

ORIGINAL ARTICLE

The Process of Undergraduates' Collaboration With a Generative Artificial Intelligence Chatbot: Insights From Conversation Content and Epistemic Network Analysis

Weipeng Shen¹  | Xiao-Fan Lin^{1,2,3}  | Jiachun Liu¹  | Xinxian Liang¹  | Ruiqing Chen¹  | Xiaoyun Lai¹  | Xinwen Zheng¹ 

¹School of Information Technology in Education, South China Normal University, Guangzhou, China | ²Guangdong Engineering Technologies Research Centre of Smart Learning, Guangzhou, China | ³Guangdong Provincial Institute of Elementary Education and Information Technology, Guangzhou, China

Correspondence: Xiao-Fan Lin (linxiaofan@m.scnu.edu.cn)

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ABSTRACT

Background: Generative artificial intelligence (GenAI) chatbots extend transformative impact in higher education. Current research requires more comprehensive evaluations of the collaborative learning fostered by students and GenAI chatbots. However, existing articles have rarely explored the dynamic process of student–AI collaboration in higher education.

Objectives: This study aims to analyse and visualise the changes in the process of undergraduates' collaboration with a GenAI chatbot. The interaction patterns of the collaboration were explored under the perspective of social constructivist learning theory. The differences between student–AI interaction patterns at 5 time points (after 5 lessons) were further compared to show the dynamic collaboration process.

Method: A 9-week course was implemented for 40 Chinese undergraduates, who completed 5 rounds of collaboration with a GenAI chatbot named ERNIE Bot. Employing a designed coding scheme, a total of 6180 codes was collected from the conversation content of each round. Based on the interval data, content analysis and epistemic network analysis (ENA) were conducted.

Results: First, undergraduates gradually became more active and targeted in their collaboration with the GenAI chatbot. Second, the focal points of their collaboration changed from “Comprehension” (the first–third lessons) to “Generation” (the third–fifth lessons), along with different interaction patterns. Notably, the interaction patterns changed more rapidly and prominently during the “Comprehension” phase than the “Generation” phase.

Implications: The findings contribute to understanding the social constructivist learning process within student–AI collaboration in higher education. Practical recommendations for students and educators were offered as well.

1 | Introduction

Students today stand poised on the brink of a future where they live and work with AI. It is incumbent upon educators to prepare students for long-term challenges. The emerging generative artificial intelligence (GenAI) has brought about shifts in numerous domains. In higher education, current undergraduates will engage in collaboration with AI for their career

development (Ansari et al. 2023). Such anticipation has catalysed inquiries into the deployment of GenAI in undergraduate learning. Currently, there is an ambivalence among educators and students—a blend of optimism for the integration of GenAI and worries regarding potential negative effects, such as privacy violations and ethical dilemmas (Chan and Hu 2023; Chiu 2023). For its integration, the chatbot is increasingly regarded as an interactive agent of GenAI in different-level education (Hwang

Summary

- What is already known about this topic
 - Generative Artificial Intelligence (GenAI) chatbots are increasingly influencing higher education by facilitating collaborative learning experiences.
 - Previous research has recognized the potential of AI chatbots in higher education but has seldom explored the dynamic processes of student-AI collaboration.
 - Social constructivist learning theory helps identify patterns of interactive learning in student-AI collaboration.
- What this paper adds
 - An in-depth analysis of undergraduates' evolving collaboration with a GenAI chatbot.
 - Description of a novel method that combined content analysis and epistemic network analysis to capture complex students-AI interaction patterns with interval data.
 - Identification of a trend that students became more active and focused in their interactions with the chatbot over time.
 - Identification of a shift in collaborative focus from “comprehension” to “generation,” defined by different interaction patterns in each phase.
- Implications for practice and/or policy
 - Educators can enhance learning outcomes by structuring AI-assisted activities for students.
 - Students can be guided to engage more actively and purposefully with AI chatbots, maximizing the educational benefits.
 - Policy-makers and curriculum developers can consider these interaction patterns to train teachers and students thoughtfully.

and Chang 2021; Okonkwo and Ade-Ibijola 2021). Compared to previous technology instruments, GenAI chatbots support human-like conversations employing large language models. Users can engage in dialogues with GenAI chatbots using natural language and receive adaptive, immediate responses. These advantages enable GenAI chatbots to be friends or collaborators by promoting knowledge acquisition and learning support (Guzdial et al. 2019).

The integration of GenAI chatbots into undergraduate education yields multiple benefits. GenAI chatbots can enhance undergraduate performance (Essel et al. 2022), self-direction (Wu et al. 2023), as well as enjoyment (Guo et al. 2023). Nevertheless, undergraduates' collaboration with GenAI chatbots like ChatGPT (“generative, pre-trained transformer”) is still challenged by various barriers. For example, Lo (2023) has identified some outstanding issues in a review: fake information, knowledge limitation, and plagiarism tendencies. To address these issues, undergraduates need appropriate approaches to bolster their collaboration with GenAI chatbots. On the other hand, Chamorro-Atalaya et al. (2023) also advocated for extensive research into the regulatory frameworks of general chatbots' integration within higher education. GenAI chatbots' application should be evaluated comprehensively for this purpose. Research on the innovative GenAI chatbot warrants similar requirements.

However, existing regulations about undergraduates' collaboration with GenAI chatbots omit consideration of its dynamic process across time (Ansari et al. 2023; Chu et al. 2022). This study aims to bridge this gap in current literature by providing nuanced insights into undergraduates' collaboration process with a GenAI chatbot.

From the lens of social constructivist learning theory, the collaboration between undergraduates and a GenAI chatbot is regarded as the social construction of knowledge in this study. Social construction of learning occurs when learners collaboratively construct meaning through interaction (Vygotsky 1978). This paradigm posits that learners' understanding can be promoted through intellectual support from GenAI chatbots and their reciprocity progression (Fathi and Rahimi 2024). In student-AI collaboration, the GenAI chatbot as a conversational agent can adapt to students' learning progress and give personalised responses during the interaction (Pereira et al. 2023; Tan et al. 2022). The remarkable progression of underlying large language models behind GenAI has supported more sophisticated interactions, enabling GenAI chatbots as collaborators (co-constructors), rather than mere platforms or tools (Guzdial et al. 2019; Seeber et al. 2020). Undergraduates can also learn from the responses of the GenAI chatbot, and gradually create more efficient discussions with it. Accordingly, social constructivist learning can also occur between students and GenAI chatbots (Fathi and Rahimi 2024).

This study evaluated the social constructivist learning between undergraduates and a GenAI chatbot with content and epistemic network analysis (ENA). The methods explored and visualised their dynamic interaction patterns throughout a series of collaborative design tasks across time. This paper initially reviewed previous research on student-AI collaboration in higher education. The methodological paradigm for our analysis was then introduced based on the social constructive learning theory. Next, we reported undergraduates' collaborative design tasks, and their interactions with a GenAI chatbot were assessed. Finally, we discussed outstanding interaction patterns in student-AI collaboration and provided practical suggestions for educators and undergraduates.

2 | Literature Review

2.1 | GenAI Chatbot in Higher Education

GenAI chatbot is a conventional agent capable of real-time, human-like communication by generating new content rather than simply analysing existing data (Dai et al. 2023; Hwang and Chang 2021). It could adaptively respond to human input in conversations (Dai et al. 2023). GenAI chatbots are gradually integrated into different domains of higher education, including administration, learning, and teaching (Ansari et al. 2023; Pereira et al. 2023). Especially for learning, GenAI chatbots were usually viewed as pedagogical assistants for students, which could offer students immediate interaction, address their inquiries, and provide general assistance (Chamorro-Atalaya et al. 2023). Present research mainly focuses on applying GenAI chatbots as pedagogical instruments to improve undergraduates' performance (Chamorro-Atalaya et al. 2023;

Lee and Moore 2024). GenAI chatbots can provide more personalised advice and guidance, unbound by time or location (Pereira et al. 2023; Tan et al. 2022). In meaningful discourse with chatbots, students can sharpen their comprehension of knowledge and enhance their engagement (Lee et al. 2022; Lin and Chang 2023). Studies have indicated the influence of GenAI chatbots in fostering academic performance, nurturing students' self-directed learning and critical thinking, as well as enhancing group collaboration (Laato et al. 2023). Some researchers have further tailored new AI chatbots for certain subjects to explore their effects on promoting students' abilities (Chen et al. 2023). In the interactions with GenAI chatbots, students could obtain immediate advice for continuous learning, thereby bolstering their confidence and self-efficacy (Lee et al. 2022).

