was the most common cognitive presence, accounting for 54.52%, followed by Integration ( $n = 6808$ ) at 23.93%. Triggering ( $n = 2536$ ) and Resolution ( $n = 843$ ) were less frequent. This suggests that pre-service teachers primarily focused on Exploration and Integration. Notably, Resolution was the least represented in both groups, indicating that fewer discussions reached the stage of applying solutions or testing ideas in practice. The proportions of Triggering, Exploration, Integration, and Resolution in the GSG (16.16%, 54.74%, 24.21%, and 4.90%) were similar to those in the SG (16.18%, 54.37%, 23.73%, and 5.72%). However, the GSG generated more posts related to cognitive presence, with 9163 posts compared to 6515 in the SG.

To further compare the differences in cognitive presence patterns between pre-service teachers using or not using GenAI, ENA was applied to explore the cognitive presence patterns of the GSG and SG. Figure 5 displays the overall ENA networks of cognitive presence. The projected points and their means in the ENA space are shown on the left side of Fig. 5. Pre-service teachers in the GSG are represented by red dots, and those in the SG by blue dots. The red square represents the centroid for the GSG, indicating the mean position of projected points, while the blue square represents the

**Table 3** Results of the U-test for ENA characteristics between the GSG and SG

Dimension	Group	N	Median	U	P-value	Effect Size (r)
ENA 1 (X axis)	GSG	54	0.13	1208.00	0.03	0.24
	SG	54	− 0.06			
ENA 2 (Y axis)	GSG	54	0.02	1593.50	0.99	0.00
	SG	54	0.02			

Median values represent the central tendency of ENA scores for each group and provide a robust comparison when data may not follow a normal distribution

**Table 4** Connection coefficients of ENA networks for the GSG and SG

Connection	GSG	SG
Triggering—exploration	0.40	0.49
Triggering—integration	0.18	0.24
Triggering—resolution	0.04	0.07
Exploration—integration	0.71	0.70
Exploration—resolution	0.24	0.19
Integration—resolution	0.15	0.12

centroid for the SG. The centroid reflects the weighted connections between cognitive presence nodes and is plotted as a corresponding dot (Bressler et al., 2019). The centroid positions highlight differences in cognitive presence structures between the GSG and SG. The horizontal axis (ENA 1) represents cognitive presence, with Resolution and Exploration codes on the right and Triggering on the left. The vertical axis (ENA 2) shows Integration at the top and Resolution at the bottom of the ENA space.

The distribution of projection points between the GSG and the SG in the ENA space was compared using a Mann–Whitney U test (Swiecki et al., 2020). Table 3 displays the results of the U-test. A statistically significant difference was shown at the  $\alpha = 0.05$  level on the horizontal axis (ENA 1) of the ENA space.

The right side of Fig. 5 shows the mean networks of the GSG and the SG, respectively. The connection coefficients of these ENA networks are detailed in Table 4. Firstly, we compared the cognitive presence patterns of the GSG and SG to detail the differences, as illustrated in Fig. 5. The red and blue lines represent the connections between cognitive nodes in the GSG and SG, respectively, with line thickness indicating connection strength. From Fig. 5, we found that pre-service teachers in the GSG exhibited slightly stronger associations in the Exploration-Resolution and Integration-Resolution connections. In contrast, those in the SG demonstrated stronger connections in the Triggering-Exploration, Triggering-Integration, and Triggering-Resolution aspects.

#### What were the differences on the cognitive presence patterns of high-creativity and low-creativity pre-service teachers who used or did not use GenAI during a six-hat thinking technique integrated discussion?

To explore the differences in the cognitive presence patterns of high-creativity and low-creativity pre-service teachers who used or did not use GenAI, we presented the frequency distribution of cognitive presence between the high-creativity pre-service

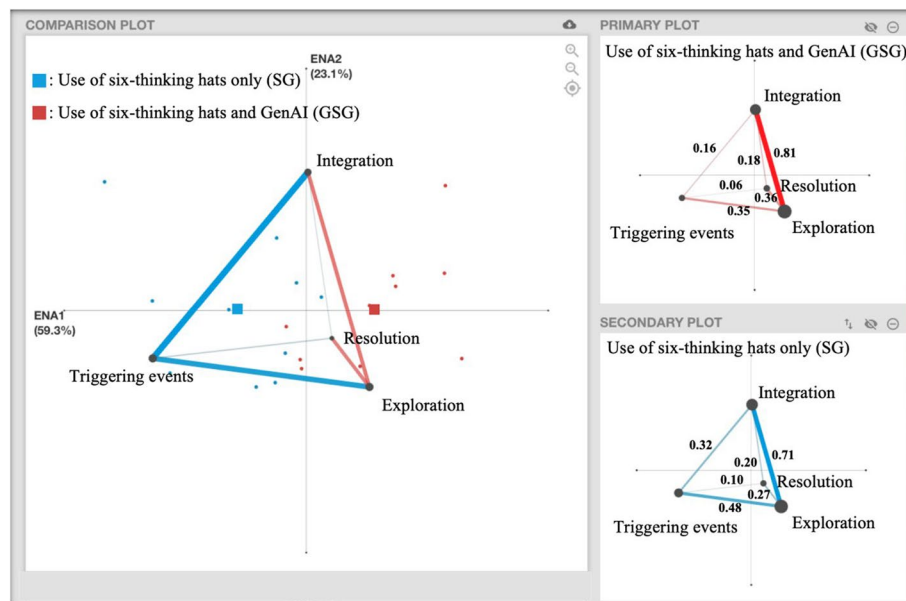
teachers in both the GSG and SG, and between the low-creativity pre-service teachers in both the GSG and SG (Table 5). As can be seen from Table 5, the chi-square test reveals significant differences in the distribution of cognitive presence levels between the GSG and SG of high-creativity and low-creativity pre-service teachers (High-creativity group:  $\chi^2 = 49.510$ ,  $df = 3$ ,  $p < 0.05$ ; Low-creativity group:  $\chi^2 = 28.654$ ,  $df = 3$ ,  $p < 0.05$ ).

