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An active instructional approach based on the SAMR framework: Integrating AIGC into undergraduate freshmen learning ☆

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ABSTRACT

The question of how to use artificial intelligence generated content (AIGC) properly to enhance learning among college students is a key concern for contemporary educators. Although previous studies have discussed the influence of AIGC on college teaching and student learning and its functions in this context, there remains a lack of discussions regarding ways of guiding students' use of AIGC and studies on the specific topic of helping college freshmen use AIGC properly. Based on the substitution, augmentation, modification and redefinition (SAMR) model, this study develops a progressively active teaching framework that integrates AIGC into learning. This framework is used to design learning activities for general education courses targeting freshmen. This exploratory study was conducted in the context of a 16-week course. During the teaching process, AIGC interaction log data and AIGC experience records were collected from students, following which data processing was conducted using the discourse analysis, quantitative statistical analysis, and epistemic network analysis (ENA) methods to obtain the ultimate results of this study: (1) A combination of active teaching with the SAMR model can improve the quality of interactions between students and AIGC; (2) teaching strategies rooted in active learning can enhance students' ability to use AIGC; and (3) improvements in students' technical skills strengthen the quality of their interactions with AIGC. This study makes novel contributions to the literature on active learning strategies for teachers and curriculum designers, and it offers practical guidance for educational practitioners and college students regarding the integration of AI technology into both teaching and learning.

1. Introduction

The rapid development of artificial intelligence (AI) technology is constantly reshaping teaching methods and learning experiences in colleges and universities (Abbasi et al., 2024; Airaj, 2024; Canonigo, 2024; Wang et al., 2025), and the rapid development of artificial intelligence generated content (AIGC) offers even greater potential to improve teachers' curriculum development and teaching process (Liang et al., 2023). Additionally, AIGC can significantly help college students complete complex learning tasks, increase their engagement, and improve their learning efficiency (Chen et al., 2024; Shang & Geng, 2024). According to a survey of undergraduates that was conducted by the Higher Education Policy Institute of the UK in 2025, 92 % of undergraduates have integrated AIGC tools into their daily learning, mainly for the purposes of explaining concepts, summarizing articles and proposing research ideas. However, many undergraduates (18 %) directly embed AI-generated text in their homework (Higher Education Policy Institute, 2025). This finding indicates that although AIGC is in widespread use, an increasing number of college students tend to use it passively—either by treating such technologies merely as question-and-answer tools or by incorporating the content they generate directly into their assignments without truly understanding the results or evaluating them critically. This "superficial application" of AIGC has given rise to concerns regarding the use of AIGC by students. Students fail to use

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AIGC as a tool to support in-depth learning and inquiry-based learning, thus giving rise to concerns regarding efforts to promote higher-order thinking abilities such as critical thinking, innovative thinking and complex problem-solving ability among college students (Zheng et al., 2024).

Zimmerman (2002) noted that many first-year students have not mastered effective self-regulated learning strategies and techniques during their early learning experiences; thus, they perform complex academic tasks less efficiently. The rapid development of AI technology has rendered the academic challenges faced by freshmen more diverse. On the one hand, students can use AI tools to complete more difficult reading and writing tasks easily (Guo et al., 2024); on the other hand, the use of AI also entails potential risks, such as bias and inappropriate information output, which may affect students' academic performance and cognitive development (Nguyen, 2025). Moreover, AI-related abilities (such as technology use, innovative thinking, problem-solving, critical thinking, and teamwork) have become important driving factors with respect to students' future academic success and ability to adapt to social developments (Mah, 2016; Ng et al., 2023). However, a 2024 study conducted by Jie et al. revealed that students may still lack basic awareness and a deep understanding of AI, thus preventing them from using these tools effectively to improve their learning. In addition, as a result of significant disparities in digital literacy and active learning strategies, the levels of learning performance exhibited by freshman students are uneven (Prior et al., 2016; Uçar & Kumtepe, 2019). Some students tend to develop an excessive level of reliance on AIGC tools to obtain instant answers while ignoring the deeper value of such tools with regard to inspiring thinking, promoting inquiry and solving problems (Hou et al., 2025; Kasneci et al., 2023). Given the deep value of complex problems, this superficial use of AI tools may exacerbate existing learning gaps and even exacerbate the issue of education polarization in the long term (Taylor, 2024). Therefore, a critical challenge emerges with regard to the task of guiding freshman students to use AIGC correctly and effectively as a learning support tool during the early stage of enrollment, thereby facilitating higher-order learning.

Although existing studies have explored AI-driven teaching strategies to enhance student learning (Liang et al., 2023; Yim & Su, 2025), there remains a notable lack of instructional guidance frameworks for effectively integrating AIGC tools among first-year university students (Wang et al., 2025). The SAMR model (Puentedura, 2014), a widely recognized framework for progressive technology integration in education, describes four levels of technology adoption—from substitution to redefinition—and supports deeper, more creative interaction between teachers, students, and technology (Blundell et al., 2022; Hamilton et al., 2016). However, the development of active teaching pedagogies based on the SAMR model, as well as their impact on the learning outcomes of first-year students, has not yet been sufficiently investigated.

2. Literature review

2.1. AIGC-assisted learning

The use of AIGC in higher education continues to develop, thus highlighting the potential to use this technology to transform learning effects, cognitive development, and literacy ability. A number of empirical studies have provided preliminary verifications of the educational efficacy of this approach. For example, Yin et al. (2024) reported that educational chatbots can not only provide personalized learning support but also significantly enhance students' learning motivation and affective experience based on affective interactions and metacognitive feedback, which can benefit the autonomous learning and knowledge acquisition of college students. Deng et al. (2025) noted that ChatGPT not only helps improve students' academic performance but also enhances their higher-order thinking tendencies and levels of affective motivation, thereby providing strong evidence to support the systematic integration of AIGC into education and teaching practices.

From the perspective of language learning, Pan et al. (2024) investigated English as a Foreign Language (EFL) students and revealed that, based on the personalized self-regulation support provided this the generative AI (GenAI) tool, students exhibited enhanced behavioral, cognitive, and affective engagement in reading activities. Notably, this research highlights a significant increase in the frequency with which students used metacognitive strategies, thus indicating that AIGC can effectively promote deeper-level meaning construction and transformative language learning. In addition, the auxiliary role played by AIGC in complex cognitive tasks has become increasingly prominent. Song et al. (2025) reported that this GenAI chatbot can effectively support the creative problem-solving ability of college students and offers unique advantages in the context of complex learning tasks; however, its generation performance is highly dependent on prompt input, thus indicating that students' questioning ability plays a critical role in human–machine collaboration. As Lee and Palmer (2025) noted, effective prompt engineering can significantly improve the relevance and quality of AI output and also represents a critical teachable and learnable skill that has substantial implications for both teachers and students.