The advent of GenAI chatbots heralds a transformative era for higher education (Lee and Moore 2024). However, it is noteworthy that academic attention is limited in this regard. Numerous previous studies concentrated only on the assessment function of chatbots, for instance, checking and correcting the mistakes in students' submissions (Hwang and Chang 2021). Currently, the adaptive responses of GenAI chatbots to students' input allow them to provide more personalised answers (Chamorro-Atalaya et al. 2023). This situates GenAI chatbots as valuable assets in guiding undergraduates through more contextual and intricate tasks like design and creation, instead of mere correction and summarization (Guo and Li 2024; Nguyen, Hong, et al. 2024). Considering the potential of GenAI chatbots in higher education, current researchers have recognised the necessity to explore and understand the collaboration between GenAI chatbots and university students, particularly in the context of complex cognitive tasks (Ansari et al. 2023).

2.2 | Undergraduates' Collaboration With AI

Nowadays, the integration of AI into higher education is advancing at an unprecedented pace (Pereira et al. 2023). Research is increasingly focusing on the benefits of students' collaboration with AI. Prior research has characterised student-AI collaboration as utilising AI as a personal learning partner in various intelligent tutoring systems (Pan et al. 2025). In intelligent tutoring systems, AI could provide personalised guidance and assist collaborative learning activities (Echeverria et al. 2023). Students' engagement in learning and academic outcomes were significantly enhanced when they communicated and collaborated with AI (Nguyen, Le, and Nguyen 2024; Wang et al. 2022). In addition, current research has delved into student-AI collaboration, viewing AI as one of students' learning partners (Lee and Moore 2024). For example, AI could offer timely feedback, tailored interventions, and intelligent evaluation in its instant interactions with students (Chang et al. 2023; Chu et al. 2022). Moreover, AI could assume the role of a collaborator or facilitator in collaboration, fostering time management, equitable participation, and providing divergent viewpoints (Guo and Li 2024; Kim et al. 2022). Recently, the evolution of GenAI has redefined AI applications, elevating them to act like collaborators in learning and teaching (Guzdial et al. 2019). Supported by advanced tools like chatbots, GenAI transcends the traditional paradigms of passive interaction. Undergraduates can interact with GenAI chatbots employing objective sentences (known as

“Prompts”). GenAI chatbots enable undergraduates to engage in dynamic interactions with them and produce various outcomes (Dai et al. 2023; Jahnke et al. 2022). For efficient student-AI collaboration, “Prompt Engineering” strategies were also highlighted (Walter 2024). Overall, previous research on student-AI collaboration has initially explored AI's role as an assistant and tutor in higher education.

Accounting for exploring undergraduates' behavioural features, existing literature has analysed the interaction patterns of collaboration between undergraduates and GenAI chatbots. Researchers compiled data from multiple sources—including coding, observation, and investigations—to understand students' engagement and performance in collaborative tasks (Fathi and Rahimi 2024; Nguyen and Nguyen 2024; Nguyen, Hong, et al. 2024; Pan et al. 2025). Undergraduates focused on producing compositions with knowledge acquisition and format adjustment when utilising GenAI chatbots (Nguyen, Le, and Nguyen 2024). They tended to acknowledge the effectiveness of GenAI chatbots as an assistant, which enhanced their abilities and engagement (Guo and Li 2024; Pan et al. 2025). These interaction patterns demonstrated students' enthusiasm and productivity in the collaboration with GenAI chatbots. Meanwhile, it also raised concerns regarding the appropriate application of GenAI chatbots among students and teachers (Barrett and Pack 2023). A more comprehensive and in-depth understanding of these interaction patterns is essential for effectively organising student-AI collaboration in higher education. However, although recent studies have explored behavioural characteristics by analysing student-AI interaction patterns in higher education, the dynamics embedded in such collaboration remain underexplored. Tracking the interaction over time captures the evolving nature of student-AI collaboration, helping educators design effective learning paths for it. An insight into the dynamic process of student-AI collaboration is novel for higher education (Ansari et al. 2023; Chu et al. 2022).

3 | Theoretical Foundation

3.1 | Social Constructivist Learning Theory

This study designed and analysed student-AI collaboration based on the social constructivist learning theory. Social constructivist learning theory was mainly built upon the comprehensive perspectives from the sociocognitive conflict theory of Piaget and the sociocultural theory of Vygotsky (Palincsar 1998). Under the umbrella term “constructivism theory”, social constructivist perspectives share its basic idea, which acknowledges the active role of individuals in constructing knowledge and forging meaning (Adams 2006). The theoretical lens that views learning as “social construction” emphasises the foundational role of the social environment and learners' contextual interactions in their intellectual development (Dudley-Marling 2012). According to social constructive learning theory, interactions between a less skillful learner and a more capable individual or platform (e.g., GenAI chatbot) can facilitate efficient knowledge co-construction (Fathi and Rahimi 2024; Vygotsky 1962). This collaboration allowed learners to achieve their zone of proximal development, thereby extending learners' zone of actual development (i.e., existing competencies) towards the zone of distant

development (i.e., out-of-reach competencies) (Vygotsky 1978). In light of this social construction process, strategic collaboration are required in educational contexts to support learners' constant progressions.

Since GenAI has become increasingly proficient in general tasks, it appears that GenAI agents can generate constructive interaction with humans when assisting their cognitive endeavours (Atkinson and Barker 2023). The human-agent teaming in their co-learning also follows the principles of constructivism (Fathi and Rahimi 2024). GenAI agent as a companion of humans facilitates social construction in their communication (Rasul et al. 2023). It's not surprising that GenAI chatbots as a kind of agent have been recognised for their substantial effect and social value to users in their human-like conversations (Skjuve et al. 2021). GenAI chatbots can learn from users' inputs and deliver personalised responses, like friends or collaborators (Guzdial et al. 2019). Students, in turn, also alter their inputs in response to the GenAI chatbot, meanwhile gathering more knowledge to clarify their thoughts. Consequently, this reciprocal progression fosters a dynamic co-learning circle for knowledge construction (Wu et al. 2023). Its advance gradually promotes social constructivist learning. Thus, the collaboration between students and the GenAI chatbot was conceptualised as an example of social constructivist learning in this study (Figure 1). The theoretical foundation underpinned the research methodology.

3.2 | Student-AI Collaboration Analysis

Drawing on the theoretical foundation, student-AI collaboration can be perceived as an embodiment of social learning (Fathi and Rahimi 2024). Therefore, this study quantified and visualised the interactive learning process within student-AI collaboration by examining the conceptual content of their dialogue. Given that verbal interaction plays a pivotal role in the process of collaboration, it can be important to focus on the conceptual content of dialogues from these interactions. In other words, the interaction patterns of student-AI collaboration can be elucidated by analysing their dialogues. To dive further into the substance of dialogues, coding schemes were effective tools for elucidating students' AI-supported

co-design, reflective practice, and problem-solving (Feng 2025; Nguyen, Hong, et al. 2024; Nguyen and Nguyen 2024). Coding schemes helped interpret dialogue content with categories and characterise concepts. The dialogic coding sequence unravels the complicated evolving structures inherent in student-AI collaboration. Accordingly, a coding scheme was developed in this research for content analysis. Besides, ENA offered a comprehensive framework for visualising the structure of interactive learning (Shaffer et al. 2016). Based on coding, ENA can facilitate the visualisation of cognitive interactions in student-AI collaboration. Previous researchers have utilised ENA to evaluate the outcomes and process of student-AI collaborative learning (Liu et al. 2024; Wang et al. 2023). This study also examined the interaction patterns of student-AI collaboration using ENA. Furthermore, this study compared the cognitive network of different periods to display the dynamic process of student-AI collaboration.

4 | Method

4.1 | Research Goals and Questions

The purpose of this current research is to design and analyse undergraduates' dynamic collaboration with a GenAI chatbot based on their human-like conversations. The conversation content was analysed to delineate their interaction patterns in the student-AI collaboration. Furthermore, ENA helped interpret the social constructivist learning process as an evolving trajectory. This research echoes recent efforts in examining the student-AI collaboration (Guo and Li 2024; Nguyen, Le, and Nguyen 2024; Wang et al. 2023). It contributes to the understanding of AI's innovative role in current higher education. It also verifies a relatively novel methodology for probing student-AI interaction patterns with coding and visualisation. Two research questions were proposed to guide this research:

RQ1. What are the outstanding interaction patterns in the process of undergraduates' collaboration with the GenAI chatbot?

RQ2. How does undergraduates' collaboration with the GenAI chatbot change over time?

4.2 | Participants

The recent study gathered 40 sophomore students majoring in educational technology from a university in southern China from September to November 2023. These undergraduates are aged between 18 and 20, including 19 males and 21 females. The study was implemented within a course taught by 2 teachers. The theme of this course is lesson design. Every student was required to use ERNIE Bot, a GenAI chatbot, to complete co-design tasks in the course. While the participants possessed a preliminary understanding of the learning topics in this study, they had not undergone any course related to lesson design and lacked experience in utilising chatbots. Before this study, the majority of students demonstrated comparable levels of learning performance.