Significant differences in cognitive presence levels are observed between the GSG and SG in high-creativity groups. Compared to the SG, pre-service teachers with high creativity in the GSG devoted a larger proportion of discourse to Exploration (GSG:  $n = 1061$ , 63.42%; SG:  $n = 554$ , 51.58%) and a significantly smaller proportion to Triggering (GSG:  $n = 118$ , 7.05%; SG:  $n = 144$ , 13.41%). Integration remained the second most frequent phase in both groups, although its proportion was slightly lower in the GSG. Resolution was rare in both groups, with similar proportions of around 6%. A similar pattern was observed among pre-service teachers with low creativity, with the proportion of Exploration again higher in the GSG (GSG:  $n = 370$ , 62.71%; SG:  $n = 383$ , 51.69%) and the proportion of Triggering nearly halved (GSG:  $n = 70$ , 11.86%; SG:  $n = 165$ , 22.27%). Differences between groups in Integration and Resolution were marginal. Additionally, although Resolution is the least frequent phase overall, it occurs more frequently among high-creativity teachers compared to their low-creativity counterparts. These findings suggest that GenAI support shifts discourse from Triggering toward Exploration in both high-creativity and low-creativity groups, indicating that pre-service teachers using GenAI generate more ideas, while those not using GenAI pose more questions on social platforms. GenAI use has minimal impact on Integration and slightly increases engagement in Resolution among high-creativity teachers. Moreover, high-creativity pre-service teachers participate more frequently in discussions ( $n = 2747$ ) than low-creativity pre-service teachers ( $n = 1331$ ), indicating greater involvement.

To further elaborate on the differences in the cognitive presence patterns, ENA networks were analyzed for high-creativity and low-creativity pre-service teachers in both the GSG and SG. Figure 6 shows the overall ENA networks of cognitive presence for high-creativity pre-service teachers in both the GSG and SG. The dots in Fig. 6 represent the centroids of high-creativity pre-service teachers in the GSG (red) and SG (blue). The horizontal axis of the ENA space (ENA 1) depicted the cognitive presence as the right side with Exploration and Resolution codes, and the left side with Triggering code. The vertical axis (ENA 2) depicted the cognitive presence with Integration codes at the upside of the ENA space, and Exploration code at the downside of the ENA space.

**Table 5** Frequencies and distributions of cognitive presence levels between pre-service teachers with high-creativity and low-creativity

	Group	Triggering	Exploration	Integration	Resolution	Total
High-creativity pre-service teachers	SG	144 (13.41%)	554 (51.58%)	306 (28.49%)	70 (6.52%)	1074
	GSG	118 (7.05%)	1061 (63.42%)	400 (23.91%)	94 (5.62%)	1673
H_Total		262 (9.54%)	1615 (58.79%)	706 (25.70%)	164 (5.97%)	2747
Low-creativity pre-service teachers	SG	165 (22.27%)	383 (51.69%)	165 (22.27%)	28 (3.78%)	741
	GSG	70 (11.86%)	370 (62.71%)	121 (20.51%)	29 (4.92%)	590
L_Total		235 (17.67%)	753 (56.57%)	286 (21.49%)	57 (4.28%)	1331



**Fig. 6** ENA networks of cognitive presence for high-creativity pre-service teachers in the GSG (red) and SG (blue)

The distribution of projection points in the ENA space for high-creativity pre-service teachers between the GSG and SG was compared using a U-test. Table 6 displays the results of the U-test. A statistically significant difference was shown at the  $\alpha=0.05$  level on the horizontal axis (ENA 1) of the ENA space.

The right side of Fig. 6 shows the mean networks for pre-service teachers in the GSG and SG, respectively. The connection coefficients of these ENA networks are detailed in Table 7. Firstly, we compared the cognitive presence patterns of high-creativity pre-service teachers in both groups to reveal the details of the differences, as illustrated in Fig. 6. The red and blue lines depict the connections between cognitive nodes in the GSG and SG, respectively, with the line thickness indicating connection

**Table 6** Results of the U-test for ENA characteristics for high-creativity pre-service teachers between the GSG and SG

Dimension	Group	N	Median	U	P-value	Effect Size (r)
ENA 1 (X axis)	GSG	10	0.13	4.00	0.00	0.92
	SG	10	− 0.07			
ENA 2 (Y axis)	GSG	10	− 0.01	47.00	0.85	0.06
	SG	10	0.01			