Although AIGC has positive effects on student learning, the degree to which AIGC is integrated into the curriculum is still limited. Moreover, although constructivism and reflective-oriented active exploration have been demonstrated at the level of teaching strategies, the role of AIGC as an "auxiliary assistant" has not received sufficient attention, thus highlighting the limitations of teachers' understanding of the mediating function of AI in this context. In general, the studies reviewed above have supported the positive effects of AIGC on students' academic performance, autonomous learning ability, affective motivation, and higher-order thinking. However, such research has also highlighted significant challenges regarding the mechanisms underlying human-AI interactions, the cultivation of prompt engineering competencies, and the depth of pedagogical integration in this context.

2.2. Hierarchical framework for technology integration: the SAMR model

To help educators integrate technology effectively, researchers have developed multiple frameworks in this field (Crompton & Burke, 2020; Falloon, 2020), such as the technological pedagogical content knowledge (TPACK) framework (Mishra & Koehler, 2006), the replacement, amplification and transformation (RAT) framework (Hughes et al., 2006), and the substitution, augmentation, modification and redefinition (SAMR) framework (Puentedura, 2006).

The SAMR framework (Fig. 1) divides technology integration into four levels. Substitution (S) refers to the use of technology to perform tasks that can be completed without the use of such technology, in which context technology is used merely as a direct replacement. Augmentation (A) refers to the acquisition of additional learning benefits with respect to the completion of the same task. Modification (M) indicates

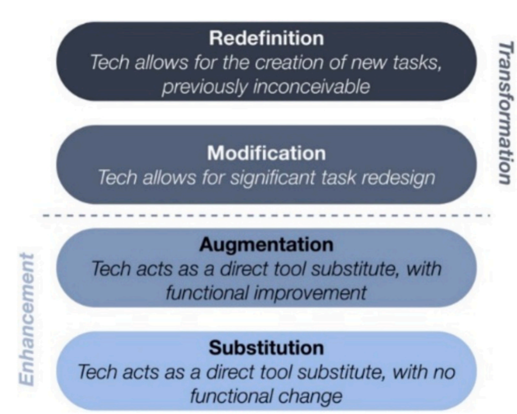

Fig. 1. Puentedura's SAMR model.

that the technology in question allows the task at hand to be redesigned significantly. Finally, redefinition (R) refers to the use of technology to perform novel learning tasks that would not have been possible to perform without such technological support (Puentedura, 2006, 2013). The bottom two levels of the SAMR model can "augment" learning based on technology, whereas the top two levels "transform" learning through technology (Crompton & Burke, 2020).

Because the SAMR model aims to provide a method to measure the extent to which technology is used (Ong & Annamalai, 2024), some researchers have employed this model to understand the different behaviors of involvement in the integration technology by teachers (Lomos et al., 2023). Wang et al. (2025) evaluated the degree to which GenAI has been integrated into the classroom setting based on the basis of the SAMR framework. The results revealed that most uses of GenAI focus on the augmentation level, and a small number focuses on the substitution level and the modification level; in contrast, fewer such uses focus on the redefinition level. At present, the integration of AIGC in higher education mostly remains at the "substitution" and "augmentation" stages of the SAMR model. Studies that genuinely "modify" and "redefine" teaching activities are rare; however, their potential to promote teaching reform is enormous (Wang et al., 2025).

In addition to classroom integration research, some studies have also applied the SAMR model to the tasks of designing and implementing technology-supported learning tasks or experiences and indicated that self-reports of the relevant results have improved (Liu et al., 2020). Some researchers have also used this model as a scaffold for planning digital transformation curricula that aim to help higher education teachers increase the digital literacy of pre-service teachers (Bernsteiner et al., 2025). However, although the SAMR framework can be used as a scaffold for the design of course tasks, it has rarely been used in studies seeking to improve the level at which college freshmen use AIGC.

2.3. Active teaching approach

The educational community has reached a consensus that AIGC should be used to promote knowledge construction rather than to generate answers directly (Chen et al., 2024; Wang et al., 2025), which aligns with active instructional approaches that support engaged learning. Active teaching refers to activities in which students participate in a task directly and reflect on their learning (Bonwell & Eison, 1991; Robertson, 2018; Sasson & Tifferet, 2025); this approach thus emphasizes the fact that students are the active constructors of knowledge in the learning process rather than merely passive recipients. Active learning encourages students to ask questions, discuss, write, solve problems, and participate in teamwork and peer support (Kozanitis & Nenciovici, 2023), thereby facilitating the application of their knowledge to real situations. Chi (2009) proposed an "active-construction-interaction" framework, which divides active learning into three stages: students effectively promoting knowledge by participating in activities, reconstructing their existing knowledge, and engaging in communication and interaction with others, thereby promoting their ability to understand and transfer knowledge. In comparison with passive learning methods, which are based on lectures from teachers and feature a core focus on content delivery, student-centered and active teaching methods can promote students' in-depth understanding more effectively and lead to more learning achievements (Boedeker et al., 2024; Rozhenkova et al., 2023). Burke and Stewart (2022) integrated the problem-solving model into an academic course in the field of general education as a core teaching method. The results of the study revealed that students who had mastered the problem-solving model and related academic skills were able to complete the courses more smoothly and achieve a higher grade point average (GPA) than were other students. This approach is especially significant for students who struggle with their academic performance. These findings indicate that well-designed active learning courses can not only improve the academic performance of students effectively but also help them cope with various challenges in their university studies and daily lives.

Although diverse AIGC teaching strategies exist, their focus is predominantly constructive and reflective (Wang et al., 2025). By contrast, strategies centered on instructional scaffolding and authenticity integration are notably underrepresented. Based on active teaching, introductory-level courses and education courses can achieve better learning effects (Kozanitis & Nenciovici, 2023). Therefore, this study integrated the SAMR model into teaching strategies rooted in active learning. In the context of actual teaching in a college freshman course, three-stage progressive, AIGC-assisted learning tasks were designed and implemented; the requirements for each stage gradually increased alongside the student's level of technology use. This study thus used hybrid research methods to investigate the effect of this inclusive teaching strategy on AIGC-assisted learning among freshman students. This study sought to answer the following three questions:

(1) How does active teaching that integrates the SAMR model impact the quality of the interactions between students and AIGC?
(2) How does active teaching that integrates the SAMR model impact students' technical skills with respect to AIGC use?
(3) What is the relationship between students' technical skills pertaining to AIGC use and the quality of the interactions between students and AIGC?

3. Methodology

3.1. Context and participants

This study was conducted in the context of a general education course for education majors at a Chinese university over a period of 16 weeks. The aim of this course was to help freshman students grasp the core concepts associated with their major, increase their professional interest and learning motivation, and acquire the ability to engage in independent learning and team cooperation. Moreover, this course was designed to help freshman students use learning strategies and digital tools effectively to improve their learning ability, thus supporting their efforts to adapt to the university learning mode and fulfill their future development needs. These teaching objectives are highly consistent with the AIGC-assisted learning discussed in this study; thus, this course provides a good educational context for this study.