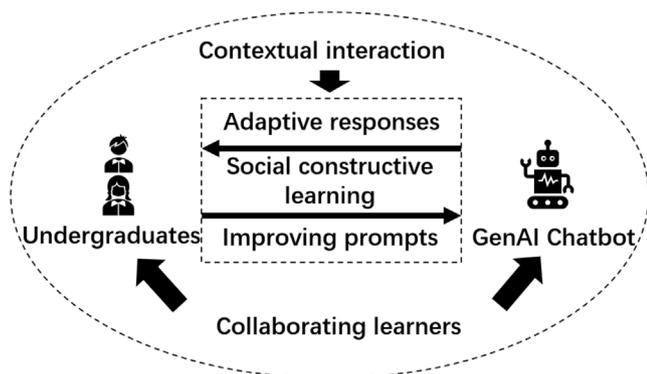


FIGURE 1 | Social constructive learning between undergraduates and GenAI chatbots.

4.3 | Instrument

4.3.1 | ERNIE Bot

Considering the location (China) and the fully Chinese-language teaching environment, ERNIE Bot 3.5 (<https://yiyian.baidu.com/>) was selected as the GenAI chatbot for this study. The reasons for our decision to choose ERNIE Bot are twofold. Firstly, launched by the Baidu company, ERNIE Bot was an advanced GenAI chatbot that integrated functions such as interactive dialogue, content creation, knowledge reasoning, and versatile output generation, thus covering the basic functions of most large-scale language models (e.g., ChatGPT). Secondly, ERNIE Bot demonstrated efficiency and accuracy in handling the complexity and nuanced expressions of the Chinese language, making it more intuitive for Chinese students to interact with (Mi et al. 2025). In this study, undergraduates engaged in tasks and collaborated with ERNIE Bot. They asked it questions, made it generate content, and checked its responses. Throughout these interactions, students continuously designed and refined their works.

4.3.2 | Coding Scheme

To explore the interaction patterns of the students-AI collaboration, this study employed the adaptive interaction analysis model (IAM) to analyse and code the content of the conversation between students and ERNIE Bot (Table 1). The model, originally developed by Gunawardena et al. (1997), was previously utilised by Zhang et al. (2017) to explore the interactive behaviours of teachers in online co-design. Similar to Zhang et al. (2017), this study recruited undergraduates to complete co-design tasks as well. A coding scheme was devised to scrutinise the interaction behaviours between students and chatbots. Each code represents a specific type of dialogue in the conversation, and these dialogues usually appear in chronological order in a conversation. Additionally, rather than coding a line of dialogue one by one, this study adjusted the coding units based on co-design task patterns. The typical sequence observed in the collaborative process of undergraduates and ERNIE Bot involved three steps: first, undergraduates provided a prompt to ERNIE Bot; second, ERNIE Bot generated content in response; third, students reviewed the response and gave a new prompt. This sequence highlighted that the undergraduates' prompts played a leading role, while the responses from ERNIE Bot were adaptive. Thus, we coded a unit of dialogue (Figure 2) instead. A more detailed introduction of each code and corresponding student-AI dialogues is in Table S1.

This coding scheme captured social constructivist learning within the dialogic co-creation between undergraduates and ERNIE Bot. Together, they gradually completed design tasks and engaged in collaborative learning. In their conversation, SE indicated that undergraduates introduced foundational concepts and established a shared understanding with ERNIE Bot for co-design. CCA and MC demonstrated undergraduates' effort to elaborate, justify, and rearticulate their thinking with ERNIE Bot, which in turn refined their own comprehension of new knowledge. CCB and RA targeted the optimization of AI output. Both undergraduates and ERNIE Bot corrected one

another with their more accurate interpretations of tasks and knowledge. Then, undergraduates adopted negotiated ideas and utilized them for new tasks. IC coded off-task moves in the conversation. The scheme tracked the student-AI social constructivist learning process: undergraduates collaborated with a more expert partner (ERNIE Bot), undertook challenging tasks with AI, extended their zone of actual development, and finally enacted a cycle of knowledge co-construction (Fathi and Rahimi 2024; Wu et al. 2023). For instance, the code sequence can encode AI-supported knowledge negotiation (SE → CCA → MC) or knowledge application/transformation (MC → CCB → RA). Moreover, students' growth in knowledge and co-design practices can be reflected by their patterns of information exchange over time, as indicated by our continuous coding across courses.

4.4 | Procedure

4.4.1 | Lesson Design Course

All the undergraduates in this study participated in a course that helped them learn the steps and methods of lesson design through collaboration with ERNIE Bot. This study spanned 9 weeks with a 120-min lesson (3 × 40 min) per week, and the course was divided into two distinct stages: lesson plan design and digital resource design (Figure 3). The theme “lesson plan design” specialised in constructing the pedagogical framework for the instructional progression of a lesson, whereas “digital resource design” concentrated on devising the digital tools required for lesson development. The first 6 weeks included the following topics: (1) introducing the functions of ERNIE Bot, (2) formulating front-end analysis for learning design, (3) formulating instructional objectives and pedagogical assessments, (4) a designated break period (vocation), (5) formulating teaching activities, and (6) summarising and offering feedback on students' learning progress of lesson design. The last 3 weeks were for digital resource design: (1) formulating project definition, (2) formulating instructional process, (3) formulating the structure of the digital resource, and (4) summarising and providing feedback on students' learning of digital resource design. In the nine-week class, undergraduates spent 5 weeks (the first to fifth lessons) on 6 co-design tasks with ERNIE Bot and practiced these strategies each week. The other 4 weeks were for preparation, vocation, and summarization.

For students' learning, teachers' instruction each week centered on three pedagogical activities: concept exposition, online exercises, and assignment feedback (Figure 4), which all aimed at promoting students' productivity, critical thinking, and self-correction in their collaborative design tasks with AI (Walter 2024). Teachers' instructional activities were implemented before, during, and after a lesson. Before a lesson, teachers needed to prepare instructional material, especially for students' 6 collaborative tasks with ERNIE Bot. The tasks targeted strategies for AI operation and design process practices. Teachers needed to ensure that undergraduates could submit work that met the requirements of each assignment. During a lesson, teachers first provided feedback on students' tasks in the previous lesson, praised excellent cases, and gave advice

TABLE 1 | Coding scheme.

Code	Phase	Description	Examples	Context
SE	Sharing and explaining	Share background and state existing ideas	The analysis of teaching content can be analysed from the aspects of knowledge attribute, knowledge structure, importance, and difficulty.	An undergraduate explained a concept to the GenAI chatbot.
CCA	Cognitive conflict	Find inconsistencies in ideas and concepts	No, please do a complete analysis of the teaching content and background of "Industrial Location Selection".	An undergraduate found that the GenAI chatbot did not understand the concept at the beginning.
MC	Meaningful consultation	Put forward suggestions to help ERNIE Bot further understand concepts and viewpoints	The front-end analysis of instructional design requires a comprehensive and in-depth analysis of instructional content and learner characteristics, such as knowledge attributes, knowledge structure, key and difficult points, initial level, learning style, and learning motivation.	An undergraduate gave more information to the GenAI chatbot to help it understand key points.
CCB	Checking and correcting	Point out what is wrong and explain the next direction of modification	Your answer seems to be insufficient, please add relevant content.	An undergraduate checked the generated content and gave feedback to the GenAI chatbot.
RA	Reaching and applying	Reach agreements and adopt ideas	Good answer; nice; you did a great job.	An undergraduate accepted the generated content.
IC	Irrelevant Content	Enter information that is not related to the topic	Although your answer is wrong, it doesn't matter. Please answer my next question.	An undergraduate found that the GenAI chatbot generated the wrong content.