**Table 7** Results of the U-test for ENA characteristics for low-creativity pre-service teachers between the GSG and SG

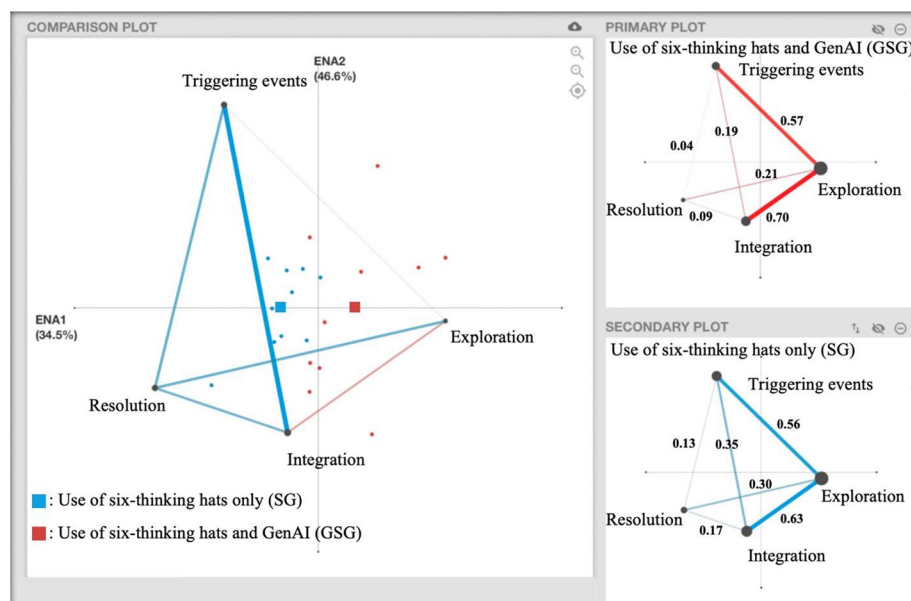
Dimension	Group	N	Median	U	P-value	Effect Size (r)
ENA 1 (X axis)	GSG	10	0.08	4.00	0.00	0.92
	SG	10	− 0.10			
ENA 2 (Y axis)	GSG	10	0.03	52.00	0.91	− 0.04
	SG	10	0.02			

strength. From Fig. 6, we found that pre-service teachers in the GSG showed stronger associations in the Exploration-Integration and Exploration-Resolution connections, particularly in the Exploration-Integration connection. In contrast, those in the SG displayed stronger connections in the Triggering-Exploration and Triggering-Integration aspects.

Figure 7 shows the overall ENA networks of cognitive presence for low-creativity pre-service teachers in both the GSG and SG. The dots in Fig. 7 represent the centroids of low-creativity pre-service teachers in the GSG (red) and SG (blue). The horizontal axis of the ENA space (ENA 1) depicted the cognitive presence as the right side with Exploration code, and the left side with Resolution code. The vertical axis of the ENA space (ENA 2) depicted the cognitive presence with Triggering code at the upside of the ENA space, and Integration code at the downside of the ENA space.

The distribution of projection points in the ENA space for low-creativity pre-service teachers between the GSG and SG was compared using a U-test. Table 7 displays the results of the U-test. A statistically significant difference was shown at the  $\alpha = 0.05$  level on the horizontal axis (ENA 1) of the ENA space.

The right side of Fig. 7 shows the mean networks for pre-service teachers in the GSG and SG, respectively. The connection coefficients of these ENA networks are detailed in Table 8. Next, we compared the cognitive presence patterns of low-creativity pre-service teachers in both groups to reveal the details of the differences, as illustrated in Fig. 7. The red and blue lines depict the connections between cognitive nodes in the GSG and SG, respectively, with the line thickness indicating connection strength. From Fig. 7, we found that pre-service teachers in the SG showed stronger associations in the Exploration-Resolution and Integration-Resolution. However, those in the GSG displayed stronger connections in the Exploration-Integration aspects.



**Fig. 7** ENA networks of cognitive presence for low-creativity pre-service teachers in the GSG (red) and SG (blue)

**Table 8** Connection coefficients of ENA networks for high-creativity and low-creativity pre-service teachers in the GSG and SG

Connection	High-creativity pre-service teachers		Low-creativity pre-service teachers	
	GSG	SG	GSG	SG
Triggering—Exploration	0.35	0.48	0.57	0.56
Triggering—Integration	0.16	0.32	0.19	0.35
Triggering—Resolution	0.06	0.10	0.04	0.13
Exploration—Integration	0.81	0.71	0.70	0.63
Exploration—Resolution	0.36	0.27	0.21	0.30
Integration—Resolution	0.18	0.20	0.09	0.17

### How did the cognitive presence patterns of high-creativity and low-creativity pre-service teachers differ on who used GenAI during a six-hat thinking technique integrated discussion?

To explore the differences in cognitive presence patterns of high-creativity and low-creativity pre-service teachers who used GenAI, we analyzed the frequency distribution of cognitive presence between the high-creativity and low-creativity pre-service teachers in the GSG (Table 5). The chi-square tests revealed significant differences in the distribution of cognitive presence levels between the two groups ( $\chi^2 = 14.776$ ,  $df = 3$ ,  $p < 0.05$ ). Exploration was the most common cognitive presence (high-creativity pre-service teachers: 63.42%; low-creativity pre-service teachers: 62.71%), followed by Integration (high-creativity pre-service teachers: 23.91%; low-creativity pre-service teachers: 20.51%). The high-creativity pre-service teachers had significantly higher proportions of Integration and Resolution. This suggests both groups focus on Exploration and Integration, with high-creativity teachers engaging more in Integration and Resolution.