The course was taught by a female faculty member who had more than 20 years of teaching experience. She has taught this course for more than three years. In addition, four master's and doctoral students served as teaching assistants and participated in the process of teaching the course. In the fall semester of 2024, this course represented a professional general studies course for education students. A total of 23 students in this course, including 22 freshmen and 1 junior, were invited to participate in this study. To avoid the influence of grade-related factors, we excluded the data collected concerning the junior student. The final sample thus included 22 freshman (8 males, 16 females) whose mean age was 18 years (with a standard deviation of 0.9 years). All participants had attended ordinary high schools and had not previously studied professional-related courses systematically. Before the beginning of the study, all participants were informed of the study design, purpose and data collection methods; furthermore, they signed informed consent forms.

3.2. The active instruction framework on the basis of SAMR

Based on the hierarchical and progressive logic associated with the SAMR model, alongside the three-stage division of active learning proposed by Chi (2009), we constructed a four-level progressive active teaching framework (Fig. 2).

The framework includes four levels (S-A-M-R), and each level features three stages of active learning activities. Specifically, at the first level (S), active learning activities were planned across three stages:

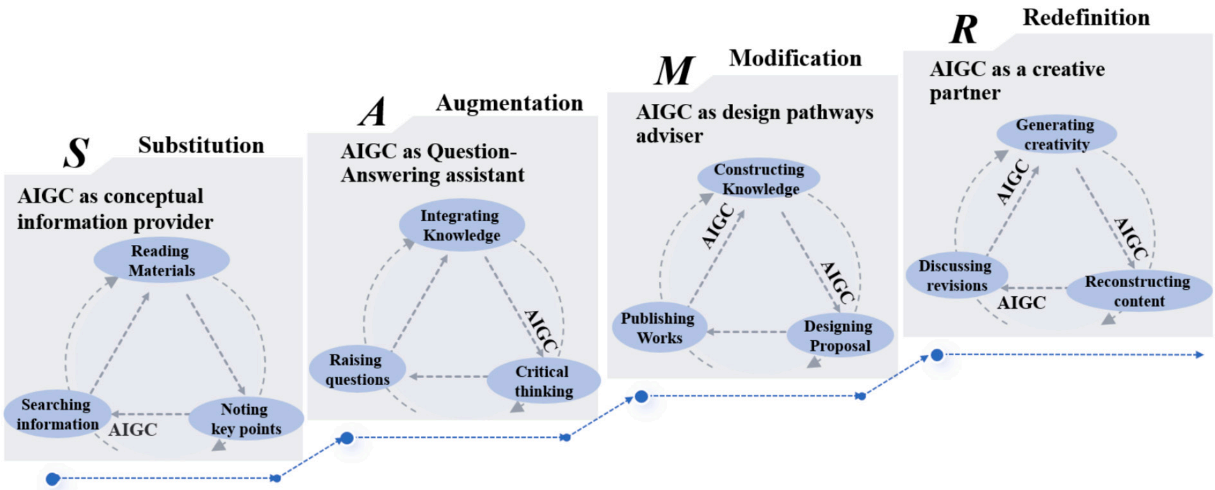

Fig. 2. The progressive active teaching framework based on the SAMR model.

"reading—note-taking—knowledge search." As a type of content object that interacts with students, AIGC helps students obtain materials and information that can meet their individual needs by providing them with conceptual information. At the second level (A), the three stages of active learning were planned as follows: "knowledge integration—thinking and questioning—release of questions." At this stage, students are proficient in the use of AIGC, can use AIGC to integrate and optimize knowledge, and can use AIGC to seek suggested answers to questions. At the third level (M), the learning activities are as follows: "knowledge construction—project design—release of results." AIGC is used as a suggestion for the design path. Students use AIGC for the purposes of project planning, the generation of a framework for thinking, role assignment and task decomposition, among other aims. We must actively guide the AIGC to output specific content and gradually shift from the level of simple information acquisition to that of knowledge construction. At the fourth level (R), AIGC is viewed as a creative partner that can support various activities on the part of students, such as "idea generation—content reconstruction—discussion and exchange." At this stage, students use AIGC to facilitate reasoning, analysis and creation; engage in in-depth dialog with AIGC; and ultimately achieve the purposes of innovation and knowledge reconstruction.

3.3. Research procedure

In line with the active teaching framework presented in Fig. 2, three rounds of teaching activities were created (see Fig. 3).

The first two rounds of activities were completed independently by the students, and the third round of activities was a group collaborative task. In the first round of activities, the teachers guided the students to use the AIGC tools to generate personalized learning materials, to help them improve their understanding of technical terms such as "educational technology" and "education digitization", and to acquire preliminary experience with the use of AIGC. In the second round of activities, the students designed a video concerning the concept of "multimedia learning". Meanwhile, the teacher instructed the students to use AIGC to generate a framework for the video script and to optimize the content of the script. In the process of completing this more complex learning task, the students explored ways of adjusting the strategies they used to interact with AIGC to improve both content quality and expression ability. The third round of the activity was a group collaboration project that lasted 6 weeks. The project required each group to

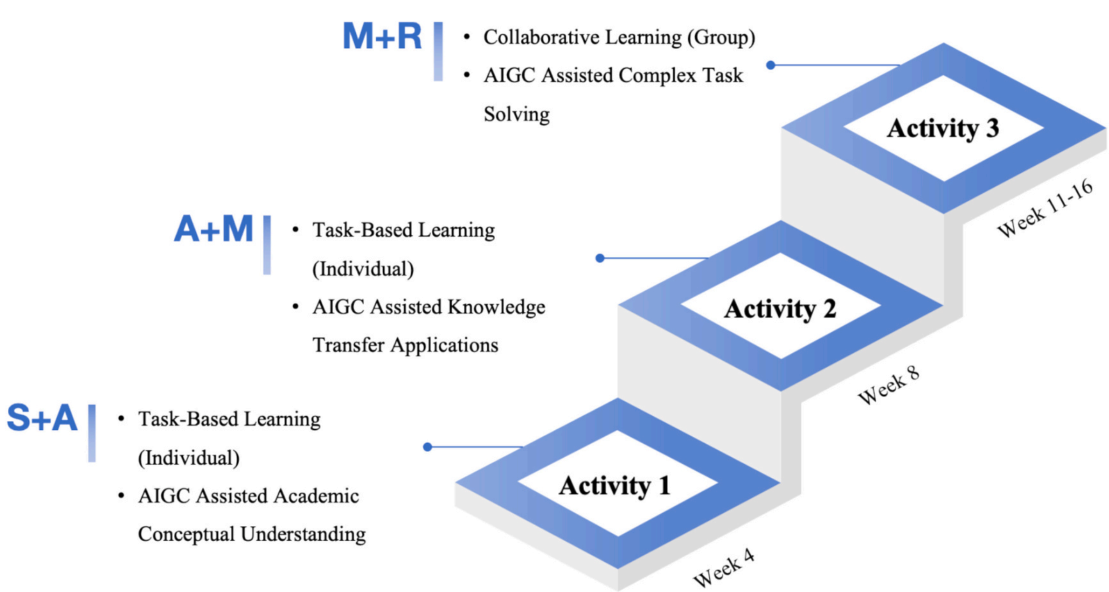

Fig. 3. The design procedure for the three instructional activities.

complete an implementation plan that focused on "the application of professional concepts in specific educational scenarios." During this period, the teacher did not provide requirements or guidance concerning the use of AIGC. The students actively used AIGC during key steps such as topic selection planning, task allocation, time planning, content drafting, material collation, result editing, and idea stimulation. This open design offered students more autonomy and room for exploration and motivated them to choose their technical support path flexibly in accordance with their actual needs. Within these instructional activities, complex tasks required AIGC-assisted solutions. AIGC was used to solve complex tasks. These three rounds of progressive teaching activities were designed to guide students to understand AIGC gradually, to improve their ability to use this technology, and ultimately to help them complete learning tasks efficiently and optimize their overall learning performance.