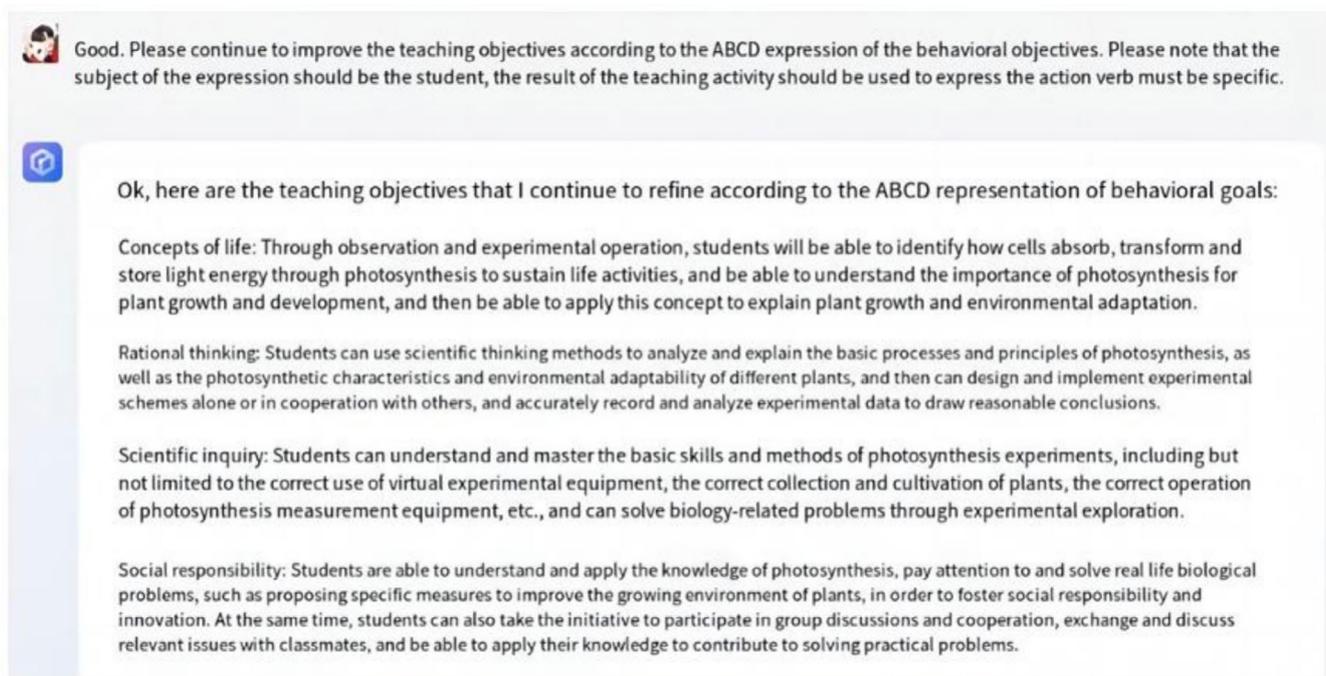


FIGURE 2 | The sample of a coding unit. The conversation content is translated from Chinese to English.

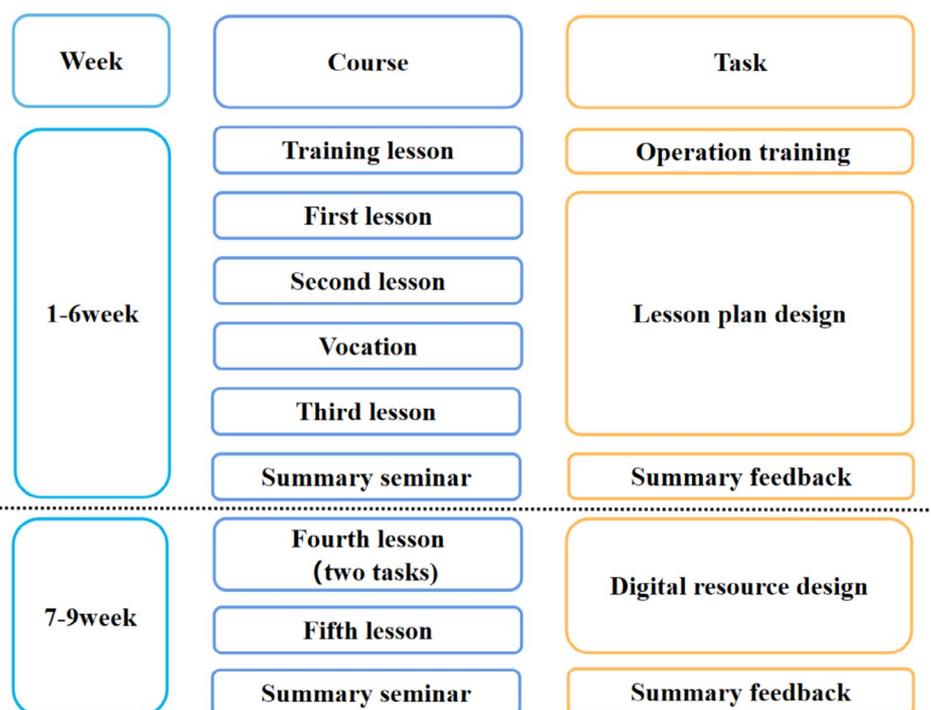


FIGURE 3 | Course procedure.

to address the problems in students' collaboration with ERNIE Bot. Teachers then taught students conceptual knowledge about AI and lesson design, and illustrated examples to help students employ ERNIE Bot for collaborative design. Students were given time to complete some initial exercises in the lesson. Teachers made classroom rounds and provided feedback to address common issues that arose from students. After a lesson, teachers evaluated the work submitted by students and identified what difficulties they encountered. Then, feedback could be provided in the next lesson.

4.4.2 | Student-AI Collaboration

Undergraduates were taught a four-step strategy to collaborate with ERNIE Bot. As Figure 5 shows, the strategy includes (1) Acquisition: Make ERNIE Bot understand necessary background information, (2) Orientation: Give ERNIE Bot task requirements step by step, (3) Discussion: Check and correct responses of ERNIE Bot, (4) Production: Organise the content generated by ERNIE Bot to produce works. Their collaboration was scaffolded by the strategy. According to the five lesson topics,

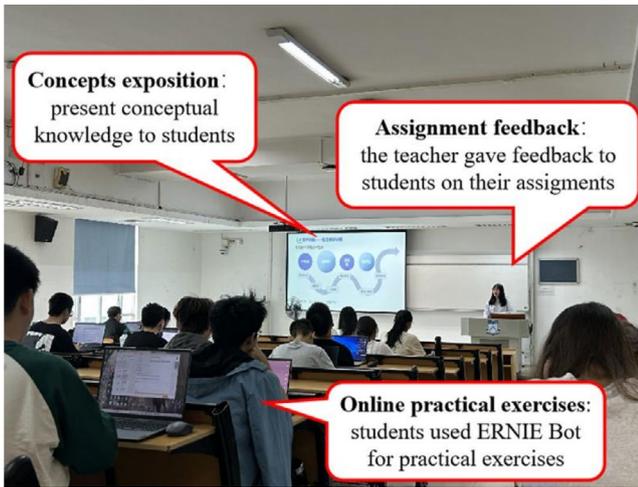


FIGURE 4 | Teachers' activities for each lesson.

undergraduates and ERNIE Bot designed goals, assessments, and digital resources for their own lesson plans week by week. They were required to co-design and submit 6 different parts of their lesson plans, along with dialogue transcripts for interval data collection. In addition, students' tasks would be evaluated through a combination of peer assessment and instructor grading in the summary seminars.

4.5 | Data Analysis

To understand the collaboration between participants and ERNIE Bot, content analysis was employed to investigate and visualise their interactive behaviours. To ensure the reliability of the analysis, two researchers proficient in content analysis engaged in a two-stage coding process. Initially, the coders were trained to familiarise themselves with the definitions and

Acquisition & Orientation

Suppose you are a college biology teacher. Describe what the blended teaching model is.

Blended teaching mode is a new teaching mode that combines online and offline teaching elements. In this model, students not only receive face-to-face instruction in a traditional classroom environment, but also self-directed learning through online resources. This model leverages the advantages of online learning and traditional classroom instruction to create a richer, more diverse and personalized learning experience.

In blended teaching, online and offline teaching elements complement each other. Online teaching provides a flexible and self-directed way of learning, where students can learn and master knowledge at their own pace, while offline teaching provides face-to-face interaction and discussion, as well as deepening and expanding the content of online learning.

Set up the role of ERNIE Bot and use it to understand the concept

Read the answers from ERNIE Bot to see if it meets expectations

Orientation & Discussion

Please divide the index that students can understand and operate the main steps of photosynthesis experiment into five grade dimensions and attach a description of the corresponding level. Note that the description should be concise

Ok, here are the five level dimensions and descriptions of the corresponding levels:

1. excellent (5) : Students can accurately understand and operate the main steps of photosynthesis experiment, and have a thorough understanding of the purpose, operation method and precautions of each step.
2. Good (4) : Students can generally understand and operate the main steps of photosynthesis experiment, and have a basic understanding of the purpose, operation methods and precautions of most steps.
3. Intermediate (3) : Students are able to perform experimental operations under guidance, but need to prompt or correct some steps.
4. General (2) : Students reluctantly carry out experimental operations under the guidance, and are prone to mistakes or unable to complete the experiment.
5. Unqualified (1) : Students are unable to understand and operate the main steps of photosynthesis experiment and are unable to meet the experimental requirements.

Find the gaps and further refine the teaching evaluation indicators

Consider and examine the output of ERNIE Bot. Compare it with the definition for teaching evaluation

Production

Very good, I decided to use your design, thank you very much!

Glad to help you! If you have any further questions or need further help, please feel free to let me know. I wish you success in your teaching and excellent learning outcomes for your students!

Take in the generated content and express gratitude

Ending

FIGURE 5 | The example of a student completing a collaborative task with ERNIE Bot. The conversation content is translated from Chinese to English.