To further elaborate on the differences in the cognitive presence patterns of high-creativity and low-creativity pre-service teachers, we conducted an analysis of the ENA networks for both groups in the GSG. Figure 8 presents the overall ENA networks of cognitive presence for high-creativity and low-creativity pre-service teachers in the GSG. The dots represent the centroids of high-creativity (red) and low-creativity (blue) pre-service teachers. The horizontal axis of the ENA space (ENA 1) depicted the cognitive presence as the right side with Triggering code, and the left side with Integration and Resolution codes. The vertical axis (ENA 2) depicted the cognitive presence with Resolution code at the upside of the ENA space, and Integration code at the downside of the ENA space.

The distribution of projection points in the ENA space for high-creativity and low-creativity pre-service teachers in the GSG was analyzed using a U-test. Table 9 displays the results of the U-test. A statistically significant difference was shown at the  $\alpha = 0.05$  level on the horizontal axis (ENA 1) of the ENA space.

The right side of Fig. 8 shows the mean networks for both groups, while the connection coefficients for these ENA networks are detailed in Table 10. Firstly, we analyzed the cognitive presence patterns of the high-creativity and low-creativity groups in the GSG, as depicted in Fig. 8. The red and blue lines represent the connections between cognitive nodes in each group, with line thickness indicating connection



**Fig. 8** Cognitive presence networks for high-creativity (red) and low-creativity (blue) pre-service teachers in the GSG

**Table 9** Results of the U-test on ENA characteristics between the high-creativity and low-creativity pre-service teachers in the GSG

Dimension	Group	N	Median	U	P-value	Effect Size (r)
ENA 1 (X axis)	High-creativity pre-service teachers	10	− 0.24	18.00	0.01	0.64
	Low-creativity pre-service teachers	10	0.20			
ENA 2 (Y axis)	High-creativity pre-service teachers	10	− 0.04	44.00	0.68	0.12
	Low-creativity pre-service teachers	10	− 0.05			

**Table 10** Connection coefficients of ENA networks for high-creativity and low-creativity pre-service teachers in the GSG

Connection	High-creativity pre-service teachers	Low-creativity pre-service teachers
Triggering—exploration	0.31	0.60
Triggering—integration	0.15	0.17
Triggering—resolution	0.06	0.03
Exploration—integration	0.84	0.61
Exploration—resolution	0.33	0.18
Integration—resolution	0.16	0.07

strength of the connections. From Fig. 8, we found that the high-creativity group showed stronger associations in Exploration-Integration, Exploration-Resolution, and Integration-Resolution, especially in Exploration-Integration and Exploration-Resolution. In contrast, the low-creativity group had stronger associations in the Triggering-Exploration connection.

## Discussion

This study collected online discourse data from pre-service teachers and revealed differences in cognitive presence patterns between the GSG and SG through ENA and statistical analysis. Additionally, the study explored the differences in cognitive presence patterns among pre-service teachers based on their creativity levels (high or low) during a six-hat thinking technique integrated discussion.

### GenAI shaped cognitive presence patterns and idea generation

This study revealed the cognitive presence patterns and idea generation of the pre-service teachers that no matter used GenAI or not, they primarily engaged in Exploration and Integration. However, the GSG generated more posts, reflecting heightened engagement due to GenAI's interactive and real-time feedback capabilities. This finding supports prior research demonstrating that GenAI enhanced idea generation and discussion engagement (Adiguzel et al., 2023; Chaudhry et al., 2023). Additionally, the GSG exhibited stronger connections in Exploration-Resolution and Integration-Resolution, whereas the SG group demonstrated stronger connections between Triggering-Exploration and Triggering-Integration. These results highlighting GenAI's role in fostering complex, iterative cognitive processes. These findings align with Essel et al. (2024) and Ahmad Al Yakin et al. (2023), who observed that using GenAI inspires students, improving creativity, critical thinking, and reflection.

This study revealed that high-creativity pre-service teachers who used GenAI generated more posts and exhibited stronger Exploration-Integration and Exploration-Resolution connections, while those without GenAI had stronger Triggering-Exploration and Triggering-Integration connections. This supports findings that GenAI enhances idea generation, discussion engagement, and learning confidence (Adiguzel et al., 2023; Chaudhry et al., 2023). GenAI helped high-creativity teachers generate more ideas and solutions, and had reached higher cognitive presence levels.

The minimal differences between low-creativity pre-service teachers in GSG and SG suggest that GenAI may have led to limited differences in their cognitive presence patterns. This could result from their low level of engagement with GenAI's interactive and feedback features. Stronger associations in the Exploration-Resolution and Integration-Resolution in SG reflected a linear, task-focused approach, where the pre-service teachers relied on surface-level connections to move quickly from identifying problems to solutions. In contrast, GSG's stronger connections in Exploration-Integration indicated that GenAI supports iterative thinking and refining ideas, though it fails to close the creativity gap for low-creativity learners. This aligns with Kumar et al. (2024)'s finding that heavy reliance on GenAI reduced creativity by fostering intellectual passivity and limiting independent problem-solving. For low-creativity individuals, such dependency may worsen difficulties in generating ideas or complex reasoning, as GenAI might reinforce routine thinking rather than challenge it.