3.4. Data collection

In terms of data collection and analysis, this study focused on students' AIGC-assisted learning performance in the context of three teaching activities. In the first activity, we collected 22 logs of interactions between students and AIGC tools, thus collecting a total of 151 interaction data points. In the second activity, we also collected 22 logs of such interactions, accounting for a total of 89 interaction data points. As a result of the open task situation associated with the third activity, the students were free to choose whether to use the AIGC tool. At the end of the course, the students were invited to share their experiences with and reflections on the use of AIGC tools in the learning process based on open questions. A total of 22 reflections were collected.

3.5. Coding scheme

3.5.1. Quality of students' interactions with AIGC

In this study, the quality of students' interactions with AIGC was measured in terms of three dimensions: depth of dialog with AIGC, question diversity, and dialog efficiency (Table 1 presents a detailed coding scheme and corresponding examples).

The analytic framework for student questioning proposed by Graesser and Person (1994) divides such questioning into a hierarchy that leads from low-order questions (such as factual questions) to high-order questions (such as those pertaining to analytical, comprehensive, and critical thinking). This study refined the depth of the dialog between students and AIGC into four levels: (1) the basic level, in which context the questions focused mainly on obtaining information directly and included factual questions and simple comprehension questions; (2) the intermediate level, which involved some reasoning or interpretive questions and focused on connecting information and understanding the logic underlying relevant concepts but did not involve any in-depth analysis; (3) the high level, which contained questions pertaining to analysis, synthesis and critical thinking, thus highlighting the reconstruction of knowledge; and (4) the ineffective low level, which referred to issues that were off-topic, vaguely expressed, or not conducive to dialog. During the specific quantification process, the four levels of dialog depth were assigned scores of 1, 2, 3, and 0 points, respectively. Both dialog depth (Depth) and question diversity (Diversity) were quantified using a unified scoring approach:

$$\mathrm{D} = \frac{\sum_{i=0}^{4} R_i * d_i}{\sum\limits_{i=0}^{4} R_i}$$

D represents the final score, R_i indicates the frequency of the corresponding category, and d_i highlights the corresponding weight for each category (Liu et al., 2025). In the first-stage reflective log of student 1 and AIGC, 3 sentences were coded at the basic level, 3 sentences at the intermediate level, 1 sentence at the high level, and 2 sentences at the invalid level. Therefore, the dialog depth of this reflective log was calculated as $\mathrm{D} = (3 \times 1 + 3 \times 2 + 1 \times 3 + 2 \times 0) / (3 + 3 + 1 + 2) = 1.33$.

Chin and Osborne (2008) noted that the learning process of students is driven by the questions that they ask. These questions can be divided into four categories depending on their functions: (1) information gathering questions, which are related mainly to the acquisition of basic factual information; (2) bridging questions, which aim to explore the connections between two or more concepts; (3) extension questions, which encourage students to explore new areas that lie beyond the scope of the questions themselves with the goal of creatively applying or expanding students' newly acquired knowledge; and (4) evaluative and reflective questions, which usually help students make decisions on the basis of critical thinking and are typically accompanied by a shifts in mindset or perspective. Accordingly, this study divided the questions asked by the students into three types in accordance with the dimension of question diversity, i.e., factual questions, relevant questions, extended questions and reflective questions, which were assigned 1, 2, 3, and 4 points, respectively. Unrelated questions were assigned 0 points.

The measurement of dialog efficiency is based on the complete

Table 1
Coding framework for the conversation logs between students and AIGC.

Types	Score	0	1	2	3	4
Dialog depth	Dimension Description	Invalid level Dialog content that is meaningless, off-topic, or fails to facilitate the achievement of the learning objectives	Basic level Simple factual question or answer	Intermediate level Content involving analysis, comparison, or causal inference	High level Critical thinking or comprehensive questions/ responses	–
	Example	What can you do?	What is the definition of a concept?	What is the relationship between education digitization and personalized learning?	How does education digitization affect student learning?	
Question diversity	Dimension Description	Other questions Questions that are unrelated to the topic on which the learning task at hand focuses	Factual issues Efforts that primarily focus on identifying basic factual information	Relevance issues Efforts to identify a connection between two or more concepts	Scalability issues Content that extends beyond the scope of the problem at hand to encompass the creative application or extension of newly acquired knowledge	Reflective questions Efforts to help students think critically in the context of decision-making
	Example	I do not know what to ask.	What is the definition of education digitization?	What is the difference between education informationization and education digitization?	How can this concept be applied to other disciplines?	What are the disadvantages of education digitization?
Dialog efficiency		Given the number of dialog rounds, a question from a student and an answer from a tool is defined as 1 round.				

performance of students in the context of a given learning activity. The dialog efficiency that is required to complete the task is calculated by counting the number of interactions between the student and the AIGC. In the process, whenever a student asked a question and received an answer from the AIGC, this exchange was counted as one interaction.

3.5.2. Levels of AIGC use on the part of students

On the basis of the SAMR framework, some researchers have refined the notion of technology use (Drugova et al., 2021). This study expands the original four levels into a coding framework that features eight subdimensions (Table 2), thus enabling the differences in the use of AIGC by students in the context of different learning tasks to be described accurately; in turn, such descriptions provide a more comprehensive characterization of students' learning performance.

4. Data analysis and results

4.1. Data analysis

Although the study involved 22 participants, each student completed multiple rounds of tasks, generating a substantial number of data points per individual. To ensure the validity of the parametric tests employed, we tested the underlying assumptions. For the paired *t*-tests, Shapiro-Wilk tests indicated that the difference scores for several variables (including S-search, S-modify, A-modify, M-detail, and R-criticize; all $p < 0.05$) deviated from normality. For these comparisons, we confirmed the robustness of the results using non-parametric Wilcoxon signed-rank tests, which yielded congruent conclusions. Furthermore, Mauchly's test of sphericity was conducted for each dependent variable. The assumption of sphericity was violated for the variable 'A-modify' ($\chi^2 = 6.27$, $p = 0.043$). Therefore, the Greenhouse-Geisser correction was applied to the ANOVA for this variable. For all other variables, the assumption of sphericity was met (all $p > 0.05$).

To answer the first research question, we coded the interaction logs pertaining to the students' efforts in the first two activities and analyzed the coding results on the basis of a paired samples *t*-test with the goal of exploring the changes in the depth of questioning, the question diversity and the efficiency of the dialog that occurred after the students used the AIGC. Two coders independently completed the coding, achieving a weighted Cohen' s k of 0.85, indicating very strong agreement (Landis & Koch, 1977). All discrepancies were then resolved through in-depth discussion to reach full consensus for the final analysis.