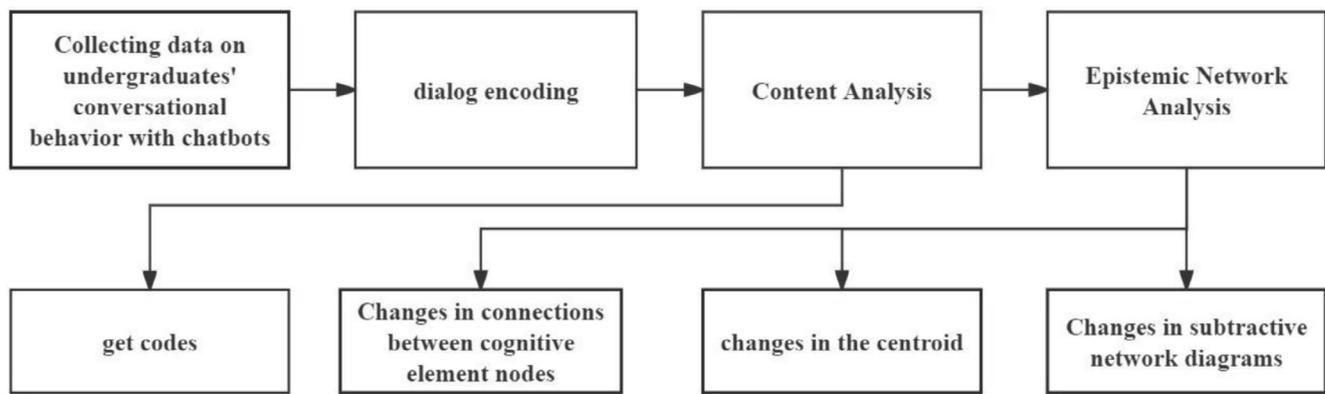


FIGURE 6 | The data analysis process.

examples of items in the coding scheme (Table 1). Next, the coders independently coded the dialogue content collected from student-AI conversations (Figure 4). Multiple codes were applied to dialogues that could have multiple meanings. After the coding, researchers identified discrepancies between the two coders' work, extracting samples with inconsistent codes for joint discussion and modifications to coding results. Finally, the coders ended up coding two datasets and selected one for analysis after verifying the reliability of the coding scheme. The final Cohen's kappa value of 0.915 indicated a high level of consistency between the two coders.

This study then analysed the frequency and sequence of the codes to explore the dynamic process of the collaboration between students and ERNIE Bot. ENA was conducted to assess the dynamic process and cognitive characteristics of student-AI collaboration. ENA assumes cognitive patterns and meaning are manifest through the interplay of elements and their interconnections (Vandenberg et al. 2021). As a dialogue analysis and comprehensive coding technique, ENA tools enable efficient visualisation of learners' cognitive elements (i.e., nodes) and their connections (i.e., edges) (Shaffer et al. 2016). The cognitive elements refer to codes in the content analysis. The strength and characteristics of elements' connections were captured by assessing their co-occurrences, which indicates a socio-cognitive structure. Serial session data was transformed into binary adjacency matrices, then combined as cumulative adjacency matrices to depict the weighted co-occurrence patterns. For interpretation, ENA visualises cumulative adjacency matrices utilising normalisation and dimension reduction, therefore constructing a high-dimensional space with two dimensions. In an ENA plot, the *x*-axis represents the dimension with the highest variance percentage, while the *y*-axis represents the second-highest variance dimension (Marquart et al. 2018). The two dimensions can best explain the variance in the data. Applying network diagrams with weighted edges, centroids, and network comparison, ENA explores features of learners' interactions in four quadrants. Furthermore, the network comparisons were characterised by subtraction network diagrams.

To illustrate variations in student-AI interaction patterns across different lessons, we coded interval data from student-AI conversations after each of the 5 lessons (as 5 time points), and then

constructed epistemic networks to identify the cross-sectional situations of their collaboration. These epistemic networks were arranged in chronological order. The arrangement illustrated the changes in the epistemic networks' centroid, connectivity coefficients, and subtraction network diagrams, which indicated the evolvement of undergraduates' collaboration with the GenAI chatbot over time. Figure 6 summarises the analysis process.

5 | Result

5.1 | The Conversation of Undergraduates and the GenAI Chatbot in the Collaborative Process

This study collected the conversations between undergraduates and ERNIE Bot to reveal important interaction patterns during co-design activities through content analysis. The descriptive statistics of interaction between undergraduates and ERNIE Bot across different lessons are presented in Table 2. Throughout the nine-week course, there was a discernible upward trend in the number of interactions between students and ERNIE Bot. Among the six types of dialogues in undergraduates' collaboration with ERNIE Bot, the frequencies of SE, CCA, and RA displayed an ascending trajectory. In contrast, the frequencies of MC, CCB, and IC exhibited a declining trend.

5.2 | Epistemic Network Analysis of Students' Collaborative Process With the GenAI Chatbot

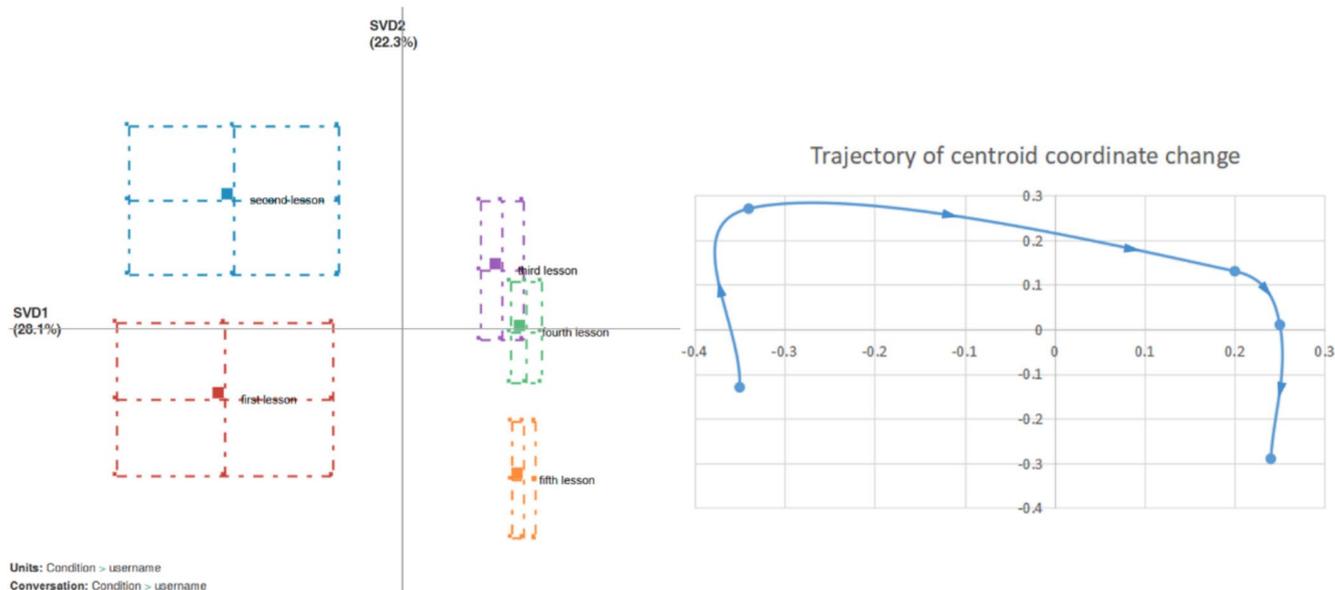
5.2.1 | Changes in the Centroid

To explore the changes in undergraduates' interactions with ERNIE Bot during the co-design process, an ENA of the five lessons was conducted. First, the centroid of a network summarizes its location by identifying the minimum distance between the centroid and all nodes of the network. The centroid is an important indicator in the epistemic network. Changes in its position indicate variations in the structure of different network connections. The changes in the centroid are shown in Figure 7. The centroid's coordinate distribution (Figure 7) reflected the overall differences between the epistemic networks of the five lessons.

TABLE 2 | Descriptive statistics of interactions in undergraduates' collaboration with ERNIE Bot.

Phase			SE	CCA	MC	CCB	RA	IC	Total
Number/ Proportion	1st lesson	Task 1	171 29.69%	15 2.60%	54 9.38%	136 23.61%	157 27.26%	43 7.47%	576
	2nd lesson	task 2	104 16.99%	34 5.56%	68 11.11%	189 30.88%	123 20.10%	94 15.36%	612
	3rd lesson	task 3	360 23.20%	120 7.73%	136 8.76%	475 30.61%	460 29.64%	1 0.06%	1552
	4th lesson	task 4	293 36.22%	54 6.67%	37 4.57%	166 20.52%	255 31.52%	4 0.49%	809
		task 5	325 29.10%	138 12.35%	100 8.95%	243 21.75%	310 27.75%	1 0.09%	1117
	5th lesson	task 6	580 38.31%	58 3.83%	65 4.29%	295 19.48%	515 34.02%	1 0.07%	1514
	Total		1833 29.66%	419 6.78%	460 7.44%	1504 24.34%	1820 29.45%	144 2.33%	6180

Abbreviations: CCA, Cognitive conflict; CCB, Checking and correcting; IC, Irrelevant Content; MC, Meaningful consultation; RA, Reaching and applying; SE, Sharing and explaining.