Furthermore, the findings indicate that regardless of creativity levels or the use of GenAI, pre-service teachers still exhibit relatively weak connections in Exploration-Resolution and Integration-Resolution, echoing prior research suggesting that learners often struggle to move beyond generating and organizing ideas toward applying

solutions in practice (Vaughan & Garrison, 2005). While the six-hat thinking technique and GenAI appeared beneficial for promoting idea generation, our instructional design did not explicitly or robustly facilitate the higher-order cognitive processes integral to Resolution, such as synthesis, practical application, and real-world testing (Garrison et al., 2001). Specifically, although participants followed a structured discussion sequence using the six-hat thinking technique, the “blue hat” role, which directs group processes and promotes reflection on actionable outcomes, was implicitly managed rather than clearly emphasized. This may have limited learners’ ability to define and achieve concrete resolutions (De Bono, 2017). This aligns with Garrison et al. (2001), who emphasize that effective integration and resolution require a strong teaching presence to diagnose misconceptions, scaffold deeper exploration, and guide learners toward actionable knowledge. Meyer (2003) also notes that resolution demands more targeted guidance than earlier cognitive phases. Consequently, one plausible explanation for the limited Resolution phase is insufficiently explicit and structured teaching presence.

#### **GenAI amplified the creativity gap in pre-service teachers’ cognitive presence**

This study found that high-creativity pre-service teachers exhibited higher levels of cognitive presence than low-creativity pre-service teachers when using GenAI. Specifically, high-creativity pre-service teachers who used GenAI showed higher frequencies in the Exploration, Integration, and Resolution, while exhibiting lower frequencies in Triggering, compared to their low-creativity counterparts. This suggests that high-creativity pre-service teachers generated more ideas and had stronger connections in the Exploration-Integration, Exploration-Resolution, and Integration-Resolution, thereby reaching higher cognitive presence levels. These findings indicate that high-creativity pre-service teachers experienced fewer challenges in transitioning between these levels, reflecting a more seamless cognitive process. This can be attributed to creativity as a higher-order cognitive skill, involving divergent thinking, associative processes, and complex knowledge structures (L. W. Anderson & Krathwohl, 2001; Serban et al., 2023). Such cognitive flexibility allows high-creative pre-service teachers to generate diverse solutions during Exploration and refine them more effectively in Integration and Resolution. This results in fewer cognitive disruptions, facilitates smoother transitions between cognitive levels, and promotes sustained engagement. Furthermore, GenAI’s real-time feedback enhances their ability to engage deeply, reflect iteratively, and develop complex ideas.

This observation aligns with prior research showing that more creative students tend to outperform their less creative peers in cognitive abilities and depth of interaction. For instance, Supena et al. (2021) found that high creativity enhanced the development of critical thinking, collaboration, and self-regulation capabilities, while low creativity constrained the development of these skills. Similarly, Sibbo et al. (2023) observed that highly creative students engage in deeper reasoning and debate, whereas less creative students often settle for quick consensus. As a result, the gap on cognition between high-creativity and low-creativity pre-service teachers is further increased, suggesting that GenAI may amplify the influence of creativity on cognitive presence. The limited improvement among low-creativity learners underscores the need for tailored interventions that align GenAI’s capabilities with their learning needs. Such approaches can promote

independent thinking, reduce over-reliance on GenAI, and ensure equitable benefits for learners of varying creativity levels.

#### **The role of the six-thinking hats as a discussion scaffold**

This study supported the previous research which suggested combination of the six-hat thinking technique and GenAI tools holds significant potential for enhancing cognitive development and collaborative learning (Chien, 2020; Mei et al., 2024). The integrating GenAI with the six-hat thinking technique amplified their benefits. GenAI provided real-time feedback and adaptive scaffolding tailored to specific thinking modes, enriching reflective and analytical processes (Essel et al., 2024; Yakin et al., 2023). The six-thinking hats promoted structured collaboration by encouraging diverse perspectives and thorough exploration of problems, which fosters innovative ideas (De Bono, 2017; Göçmen & Coşkun, 2019). Team creativity was boosted with a clear framework for ideation and problem-solving, enabling smooth transitions between critical analysis and creative brainstorming (Chen et al., 2023). Therefore, the six-hat thinking technique worked as a scaffold for the use of GenAI tools, developing higher-order cognitive skills while aligning with GenAI's personalized learning features.

In conclusion, while our study demonstrates that integrating GenAI within a six-thinking hats framework can enhance cognitive presence and idea generation, it is essential to consider its ethical implications. Overreliance on GenAI may impede the development of independent critical thinking and problem-solving skills (Chan & Hu, 2023; Cooper, 2023). Additionally, GenAI tools can generate hallucinations, which are confident yet factually inaccurate responses, significantly increasing the risk of spreading unverified or misleading information (Ji et al., 2023). Therefore, ensuring that GenAI serves as a complementary tool rather than a substitute for human cognition will require robust digital literacy initiatives and clearly defined ethical guidelines in educational settings.