To answer the second research question, we conducted an epistemic network analysis (ENA) to investigate the differences in students' use of AIGC across the three teaching activities. By calculating the co-occurrence relationship of elements included in the dialog, ENA is used to construct a connection network among knowledge elements and to generate a weighted co-occurrence map, thus providing a visualized network for each unit of analysis in the data (Shaffer et al., 2016; Shaffer & Ruis, 2017). The ENA demonstrated the connection structure and strength of the codes and helped quantify the time-varying changes in composition and connection strength. In this study, we used the four levels and eight subdimensions included in the SAMR framework as a basis for coding, and we used the webENA platform (https://app.epistemicnetwork.org/login.html) to construct a cognitive network model that reflected the variations in students' levels of utilization.

To answer the third research question, we used a comprehensive range of quantitative and qualitative methods. The quantitative analysis included a correlation analysis and the development of a linear regression model to explore the relationship between students' ability to use AIGC and the quality of their interactions with this technological tool. Multicollinearity diagnostics were performed prior to regression analysis. Variance inflation factors (VIF) ranged from 1.28 to 2.17, well below the commonly accepted threshold of 5, indicating no serious multicollinearity concerns (O'Brien, 2007). The qualitative analysis focused on the views expressed by students in response to the open-

Table 2
Levels of the coding framework used by students with respect to AIGC.

Coding unit		Definition	Example
Substitution Level 1	Substitution search	AI helps students obtain information by replacing traditional retrieval methods (such as the use of search engines to find materials) with AI tools	Please tell me the definition of educational technology
	Substitution correction	AI tools replace the function of manual correction and error correction to help students improve existing content	Please help me correct the errors in this part of the answer
Augmentation Level 2	Augmentation search	AI is used not only to replace traditional retrieval methods but also to augment students' learning experience by providing more dimensions of auxiliary information (such as content relevance or recommended materials)	Please identify the differences in the definitions of educational technology provided by different schools of thought
	Augmentation correction	AI not only replaces the traditional modification function but also improves the modification effect by offering more suggestions and ensuring contextual optimization.	Please use Professor He Kekang's definition of educational technology as a standard to revise my answer
Modification Level 3	Framework generation	AI helps students generate a framework or basic structure for thinking and provides them with guidance concerning subsequent detailed content	Please help me generate a syllabus for a course in behavioral psychology
	Detail generation	On the basis of the existing framework, AI provides specific details or expanded content to help students deepen their understanding	Please help me generate a microlecture video script concerning "multimedia learning," which needs to reflect the "multichannel" multimedia learning principle at the beginning
Redefinition Level 4	Inspiration for questions	AI not only provides specific answers but also drives students to think, asks new questions or generates new ideas, and helps students deepen their learning.	What suggestions can be provided with regard to multimedia-based learning?
	Question and answer	Students not only accept the answers provided by the AI but also actively criticize or question the information thus provided, thereby promoting more in-depth thinking and reflection.	In addition to its advantages, does educational technology entail any deficiencies?

ended questions with regard to efforts to refine their confidence in their ability to use AIGC tools, relevant use strategies, and their views concerning the potential of AIGC in future studies.

4.2. RQ1. The effect of teaching rooted in active learning on the quality of student-AIGC interactions

We conducted a coding analysis by reference to the logs of these interactions to obtain proportion data concerning the depth of dialog and the question diversity in the first two rounds of interaction between students and AIGC (Table 3). A paired t-test was performed with respect to the depth of dialog and the types of questions associated with the two activities to evaluate the effects of these two activities on the quality of the interactions between students and AIGC (Table 4).

Between the two rounds of activities, the proportion of students' dialogs with AIGC that occurred at the intermediate level ($p = 0.010$) and the basic level ($p = 0.012$) decreased slightly, whereas the proportion of dialogs that occurred at the high level increased significantly ($p < 0.001$). Dialog at the invalid level decreased significantly after two rounds of practice and ultimately fell to 0 %. These results reveal that the integration of active teaching into the SAMR model significantly changes the depth of dialog that characterizes the interactions between students and AIGC and significantly improves the proportion of higher-level dialog between students and AIGC.

In terms of question types, factual questions (32.45 %, 23.6 %), extensive questions (25.83 %, 61.8 %) and reflective questions (19.21 %, 11.23 %) played a leading role, whereas the ratio of irrelevant to relevant questions was low. The paired test data pertaining to the two activities revealed that factual questions ($p = 0.018$) and irrelevant questions decreased significantly, extended questions increased significantly ($p = 0.003$), and relevant and reflective questions ($p = 0.021$) decreased slightly. These findings indicate that students gradually transitioned from simple questions to deeper levels of exploration and thinking, and the goals of their interactions became more focused and efficient.

In general, as SAMR-based progressive active teaching continued to develop, students experienced significant changes in terms of the depth of dialog and the question diversity observed in the context of their use of AIGC; furthermore, particularly notable improvements observed with regard to high-level dialog and the expansive questions. In terms of dialog efficiency, the average numbers of conversational turns for each student across the two activities were 6.29 and 3.71, respectively, thus indicating a clear downward trend. This finding indicates that students can complete more challenging learning tasks over fewer rounds of interaction with AIGC through the use of higher-quality dialog.

4.3. RQ2. The effect of teaching rooted in active learning on the levels at which students use AIGC

This study involved an ENA that was conducted to investigate students' levels of AIGC use across three rounds of teaching activities. This method visualizes the relationship schema among different dimensions within data partitions of dialog, referred to as windows. Specifically, ENA calculates the co-occurrence counts of each line of dialog relative to all preceding lines within the same window, with the aim of revealing the hierarchical characteristics of the AIGC technologies used by students to address different problems. In the present analysis, the standard ENA settings were applied, with the size of each analysis unit (window) set to 4.

Fig. 4 presents the initial coordinate axes composed of nodes: the x-axis (mean rotation) explains 32.4 % of the variance (Pearson correlation coefficient $r = 0.98$), and the y-axis (singular value decomposition) explains 16.2 % of the variance (Pearson correlation coefficient $r = 0.99$). These results indicate that the cognitive attribute plane formed by the encoding exhibits a high goodness-of-fit. In the cognitive network diagram, the size of each node varies significantly. In this context, enhanced retrieval, alternative retrieval, and frame generation are the behaviors that are associated with the heaviest weights and the most

Table 4
Paired samples t-test pertaining to the depth of dialog and the question diversity that characterize the interactions between students and AIGC.

Dimension	Type	Mean difference	Standard error	p
Dialog depth	Basic level	−0.141	0.051	0.012*
	Intermediate level	−0.157	0.055	0.010*
	High level	0.334	0.086	<0.001**
Diversity of questions	Factual questions	−0.128	0.050	0.018*
	Extended questions	0.253	0.075	0.003**
	Reflective questions	−0.121	0.049	0.021*

* $p < 0.05$.
** $p < 0.01$.