**FIGURE 7** | Centroids and outlier interval of five lessons, and the trajectory of centroids.

A *t*-test was also conducted to compare the *x* and *y*-axis of the generated epistemic network diagrams, confirming their differences and the extent of centroid coordinate change (Table 3). There was a significant difference between the first and second lessons on the *y*-axis, indicating a significant change across the two lessons. There was also a significant difference between the second and third lessons on the *x*-axis, as well as between the fourth and fifth lessons on the *y*-axis. In general, the change in epistemic network diagrams varied significantly between four and five lessons. Notably, the trajectory of centroid changes was nonlinear (Figure 7), with substantial shifts from the first to the third lessons, followed by relatively smaller changes from the third lesson

to the fifth lesson. The result depicted the dynamics of undergraduates' process of collaboration with the GenAI chatbot.

5.2.2 | Changes in Connections Between Cognitive Element Nodes

The epistemic networks generated on the basis of cognitive coding had correlations of 0.98 (Pearson) and 0.91 (Spearman) on the *x*-dimension, while co-registration correlations reached 0.98 (Pearson) and 0.98 (Spearman) on the *y*-dimension. These data showed a strong fit between the visualisation and the original

TABLE 3 | Descriptive statistics and *t*-test results of different epistemic networks.

Serial number	Comparison standard	The first dimension (X-axis)			The second dimension (Y-axis)		
		Mean	<i>t</i> value	<i>p</i> -value	Mean	<i>t</i> value	<i>p</i> -value
①	First lesson	-0.20	<i>t</i> = -0.12	<i>p</i> = 0.90	-0.07	<i>t</i> = -3.77	<i>p</i> = 0.00***
	Second lesson	-0.19			0.15		
②	Second lesson	-0.19	<i>t</i> = -5.07	<i>p</i> = 0.00***	0.15	<i>t</i> = 1.39	<i>p</i> = 0.17
	Third lesson	0.11			0.07		
③	Third lesson	0.11	<i>t</i> = -1.86	<i>p</i> = 0.07	0.07	<i>t</i> = 1.46	<i>p</i> = 0.15
	Fourth lesson	0.14			0.00		
④	Fourth lesson	0.14	<i>t</i> = 0.27	<i>p</i> = 0.79	0.00	<i>t</i> = 3.87	<i>p</i> = 0.00***
	Fifth lesson	0.14			-0.16		

Note: ****p* < 0.001.

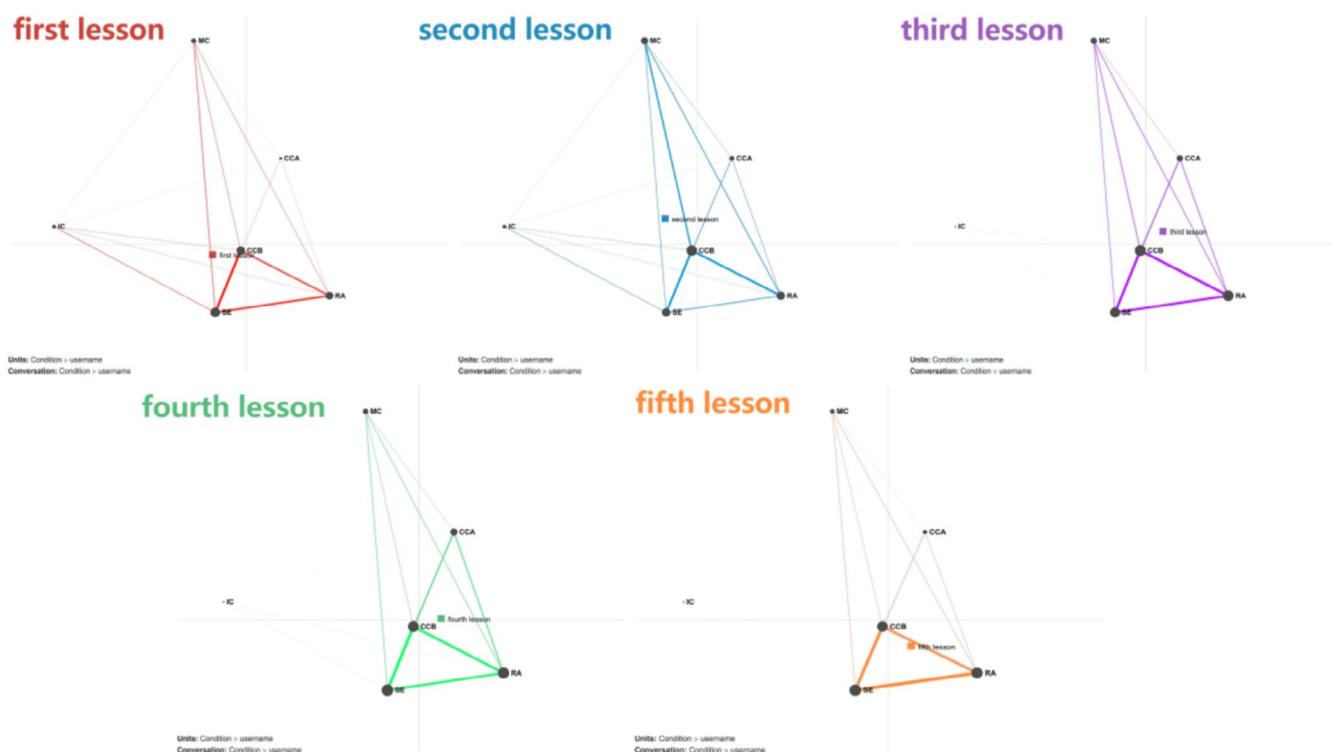


FIGURE 8 | Epistemic network profiles of the five lessons. CCA, Cognitive conflict; CCB, Checking and correcting; IC, Irrelevant Content; MC, Meaningful consultation; RA, Reaching and applying; SE, Sharing and explaining. Figures of each lesson are Figures S1–S5.

model, which confirmed that the epistemic network is valid. Moreover, the epistemic networks of student-AI collaboration in each lesson were separately mapped (Figure 8). In the epistemic network diagram, the size of a node represents how many connections the node establishes with the surrounding epistemic elements. According to the size of the nodes, it could be discovered that the number of IC decreased over time, and almost disappeared at the end.

In ENA, the strength of connections between nodes was represented by the thickness of the connecting edges and the saturation of colour. Thicker edges and darker colours indicated

stronger connections between nodes. In Figure 8, the stronger connections in the first lesson were CCB-RA (0.31; weight of the edge), SE-RA (0.34), and SE-CCB (0.40). In the second lesson, the connections were gradually shifted to MC-CCB (0.30), SE-CCB (0.37), and RA-CCB (0.36). From the third to the fifth lesson, a more stable structure was gradually formed between SE, CCB, and RA. This change indicated that undergraduates initially utilised SE and IC to negotiate and adapt their interactions with the GenAI chatbot. As the lessons progressed, they showed a greater preference for utilising CCA and CCB in the collaboration. They also gradually adopted more stable collaboration strategies.

5.2.3 | Changes in Subtractive Network Diagrams

Subtraction diagrams were employed to identify the differences between two networks, which can visualise these differences by subtracting the weight of each connection within one network from the weight of the corresponding connection in another network. The two networks have different colours, which allows for comparisons between connections of the same nodes. Edges that appeared darker and thicker in the networks informed larger differences in connection strength, while thinner and lighter edges implied smaller differences in the strength of the connections. Based on the analysis in 5.2.2, it is evident that the third lesson was a turning point, as faster changes were observed from the first lesson to the third lesson, and slower changes were observed from the third lesson to the fifth lesson. Therefore, this study analysed the overall trend of change by taking the third lesson as the dividing point. Specifically, three lessons were selected and compared: the first lesson was compared with the third lesson and the fifth

lesson, and then the third lesson was compared with the fifth lesson.