#### **Limitations and future research**

Several limitations existed in this study. First, we did not collect qualitative data on students' perceptions of GenAI or their experiences using it, which means the learners' personal viewpoints and reflections remain unexamined in our analysis. Second, although we aligned GenAI use with the intended focus of each thinking hat, such as using the white hat for information retrieval and the green hat for idea generation, we did not further distinguish between specific types of GenAI interactions. Types of interactions like summarization, synthesis, and critique were not analyzed separately, nor was their potential influence on different phases of cognitive presence. Third, the cognitive presence patterns observed in this study revealed an underrepresentation of Resolution. Very few contributions reached this highest cognitive presence phase, suggesting that the course design might not have adequately supported students in progressing toward Resolution. Fourth, this study focused exclusively on pre-service teachers in China, which may limit the applicability of these findings to other cultural or institutional contexts. Different educational systems, cultural values, and curricular structures could influence how GenAI-based interventions are perceived, adopted, and integrated. Finally, the small sample size posed challenges. Only the top and bottom 20% of students in each

condition were classified as high-creativity or low-creativity, resulting in four small groups, which might have overlooked key patterns.

These limitations point to several directions for future research. Qualitative methods such as interviews, focus groups, and reflective journals should be employed to capture students' perceptions, challenges, and satisfaction with GenAI, thereby complementing quantitative data and clarifying underlying mechanisms. Future studies should also examine the effects of different types of GenAI support on learning processes and outcomes in collaborative learning environments. For instance, comparative studies could investigate whether using GenAI for summarizing course content versus providing feedback or critical evaluation leads to distinct patterns of cognitive presence. To address the scarcity of Resolution, future interventions should strengthen teaching presence and provide more explicit scaffolding that helps learners apply and test newly constructed knowledge. Researchers should also explore how GenAI-supported instruction is implemented and adapted across diverse cultures, educational levels, and subject domains, using larger and more balanced samples that capture the full spectrum of creativity. Studies that include in-service teachers and learners from different national contexts and that span STEM, humanities, and social-science disciplines will help distinguish universal from context-specific mechanisms of GenAI integration in education.

### **Implications**

Based on these empirical findings, First, educators should utilize GenAI tools to stimulate students' higher-order cognitive potential, offering enhanced support and guidance to facilitate knowledge integration and effective problem-solving. Second, educators should leverage GenAI as an adaptive learning scaffold, especially when integrated with structured thinking tools like the six-thinking hats. This integration can serve as a powerful mechanism to enhance cognitive engagement by providing learners with dynamic, personalized support that evolves with their thinking processes. Finally, it is essential to recognize the limitations of GenAI. While these tools effectively support learning, they cannot replace higher-order cognitive abilities such as creativity. To fully realize the potential of GenAI in education, instructional design should focus on cultivating these advanced cognitive skills.

### **Conclusions**

This study examined the cognitive presence patterns of pre-service teachers who used and did not use GenAI during a six-hat thinking technique discussion. It also explored how these patterns varied based on creativity levels (high or low). Results showed that students who used GenAI demonstrated stronger connections at higher levels of cognitive presence, reached a high level of cognitive presence. Notably, GenAI especially benefits highly creative individuals. It helps high-creativity teachers generate more ideas and solutions, leading to a higher level of cognitive presence. In contrast, low-creativity pre-service teachers, whether they used GenAI or not, showed minimal differences in cognitive presence patterns. This suggests that GenAI has a limited impact on low-creativity individuals and may amplify the influence of creativity on cognitive presence. High-creativity teachers consistently demonstrated higher cognitive presence than their

low-creativity peers, highlighting that GenAI cannot replace advanced cognitive skills like creativity.

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#### Author contributions

Manli Yu: Writing, Editing, and Methodology. Zhi Liu: Writing, Conceptualization, and Supervision; Taotao Long: Methodology, Resources, and Writing; Dong Li: Conceptualization and Methodology. Lei Deng: Conceptualization and Methodology. Xi Kong: Conceptualization and Methodology. Jianwen Sun: Project administration, Funding acquisition, and Supervision.

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#### Availability of data and materials

Data will be made available on request.

#### Declarations

##### Ethics approval and consent to participate

This study received approval from the Human Research Sub-Committee of the Ethic Review Committee at Central China Normal University. The IRB Number is: CCNU-IRB-202412001A. All individuals involved in the research have provided informed consent.

##### Competing interests

There is no potential competing interest.