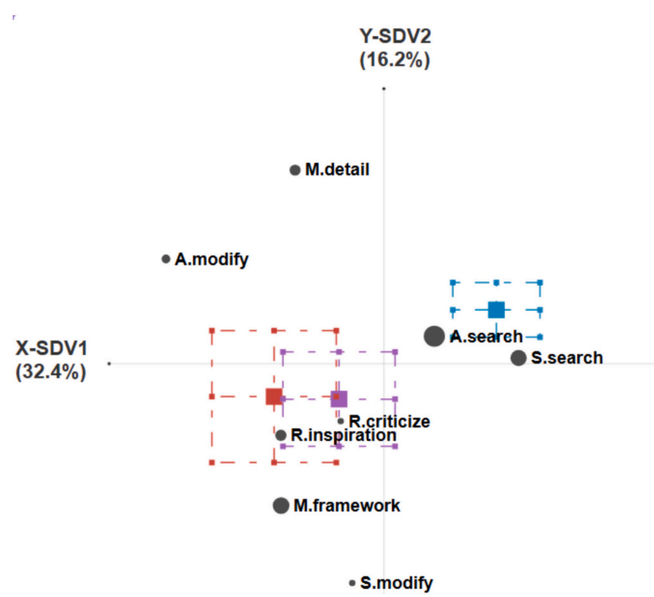

Fig. 4. Cognitive network models and distributions of centroids across the three rounds of activities.

Table 3
Proportions of dialog depth and question diversity in students' interactions with AIGC.

Dialog depth	Basic level	Intermediate level	High level	Invalid level	/
First	49(32.45 %)	46(30.46 %)	30(19.87 %)	26(17.22 %)	
Second	18(20.22 %)	17(19.10 %)	54(60.68 %)	0(0 %)	
Question diversity	Factual questions	Relevant questions	Extended questions	Reflective questions	Irrelevant questions
First	49(32.45 %)	8(5.29 %)	39(25.83 %)	29(19.21 %)	26(17.22 %)
Second	21(23.60 %)	3(3.37 %)	55(61.80 %)	10(11.23 %)	0(0 %)

occurrences; the behaviors of obtaining inspiration for questions, enhancing modification, and generating details are moderately frequent; and the content of questions and answers and alternative revisions are least frequent. The blue, purple and red boxes shown in the figure represent the cognitive network centroids at the AIGC levels used by students during the first, second and third rounds of teaching activities, respectively. According to the between-group difference analysis, pairwise comparisons of the instructional activities both revealed statistically significant differences along both the X- and Y-axis dimensions ($p < 0.05$). The centroid (blue) of the first-round teaching activity is located in the area indicating a low level of AIGC use on the axis. Students use AI as a retrieval tool to acquire conceptual knowledge and have not yet taken advantage of the potential use of AIGC. The centroid (purple) associated with the second round teaching activity is very close to the vertical axis and very close to the two nodes under the redefinition index, thus indicating that students are able to use AIGC to perform creative work when they encounter more complex and open problems, and AI has come to be used as an intelligent learning companion rather than an ordinary retrieval tool. The centroid (red) of the third-round teaching activity exhibits a leftward shift in comparison with the previous task, and it is characterized by a broader radiation range. This finding indicates that the students can use AIGC tools comprehensively at various levels in the third round of the teaching process, while simultaneously maintaining competence in both intermediate and advanced-level uses of AIGC.

Fig. 5a represents the cognitive network for the first-round teaching activity. The characteristics of the network are a close match for the locations of the centroids; that is, the level at which AIGC is used remains low. Students employ individual methods, and with the exception of a strong association between alternative retrieval and enhanced retrieval, the other associations are not significant. Fig. 5b represents greater changes observed in the density and thickness of the cognitive network pertaining to the teaching activity in the second round. The original low-use level associations remain strong, but at this time, generative frame-enhanced retrieval and generative frame substitution are added. As a result of the strong connection with the retrieval, a relatively stable triangle is evident between the intermediate and low levels of use. Fig. 5c represents the cognitive network in the third-round teaching activity, and it is also the densest and has the strongest connection and the richest level of use among the three rounds of teaching activities. The main differences between this model and (b) lie in the facts that the connections among low-level nodes no longer have an absolute advantage; the strength of the connections among middle- and high-level nodes increases; the cognitive network diagram indicates a trend of richness and diversity; and the triangle expands to encompass the low, middle and high levels of a quadrilateral.

This trend toward a more balanced network structure is further substantiated by statistical evidence. In terms of inter-session differences along the two-dimensional space, significant shifts in centroid positions were observed across the three sessions. Along the first dimension (X-axis, left–right direction), the network centroid shifted progressively toward the right ($t_{1\rightarrow2} = -4.61$, $t_{2\rightarrow3} = -1.64$). In the second dimension (Y-axis, vertical direction), the centroid exhibited an upward shift from the first to the second session ($t_{1\rightarrow2} = 3.41$). These regions with shifted centroids are characterized by a higher density of advanced-level nodes—such as M.framework, R.inspiration, and M.detail—which aligns with the semantic interpretation of the framework.

Notably, in the three diagrams (a), (b) and (c), the substitution modification node is always located at the edge of the network. We speculate that this phenomenon is the result of the fact that, after students have obtained certain answers, they usually ask the AIGC directly to revise these answers, skip the substitution step, and thus employ the strategy of augmentation and modification. Therefore, the substitution and modification nodes exhibit only a low degree of association with other nodes and have relatively small weights in the entire cognitive network.

4.4. RQ3. The relationship between the level of student AIGC use and the quality of their interactions with AIGC

To explore the relationships between students' levels of AIGC use and the quality of their interactions with AIGC, we first calculated a correlation score (Table 5). The quality of the interactions between students and AIGC, including in terms of depth of dialog and question diversity, as well as the ability of students to use AIGC were then incorporated into the correlation model. The results reveal that the quality of the interactions between students and AIGC is significantly positively correlated with their ability to acquire inspiration for questions at the redefinition level but significantly negatively correlated with substitute retrieval at the substitution level. In addition, the dimension of question diversity in the context of interaction quality was significantly negatively correlated with the generation framework at the modification level.