Considering the stacked subtraction diagrams of the first and third lessons (Figure 9), the changes were mainly reflected in two aspects. The SE-IC (0.17) connection in the first lesson was darker, while the CCA-CCB (-0.18), RA-CCB (-0.15), and CCA-RA (-0.16) connections appeared darker in the third lesson. This illustrated that, as the lesson progressed, undergraduates gradually reduced the input of extraneous content during the co-design process. Instead, they focused more on recognising conflicts, evaluating and revising the responses of EREIN Bot, and ultimately adopting its responses. Second, when observing the subtractive network diagrams of the third and the fifth lessons, it was not surprising to find that the changes were limited, without distinct changes in all edges. The result indicated a lack of discrepancies. Finally, the overall trend (the first to the fifth lesson) was illustrated, which revolved from frequent

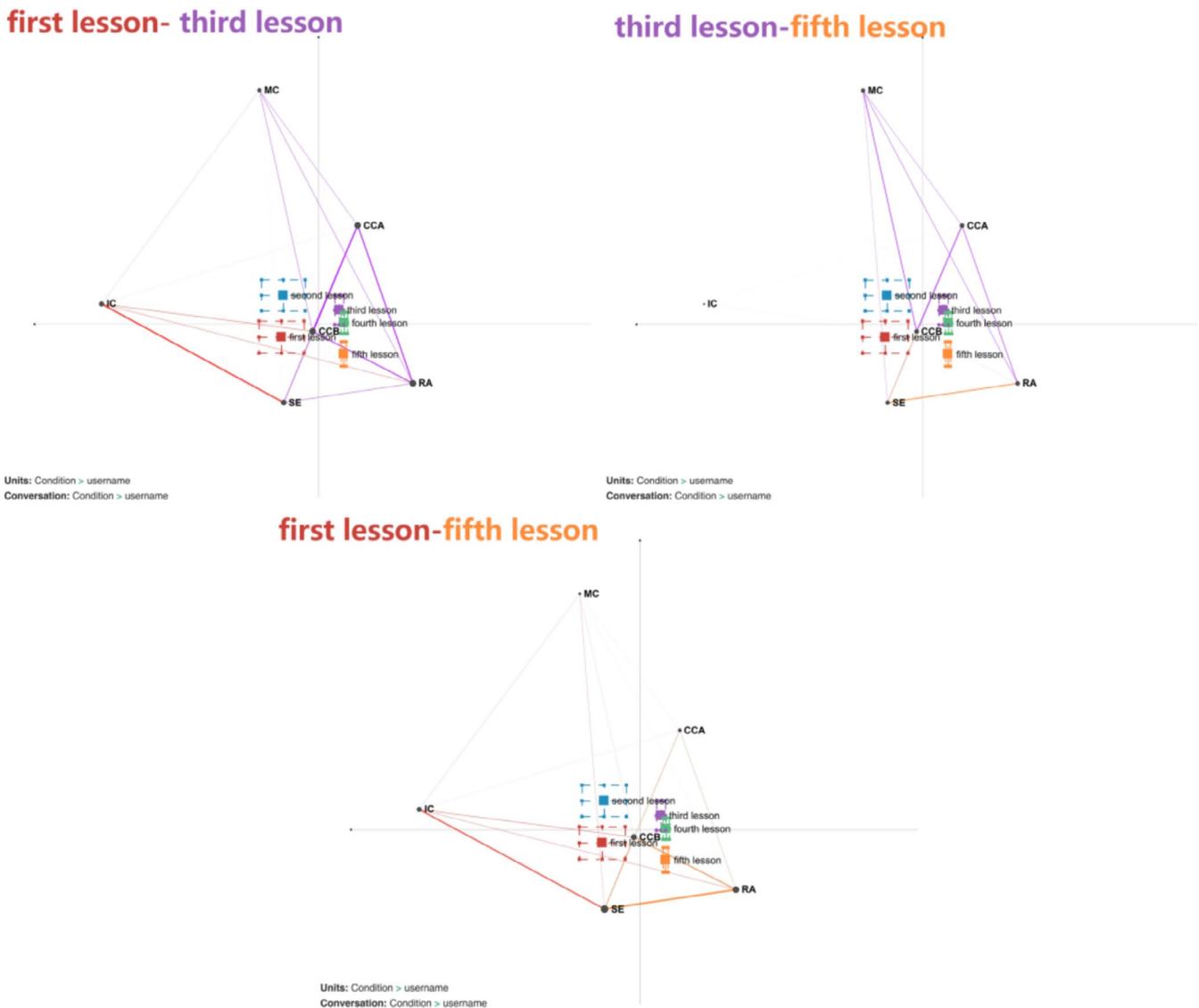


FIGURE 9 | The comparisons of ENA graphs. CCA, Cognitive conflict; CCB, Checking and correcting; IC, Irrelevant Content; MC, Meaningful consultation; RA, Reaching and applying; SE, Sharing and explaining. The average network map for the first lesson is red. For the third lesson, it is purple. And for the fifth lesson, it is orange. The cores of rectangles are the centroid of each lesson's epistemic network. Figures of each comparison are Figures S6–S8.

use of SE-IC (0.17) at the beginning to its almost disappearance at the end.

6 | Discussion

6.1 | Interaction Patterns in Undergraduates' Collaboration With the GenAI Chatbot

For research question 1, the results of the content analysis (Table 2) revealed that students gradually became more active and targeted by identifying the interaction patterns of their collaboration. This approach bridged a gap in previous research, which overlooked the dynamic interaction patterns of the collaboration between undergraduates and GenAI chatbots over time (Ansari et al. 2023; Chu et al. 2022). Generally, the number of student-AI dialogues increased, indicating a trend that students had more interactions with the GenAI chatbot in their long-term co-design. In their conversation, the immediate feedback from the GenAI chatbot enabled undergraduates to take the initiative in the collaboration tasks, thereby leading to undergraduates' more active participation in the learning process (Guo and Li 2024; Nguyen, Le, and Nguyen 2024; Pan et al. 2025).

To explain the interactions between undergraduates and the GenAI chatbot, this research applied the social constructivist learning theory. The student-AI collaboration revealed important interaction patterns of social constructivist learning, such as structuring content and exchanging feedback (Zhang et al. 2023). The amount of IC gradually reduced, indicating a decrease in extraneous content in undergraduates' conversations with the GenAI chatbot. As the lessons became more demanding, undergraduates increased their dialogue to clarify requests for the chatbot. They consciously operationalize the tasks and improve the interaction by eliminating irrelevant information, thereby enhancing the GenAI chatbot's comprehension of their inputs and receiving more tailored responses (Fathi and Rahimi 2024). Consequently, undergraduates could gradually handle the lesson design tasks in their collaboration with the GenAI chatbot.

Besides, it appeared that undergraduates' interaction patterns with the GenAI chatbot were predominantly centered on SE (Sharing and explaining), CCB (Checking and correcting), and RA (Reaching and applying). In our study, SE refers to starting a conversation with the GenAI chatbot, and CCB implies that undergraduates identified the mistakes in the output and provided some comments for modification, while RA indicates the intention to end a conversation. The increased frequency of these three types demonstrated that undergraduates more frequently started a new conversation, checked and corrected the output of the GenAI chatbot, and then ended the conversations. As the conversations repeated, undergraduates gradually comprehended the strategies of collaboration with the GenAI chatbot and became more purposeful in their tasks (Kim and Adlof 2024). Nevertheless, students' effort was still limited in the study.

Considering the collaborative learning of undergraduates and AI tools, previous research has classified the collaboration according to the low or high level of interaction (Zhang et al. 2023). The

patterns of low-level interaction were similar to the interaction patterns we observed, which reflected undergraduates' information sharing and comparisons in knowledge construction. In high-level collaboration, undergraduates should achieve a more effective co-construction of knowledge, involving more interaction such as CCA (Cognitive Conflict) and MC (Meaningful Consultation), which means finding inconsistencies in ideas and integrating different ideas to construct students' own viewpoints. It should be noted that the frequency of CCA and MC was limited in this research. The findings indicated that the collaboration between undergraduates and the GenAI chatbot mainly consisted of iterative conversations. Undergraduates merely regarded the GenAI chatbot as a tool rather than a collaborator in their lesson design tasks. Consequently, this study found that the collaboration between undergraduates and the GenAI chatbot in our research was rather superficial, lacking in constructive and intensive knowledge construction. Undergraduates gradually overlooked the potential for more meaningful knowledge construction when collaborating with the GenAI chatbot.

6.2 | Undergraduates' Collaboration With the GenAI Chatbot Changed Significantly Over Time

For research question 2, the results revealed distinct evolution in the interaction patterns of the student-AI collaboration process. From the first to the fifth lesson, the centroids exhibited significant differences along both the x and y -axis in the ENA (Table 3). According to the changes in the centroids (Figure 7), the trajectory was curved, with the centroids moving rapidly from the first to the third lesson and slowly from the third to the fifth lesson. This finding addressed the research gap in analyzing the dynamic process of undergraduates' collaboration with the GenAI chatbot.