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#### References

- Adiguzel, T., Kaya, M. H., & Cansu, F. K. (2023). Revolutionizing education with AI: Exploring the transformative potential of ChatGPT. *Contemporary Educational Technology*, 15(3), 429.
- Amabile, T. M. (1996). *Creativity in context: Update to the social psychology of creativity*. Westview Press.
- Anderson, L. W., & Krathwohl, D. R. (2001). *A taxonomy for learning, teaching, and assessing: A revision of Bloom's taxonomy of educational objectives*. Longman.
- Anderson, T., Rourke, L., Garrison, D. R., & Archer, W. (2001). Assessing teaching presence in a computer conferencing context. *Journal of Asynchronous Learning Networks*, 5(2), 1–17.
- Bressler, D. M., Bodzin, A. M., Eagan, B., & Tabatabai, S. (2019). Using epistemic network analysis to examine discourse and scientific practice during a collaborative game. *Journal of Science Education and Technology*, 28(5), 553–566.
- Chan, C. K. Y., & Hu, W. (2023). Students' voices on generative AI: Perceptions, benefits, and challenges in higher education. *International Journal of Educational Technology in Higher Education*, 20(1), 43.
- Chaudhry, I. S., Sarwary, S. A., El Refae, G. A., & Chabchoub, H. (2023). Time to revisit existing student's performance evaluation approach in higher education sector in a new era of CHATGPT—a case study. *Cogent Education*, 10(1), 2210461.
- Chen, D., Liu, F., Hu, Y., Du, X., Bai, Y., Ren, Z., Lan, L., & Yu, W. (2023). Service design from the perspective of "six thinking hats": A comparison of storytelling strategies of experts and novices. *Thinking Skills and Creativity*, 47, Article 101219.
- Chen, W., & Ye, F. (2024). Evaluation and recommendations on the application effects of domestic and international artificial intelligence tools in Chinese proofreading [Chinese version]. *Bianji Xuebao*, 36(3), 313–317.
- Chien, C. (2020). A case study of the use of the Six Thinking Hats to enhance the reflective practice of student teachers in Taiwan. *Education*, 3–13, 49(5), 606–617.
- Cooper, G. (2023). Examining Science Education in ChatGPT: An Exploratory Study of Generative Artificial Intelligence. *Journal of Science Education and Technology*, 32(3), 444–452.
- De Bono, E. (2017). *Six Thinking Hats: The multi-million bestselling guide to running better meetings and making faster decisions*. Penguin.
- Essel, H. B., Vlachopoulos, D., Essuman, A. B., & Amankwa, J. O. (2024). ChatGPT effects on cognitive skills of undergraduate students: Receiving instant responses from AI-based conversational large language models (LLMs). *Computers and Education Artificial Intelligence*, 6, Article 100198.
- Galikyan, I., & Admiraal, W. (2019). Students' engagement in asynchronous online discussion: The relationship between cognitive presence, learner prominence, and academic performance. *The Internet and Higher Education*, 43, Article 100692.
- Garrison, D., Anderson, T., & Archer, W. (1999). Critical inquiry in a text-based environment: computer conferencing in higher education. *The Internet and Higher Education*, 2(2–3), 87–105.
- Garrison, D. R., Anderson, T., & Archer, W. (2001). Critical thinking, cognitive presence, and computer conferencing in distance education. *American Journal of Distance Education*, 15(1), 7–23.