Subsequently, we conducted a linear regression analysis to explore the relationships between students' levels of AIGC use and the quality of their interactions. Specifically, we employed students' ability to use AIGC as an independent variable (X) and the quality of the interactions (i.e., depth of dialog and question diversity) between students and AIGC as a dependent variable (Y). Table 6 presents the significant predictors and standardized regression coefficients. The results revealed that at the substitution level and the modification level, the use of AIGC had a negative effect on the quality of students' interactions with AIGC, especially when the level of question diversity became significant. At the redefinition level, the use of AIGC had a significant positive effect on interaction quality. These results indicate that when students can apply AIGC tools to more creative and complex tasks, the quality of their

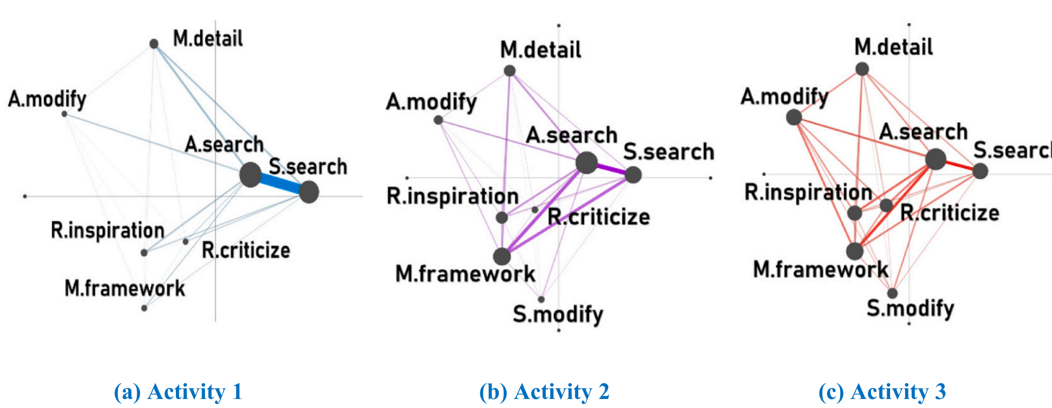

Fig. 5. Epistemic network analysis of students' use of AIGC over the three rounds of teaching activities.

Table 5
Correlation analysis between the different levels at which students use AIGC and their learning performance.

	S Search	S Modify	A Search	A Modify	M Framework	M Detail	R Inspiration	R Criticize
Dialog depth	−0.464*	0.291	0.229	0.19	−0.35	0.27	0.797**	0.051
Question diversity	−0.486*	0.157	0.15	−0.055	−0.537*	0.061	0.652**	0.071

* $p < 0.05$.
** $p < 0.01$.

Table 6
Regression analysis between students' use of AIGC and their learning performance.

	Dialog depth	Question diversity
Substitution level	−0.208	−0.348*
Augmentation level	0.162	0.205
Modification level	−0.308	−0.647**
Redefinition level	0.719**	0.643**

* $p < 0.05$.
** $p < 0.01$.

interactions with AIGC improves significantly.

Ultimately, according to the open-ended interviews conducted with the students, as their ability to use AIGC improved, 21 students believed that AIGC had helped increase their confidence, thus highlighting the positive role played by AIGC in the learning process. One student reported that his confidence had not changed significantly. This student noted that he hoped to do his best at every stage of the task, but as a result of limitations pertaining to his own technical level and knowledge, he became aware of a gap between his own ability and his expectations. Therefore, no significant increase in confidence was observed in this case.

5. Discussions

5.1. A teaching strategy rooted in active learning that includes the SAMR model can improve the quality of the interactions between students and AIGC (RQ1)

The results of the study show that a combination of a teaching strategy rooted in active learning with the SAMR model was associated with improving the quality of the interactions between students and AIGC, and students exhibit particularly good performance in terms of the depth of dialog, question diversity, and the efficiency of dialog. This finding may be attributed to two key factors.

First, teaching strategies that are rooted in active learning (such as group discussion or task-oriented learning) emphasize active participation and in-depth thinking on the part of students, which motivate them to ask questions, reflect on outputs, and continuously optimize the dialog content in the process of interacting with AIGC, thus increasing the quality of their cognitive interactions. This finding is similar to the results reported by Khosravi et al. (2023). These authors reported that when students interact with AIGC under the guidance of the teacher with the goal of promoting inquiry and creation, this approach improves not only the efficiency of creation but also the quality of the content of this creative process. This approach effectively increases the depth and effectiveness of human–computer interactions.

Second, in the design of teaching activities based on the SAMR model, as a result of the continuous increase observed in the level at which AIGC tools are used, students gradually master the abilities associated with prompt engineering and information screening, thus allowing them to engage in more efficient and collaborative human–computer interactions. It is also possible that part of this improvement reflects students' growing familiarity with AIGC tools over time, which may have enhanced their ability to formulate prompts and guide the interaction independently of the instructional design (Lee & Palmer, 2025). This finding is consistent with the conclusions reported by Xiao et al. (2024). Students who exhibit higher levels of AI literacy tend to perform better in their studies because they can effectively use AI to facilitate thinking and generation during the learning process, thus achieving higher-quality learning outcomes in actual interactions.

According to Mason (2024), active learning occurs in environments that are established by teachers, students, and the teaching content. This study confirmed the existence of this initiative through experimentation. The use of AIGC tools gradually shifts from the basic substitution function to the functions of task modification and redefinition, and this transition is accompanied by the gradual embedding of high levels of use in teaching tasks and the teacher's active learning guidance. Students no longer rely exclusively on this tool for information acquisition and problem-solving; rather, they can also use it for the purposes of constructing complex knowledge and stimulating higher-order thinking (Chen et al., 2023). The results of the study indicate that when AIGC tools are used in depth, students' performance with respect to the depth of dialog ($p < 0.001$) and question diversity ($p = 0.003$) increase significantly, especially in the contexts of high-level dialog and extended questions. This result supports the progressive relationship leading from "substitution" to "redefinition" in the SAMR model, thus indicating that the gradual introduction and deepening of technology in the context of teaching can promote the transition from basic tool use to higher-order learning behaviors.

5.2. A teaching strategy rooted in active learning that includes the SAMR model can improve the level at which students use AIGC (RQ2)

This study also revealed that a teaching strategy rooted in active learning that includes the SAMR model was associated with the development of students' ability to use AIGC from a basic level to a high level. Specifically, in the process of completing the learning tasks, students' use of AIGC gradually transitioned from the simple "substitution" operation to the "augmentation", "modification" and even "redefinition" operations. This conclusion may be attributable mainly to the guiding role played by the integration of teaching strategies rooted in active learning and technologies in this context. By engaging in group collaboration and employing both task-driven methods and other methods, students are encouraged to engage in an active process of exploration and construction and to adjust and optimize their use methods constantly in a process of continuous interaction with AIGC with the aim of obtaining an in-depth understanding of technology and simultaneously increasing the level at which they apply such technology.

As in the study conducted by Muslimin et al. (2024), with the support of the teacher's SAMR-based model-oriented design task, the level at which students use AI tools can be effectively improved, progressing from basic substitution operations to higher-order levels of technology use. Learning behavior is also more in-depth and creative in this context. In addition, Haroud and Saqri (2025) emphasized the fact that through systematic training and improvements in digital literacy, the use of GenAI can be shifted gradually toward "modification" and "redefinition," thus promoting a profound reshaping of teaching. This finding also indirectly indicates that continuous improvement in students' AI literacy is an important foundation for the implementation of high-level uses of AIGC.

Furthermore, the uniqueness of AIGC tools provides students with more flexibility and autonomy so that they can make adjustments in accordance with the needs of different teaching activities. This technology can not only process large amounts of information and read the context at hand but also generate new content and feedback on the basis of students' learning (Tapalova et al., 2022). This approach thus enables students to adjust their learning methods at any time with the support of AIGC tools, thereby enabling them to meet their flexible active learning needs.