Regarding the trajectory of centroid migration and the changes in cognitive networks across each lesson, the student-AI collaboration process revealed two distinct phases (Figure 7). In the first phase (the first–third lesson), undergraduates performed gradual comprehension. According to the student-AI collaboration, it was found that CCA was located in the first quadrant, MC and IC in the second quadrant, SE in the third quadrant, while the fourth quadrant contains CCB and RA. Examining the trajectory of centroid migration from the first to the third lesson, it appeared that the centroid progressively shifted from the third quadrant to the first quadrant, indicating an outstanding change. This change implied that CCA demonstrated a more rapid growth trend compared to other codes. The increase in CCA also suggested that undergraduates have been actively negotiating with the GenAI chatbot and evaluating the GenAI chatbot's responses. Besides, the subtractive network diagrams indicated that undergraduates predominantly featured sharing extraneous content in the first lesson. By the third lesson, the most frequent interactions included cognitive conflict, checking, and correcting, as well as the final application. These patterns revealed undergraduates' rapid comprehension of knowledge in their collaboration with the GenAI chatbot from the first to the third lesson. Consistent with previous findings, students who successfully completed the task were those capable of sharing their understanding of the task content with

the GenAI chatbot in their collaboration (Liu et al. 2023; Zhu et al. 2019). Drawing on these distinctive features, this phase is named the “Comprehension” phase. Moreover, considering the change in centroid position from the third to the fifth lesson, it is evident that the centroid transitioned from the first quadrant to the fourth quadrant (Figure 7). This shift implied that CCB and RA are growing more rapidly compared to other codes. Accordingly, this phase is designated as the “Generation” phase. In the “Generation” phase, the subtractive network diagrams indicated undergraduates’ interactions with the GenAI chatbot evolved from negotiation and iterative refinement to sharing, presentation, and application. In other words, when students had a clearer understanding of the task objectives and could articulate their needs to the GenAI chatbot accurately, they were more likely to frequently receive and apply satisfactory answers (Shin et al. 2022).

Overall, during the “Comprehension” phase, it could be noticed that CCA and CCB were increasing while IC (Irrelevant Content) was decreasing. In the “Generation” phase, the focus of the students–AI collaboration shifted from CCA and CCB to SE and RA. This trend suggested that undergraduates initially engaged SE and IC for frequent negotiation and adjustment with the GenAI chatbot, and then gradually advanced to more sophisticated handling of the collaboration with the GenAI chatbot. During the gradual exploration process (comprehension), undergraduates preferred to apply CCA and CCB for collaboration. As they gained a deeper understanding of the collaboration strategies, they preferred to simply utilise SE and RA, focusing on constant generation. As the collaboration progressed, the undergraduates shifted from rapid comprehension to generation under specific goals as they interacted with the GenAI chatbot. In line with our previous discovery, where undergraduates perceived the GenAI chatbot as a tool later in the course, this study presented the process of how undergraduates’ perceptions of the GenAI chatbot evolved from collaborating with a partner to utilising a tool. The student–AI interaction patterns revealed that undergraduates comprehended how to collaborate with the GenAI chatbot by resolving the recognition conflicts with the GenAI chatbot at first, and gradually focused on simply applying the GenAI chatbot as a tool to generate content for specific tasks. This transformation supplemented previous studies, which suggested challenges in the collaboration between undergraduates and chatbots (Liu et al. 2024; Mi et al. 2025). Such behavioural changes can hinder students’ performance. Although studies have indicated that chatbots can take on the role of mentor or collaborator and facilitate undergraduates’ learning (Kim et al. 2022; Nguyen, Hong, et al. 2024), the results suggested that achieving this level of collaboration requires additional support.

6.3 | Practical Implications

Based on our findings, this study provides suggestions for students, teachers, and administrators. Undergraduates are recommended to consistently discuss, check, and correct the input and output in their collaboration with GenAI chatbots. These social interactions foster undergraduates to get an interactive learning experience for their knowledge construction in personalised learning (Hassan 2023). Furthermore, undergraduates are encouraged to interact more constructively with GenAI

chatbots in their collaboration, such as refining their expressions, discussing conflicts, and negotiating, rather than merely completing their assignments (Guo et al. 2023; Nguyen and Nguyen 2024). At the same time, undergraduates should refrain from simply utilising the content generated by GenAI, as this may lead to issues of plagiarism or academic integrity violations (Chan and Hu 2023). By these approaches, undergraduates can make a GenAI chatbot a helpful collaborator rather than just a tool, develop more constructive ideas, and achieve meaningful knowledge construction.

Teachers should also view GenAI chatbots as undergraduates’ collaborators, designing scaffolded student–AI collaboration and facilitating their interactions. Although this study showed that undergraduates can become more active in the collaboration with GenAI chatbots, they still need adequate support to overcome barriers in the process. For students’ comprehension, teachers should assist them by reviewing and correcting their behaviors in content-generation tasks (Jahnke et al. 2022). Moreover, instead of merely showing students how to generate content in the “Generation” phase, teachers could incorporate Prompt strategies in teaching, enabling students to employ prompts for complex problem-solving and co-design with GenAI chatbots. For instance, a well-crafted Prompt provided by teachers could assist students in generating images and foster the expansion of creative concepts in GenAI-supported courses (Lee et al. 2023).

For educational administrators, given the difficulties students encounter in the dynamic collaboration with GenAI chatbots, teachers may lack the necessary knowledge to resolve students’ various problems. Professionals can be invited to assist students and teachers in training programs. In a broader regard, AI education should incorporate human–AI collaboration strategies. It will be a requisite skill that equips the forthcoming generation to fully leverage the potentialities of GenAI as an agent.

7 | Conclusion, Limitations and Future Directions

This research demonstrated that when undergraduates collaborated with GenAI chatbots under scaffolded support, they gradually became more active and targeted in the process. In alignment with the social constructivist learning theory, undergraduates are more likely to engage in learning with effective social interaction (Fryer et al. 2019). Through constant explanation, GenAI can participate in discussions for solutions and dispense customised feedback (Seeber et al. 2020). Two outstanding phases were explored in student–AI interaction patterns. In the “Comprehension” phase, undergraduates could rapidly understand knowledge during collaborative learning. In the “Generation” phase, the change in undergraduates’ interaction patterns wasn’t obvious, as they repeated a similar mode of interaction. They primarily utilised the GenAI chatbot as a tool for conveniently generating content, thereby neglecting more complex knowledge construction and diminishing the potential of their collaborative learning with GenAI chatbots. These findings contribute to the application of social constructivist learning theory in student–AI collaboration and the implementation of AI-supported design in university curricula.

Some limitations of this study could be addressed in the future. Firstly, the course lasted only one semester, which limited the generality of our conclusion. The duration of the study can be extended to examine the reliability and universality of the findings. Secondly, the findings may be culturally specific since Chinese adult students emphasize self-control and collectivism (Li et al. 2018; Zha et al. 2006). Undergraduates may feel stressed; thus, they tend to finish the tasks rather than explore and creatively think in the collaborative process, which may influence their interaction patterns. Future research should consider extending investigations to cross-cultural settings to enhance the generalizability of the results.

Thirdly, although the 40 sample size was relatively small, we regarded it as acceptable because prior research has proved that a similar sample size could generate reliable results with sufficient coding and reveal student-AI interaction patterns (Nguyen, Hong, et al. 2024). It is also notable that this study only employed one GenAI chatbot in the collaboration, while different chatbots should have various performances. Future studies with more samples and chatbots can support expensive analyses. Lastly, this study did not include a control group to ascertain the GenAI chatbot's efficacy on learning outcomes. We considered that previous studies have certified the GenAI chatbot's positive impacts (Lee et al. 2022). This study focused on investigating the dynamic process of undergraduates' collaboration with a GenAI chatbot. Future studies are suggested to compare the dynamics between different groups when examining the efficacy of GenAI chatbots in undergraduates' learning.

Author Contributions

Weipeng Shen: conceptualization, methodology, investigation, project administration, formal analysis, writing – original draft. Xiao-Fan Lin: resources, supervision, writing – review editing. Jiachun Liu: conceptualization, investigation, formal analysis, writing – original draft. Xinxian Liang: conceptualization, investigation, formal analysis, writing – original draft. Ruiqing Chen: conceptualization, writing – original draft. Xiaoyun Lai: investigation, data curation, Formal analysis, writing – original draft. Xinwen Zheng: investigation, data curation, formal analysis.

Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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Supporting Information

Additional supporting information can be found online in the Supporting Information section. **Table S1:** Examples of student prompts and chatbot responses. **Figure S1:** The epistemic network profile of the first lesson. **Figure S2:** The epistemic network profile of the second lesson. **Figure S3:** The epistemic network profile of the third lesson. **Figure S4:** The epistemic network profile of the fourth lesson. **Figure S5:** The epistemic network profile of the fifth lesson. **Figure S6:** The comparison of ENA graphs (first lesson-third lesson). **Figure S7:** The comparison of ENA graphs (third lesson-fifth lesson). **Figure S8:** The comparison of ENA graphs (first lesson-fifth lesson).