- Garrison, D. R., & Arbaugh, J. (2007). Researching the community of inquiry framework: Review, issues, and future directions. *The Internet and Higher Education*, 10(3), 157–172.
- Göçmen, Ö., & Coşkun, H. (2019). The effects of the six thinking hats and speed on creativity in brainstorming. *Thinking Skills and Creativity*, 31, 284–295.
- Guilford, J. P. (1967). *The nature of human intelligence*. McGraw-Hill.
- House, S., Martínez, R. D., Hobbs, V. H., Lin, M., Paran, A., Alonso, M. R. A., & García, L. C. (2011). Inglés. In S. House (Ed.), *Investigación, innovación y buenas prácticas: Teacher Development*. (Vol. 93). Grao.
- Ji, Z., Lee, N., Frieske, R., Yu, T., Su, D., Xu, Y., Ishii, E., Bang, Y. J., Madotto, A., & Fung, P. (2023). Survey of hallucination in natural language generation. *ACM Computing Surveys*, 55(12), 1–38.
- Kanuka, H., & Garrison, D. R. (2004). Cognitive presence in online learning. *Journal of Computing in Higher Education*, 15, 21–39.
- Kivunja, C. (2015). Using De Bono's Six Thinking Hats model to teach critical thinking and problem solving skills essential for success in the 21st century economy. *Creative Education*, 06(3), 380–391.
- Kong, X., Liu, Z., Chen, C., Liu, S., Xu, Z., & Tang, Q. (2024). Exploratory study of an AI-supported discussion representational tool for online collaborative learning in a Chinese university. *The Internet and Higher Education*, 64, Article 100973.
- Kumar, S., Mahajan, S., Gadh, P., Jain, R., & Jain, D. (2024). Reliance of high school students on chat bots and its relationship with creativity. *Educational Research (IJMCE)*, 6(4), 286–290.
- Law, K. M., Geng, S., & Li, T. (2019). Student enrollment, motivation and learning performance in a blended learning environment: The mediating effects of social, teaching, and cognitive presence. *Computers & Education*, 136, 1–12.
- Lee, H., Chen, P., Wang, W., Huang, Y., & Wu, T. (2024). Empowering ChatGPT with guidance mechanism in blended learning: Effect of self-regulated learning, higher-order thinking skills, and knowledge construction. *International Journal of Educational Technology in Higher Education*, 21(1), 16.
- Lee, S. (2014). The relationships between higher order thinking skills, cognitive density, and social presence in online learning. *The Internet and Higher Education*, 21, 41–52.
- Li, H. (2023). Effects of a ChatGPT-based flipped learning guiding approach on learners' courseware project performances and perceptions. *Australasian Journal of Educational Technology*, 39(5), 40–58.
- Liu, Z., Kong, X., Chen, H., Liu, S., & Yang, Z. (2023a). MOOC-BERT: Automatically identifying learner cognitive presence from MOOC discussion data. *IEEE Transactions on Learning Technologies*, 16(4), 528–542.
- Liu, Z., Kong, X., Liu, S., & Yang, Z. (2023b). Effects of computer-based mind mapping on students' reflection, cognitive presence, and learning outcomes in an online course. *Distance Education*, 44(3), 544–562.
- Liu, Z., Tang, Q., Ouyang, F., Long, T., & Liu, S. (2024). Profiling students' learning engagement in MOOC discussions to identify learning achievement: An automated configurational approach. *Computers & Education*, 219, Article 105109.
- Lo, C. K. (2023). What is the impact of CHATGPT on education? A rapid review of the literature. *Education Sciences*, 13(4), 410.
- Marrapodi, J. (2003). *Critical thinking and creativity: An overview and comparison of the theories* (Unpublished manuscript). ED7590 Critical thinking and adult education, Doctoral Program, Providence, RI.
- Mei, A., Long, T., & Liu, Z. (2024). How Blue Hat Co-Regulate Pre-Service Teachers' Collective Reflection Based upon the Six-Hat Thinking Technique: A Lag Sequential Analysis. *Thinking Skills and Creativity*, 53, Article 101626.
- Meyer, K. A. (2003). Face-to-face versus threaded discussions: The role of time and higher-order thinking. *Journal of Asynchronous Learning Networks*, 7(3), 55–65.
- Morsy, A. A., & Darweesh, H. A. (2021). Effect of six hats thinking technique on development of critical thinking disposition and problem solving skills of nursing students. *American Journal of Nursing Research*, 9(1), 8–14.
- Runco, M. A., & Chand, I. (1995). Cognition and creativity. *Educational Psychology Review*, 7(3), 243–267.
- Saariaho, E., Pyhältö, K., Toom, A., Pietarinen, J., & Soini, T. (2015). Student teachers' self- and co-regulation of learning during teacher education. *Learning Research and Practice*, 2(1), 44–63.
- Serban, A., Kepes, S., Wang, W., & Baldwin, R. (2023). Cognitive ability and creativity: Typology contributions and a meta-analytic review. *Intelligence*, 98, Article 101757.
- Sevnanarayan, K. (2024). Exploring the dynamics of ChatGPT: Students and lecturers perspectives at an open distance e-learning university. *Journal of Pedagogical Research*, 8(2), 212–226.
- Shaffer, D. W., Collier, W., & Ruis, A. R. (2016). A tutorial on Epistemic network analysis: Analyzing the structure of connections in cognitive, social, and interaction data. *Journal of Learning Analytics*, 3(3), 9–45.
- Sibo, I. P., Celis, D. A., Liou, S., Koh, B., & Leung, A. K. (2023). The role of argumentation on high- and low-creative performing groups: A structuration analysis of undergraduate students' group discussion. *Thinking Skills and Creativity*, 47, 101217.
- Sok, S., & Heng, K. (2023). ChatGPT for education and research: A review of benefits and risks. *Cambodian Journal of Educational Research*, 3(1), 110–121.
- Stojanov, A. (2023). Learning with ChatGPT 3.5 as a more knowledgeable other: an autoethnographic study. *International Journal of Educational Technology in Higher Education*, 20(1), 35.
- Supena, I., Darmuki, A., & Hariyadi, A. (2021). The influence of 4C (constructive, critical, creativity, collaborative) learning model on students' learning outcomes. *International Journal of Instruction*, 14(3), 873–892.
- Swiecki, Z., Ruis, A., Farrell, C., & Shaffer, D. W. (2020). Assessing individual contributions to collaborative problem solving: A network analysis approach. *Computers in Human Behavior*, 104, Article 105876.
- Torrance, E. P. (1966). *Torrance tests of creative thinking. Educational and psychological measurement*.
- Urban, M., Děchtěrenko, F., Lukavský, J., Hrabalová, V., Svacha, F., Brom, C., & Urban, K. (2024). ChatGPT improves creative problem-solving performance in university students: An experimental study. *Computers & Education*, 215, Article 105031.
- Vaughan, N., & Garrison, D. R. (2005). Creating cognitive presence in a blended faculty development community. *The Internet and Higher Education*, 8(1), 1–12.
- Wei, C., & Fei, Y. (2024). Guoneiwai rengong zhineng gongju zai zhongwen bianxiao zhong yingyong xiaoguo pingjia yu jianyi [Evaluation and recommendations on the application effects of domestic and international artificial intelligence tools in Chinese proofreading]. *Bianji Xuebao*, 3, 313–317.

- Wei, Y. S., Ahmad, A. R., Abdullah, R., Peng, C. F., Salleh, U. K. M., & Hutagalung, F. (2018). Cognitive effects of thinking hats and taxonomy bloom on Indigenous pupils in Malaysia. *Advanced Science Letters*, 24(7), 5289–5291.
- Wisniewski, B., Zierer, K., & Hattie, J. (2020). The power of feedback revisited: A meta-analysis of educational feedback research. *Frontiers in Psychology*, 10, Article 487662.
- Wu, T., Lee, H., Li, P., Huang, C., & Huang, Y. (2023). Promoting self-regulation progress and knowledge construction in blended learning via ChatGPT-based learning aid. *Journal of Educational Computing Research*, 61(8), 3–31.
- Yakin, A. A., Muthmainnah, M., Apriani, E., Obaid, A. J., & Elngar, A. A. (2023). Transforming online learning management: generative models on ChatGPT to enhance online student engagement scale (OLE). *Idarah (Jurnal Pendidikan Dan Kependidikan)*, 7(2), 135–148.
- Zhang, S., Gao, Q., Sun, M., Cai, Z., Li, H., Tang, Y., & Liu, Q. (2022). Understanding student teachers' collaborative problem solving: Insights from an epistemic network analysis (ENA). *Computers & Education*, 183, Article 104485.

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