5.3. The level at which students use technology to support their learning increases, thereby increasing the quality of the interactions between students and AIGC (RQ3)

This study also revealed that as the technical level at which students use AIGC increased, the quality of their interactions with AIGC also improved. Specifically, when students used AIGC at the level of "redefinition", they tended to show positive changes in the depth of dialog and question diversity. At this level, students' depth of dialog ($\beta = 0.719$, $p < 0.01$) and question diversity ($\beta = 0.643$, $p < 0.01$) both increased significantly, thus indicating that students who use technology at a higher level are able to engage in more in-depth thinking and more extensive exploration. This finding indicates that when students use technology at a higher level, they are able to ask more complex questions and implement more in-depth prompts in their projects, thereby allowing them to engage in more in-depth thinking and more extensive exploration. This finding is consistent with the results reported by Lawasi et al. (2024). This study reveals that when AI is used to help students expand their thinking, provide in-depth insights, and expand the cognitive boundaries of learners, rather than just merely as an information tool, students' thinking ability, especially their critical thinking ability, develops. In contrast, the study indicated that when students use AIGC at the "modification" level, although the depth of dialog and the question diversity increase, this effect is limited. Technology use at this stage focuses more on the adjustment of task forms and the partial reorganization of information, and no fundamental transformation of learning methods occurs. At the "augmentation" and "substitution" levels, students mainly use AIGC as an auxiliary tool for information retrieval or task execution, the methods of use that they employ are unitary, and the quality of such interactions is relatively low, thereby failing to take advantage of AIGC to support complex tasks. This phenomenon confirms the key perspective associated with the SAMR model proposed by Puentedura. Only when technology is used merely at the levels of "Substitution" or "Augmentation," its impact is primarily limited to improving efficiency; furthermore, when it reaches the stages of "Modification" and "Redefinition," technology has potential abilities to change learning methods and cognitive processes, thus promoting cognitive development at a higher level.

6. Conclusions

6.1. Core findings

First, the results of the present study indicate that students continue to face certain challenges with respect to their use of AIGC tools, especially in the context of advanced tasks. Some students have not yet fully grasped the complex functions of such tools and are in urgent need of additional support and guidance. Accordingly, active learning does not entail allowing students to "learn by themselves" in the absence of any without guidance. Teachers should provide students with more detailed guidance in their teaching practices, build scaffolding to support active learning on the part of students, help students gradually adapt to the diverse functions of AIGC, and promote the deep integration of technology with teaching. Only through the continuous optimization of teaching design and the strengthening of technical support can students smoothly enter the "redefinition" stage and take full advantage of AIGC tools.

Second, the use of AIGC tools in the context of teaching provides students with more learning possibilities and renders teaching tools that can only be used at a specific level more versatile. This characteristic emphasizes the fact that educators must closely monitor the development of emerging technologies, fully foster student initiative, and design teaching strategies that can gradually increase the level at which students use these technologies.

Third, as students' ability to use AIGC technology gradually improves, the quality of their interactions with AIGC also improves significantly. Particularly in the context of high-level tasks, AIGC can effectively promote active participation among students and encourage them to engage in in-depth thinking and creative expression. Therefore, educators should focus on ways of helping students gradually transition to the advanced level of technology use on the basis of well-designed teaching activities that aim to maximize the potential of AIGC technology in the field of education.

6.2. Significance of the study

This study highlights the theoretical innovative significance of teaching strategies rooted in active learning for teachers and curriculum designers. For teachers, this study reveals that a combination of an active learning strategy with the SAMR model can effectively help freshman students use AIGC tools to support their learning and ensure in-depth learning in a standardized and efficient manner. This teaching strategy can help teachers gradually transition from "technology substitution" to "teaching reconstruction" and achieve an upgrade from tool use to a transformation of their teaching philosophies. For course designers, this study highlights a case of progressive activity design in the context of technology-embedded teaching. Based on activity design at different levels of technology use, students can construct more adaptable and progressive learning activities, thus fostering a state of adaptability between teaching and students' technical abilities.

In addition, this study provides practical guidance for education practitioners and college freshmen on concerning the integration of AIGC technology into teaching. For education practitioners, this study emphasizes the necessity of the in-depth integration of teaching strategies rooted in active learning and technology. Research has revealed that it is difficult to motivate students to engage in in-depth learning when their use of technology remains at the "substitution" or "augmentation" level. Only through the guidance provided by systematic teaching strategies can the potential of technology-enabled education be truly fulfilled, thus providing a practical reference for the reform of teaching and learning with the support of AI. This research thus provides a practical reference for teaching reforms supported by AI. For college freshmen, the use of AIGC as a proposer to generate design works and its use as a partner to produce creative works represent effective ways of using technology to promote learning.

6.3. Limitations

Although this study confirmed the positive effect of the combination of an active teaching strategy with the SAMR model on students' ability to use AIGC tools, it nevertheless exhibits certain limitations. First, this study focused mainly on freshman students and failed to examine those from other grades, disciplines, or educational backgrounds, thus limiting the generalizability of its conclusions about the teaching strategy. Second, this study provides a progressive teaching strategy that includes the SAMR model, in the context of actual teaching, effectively engaging students to leverage the multidimensional affordances of AIGC, enhancing their motivation to tackle challenging problems, and adopting diverse strategies in problem-solving remain pedagogical challenges. Students maintain the habit of using AIGC as a single tool for information queries and lack the initiative to use it at the levels of "modification" or “redefinition.” It remains uncertain how to effectively integrate AIGC tools across the multiple levels of the SAMR model, resulting in limited options for teaching strategies that can actively engage students in comprehensive interdisciplinary collaboration or creative tasks.

6.4. Future research

Future research, in light of the limitations of the present study, should further investigate how to optimize instructional design to enhance students' technological application capabilities in higher-order tasks. First, the scope of the study population should be expanded to include students from multiple grade levels, allowing the exploration of methods for integrating artificial intelligence into instructional design. This approach would increase the generalizability of the findings and provide broader practical implications for guiding instructional design in higher education. Second, to address the issue of students' potential overreliance on technology, subsequent research should focus on strategies to effectively guide students in advancing their levels of technology use, thereby improving both their AI usage proficiency and overall learning performance. Finally, with the continual advancement of technology, the functionalities and application scenarios of AIGC tools are constantly expanding. To better meet students' needs, future studies should integrate more diverse active teaching approaches, thereby injecting greater flexibility and more potential into higher education instructional practices.

Availability of data and materials

The datasets used and analyzed during the current study are available from the corresponding author on reasonable request.

CRediT authorship contribution statement

Juan Wu: Writing – review & editing, Writing – original draft, Methodology, Funding acquisition, Conceptualization. **Jingwen Pan:** Writing – review & editing, Writing – original draft, Resources, Investigation, Formal analysis, Data curation. **Yaoyuan Zhou:** Writing – original draft, Visualization, Formal analysis, Data curation. **Mengyu Liu:** Writing – review & editing, Validation, Formal analysis. **Yanling Li:** Writing – review & editing, Writing – original draft, Validation, Supervision. **Ronghuai Huang:** Writing – review & editing, Validation, Resources, Project administration.

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Declaration of competing interest

The authors declare that they have no competing interests.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.iheduc.2025.101056.

Data availability

Data will be made available on request.

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