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An empirical study on the impact of generative artificial intelligence-based learning activities on college students' deep learning

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Abstract

Deep learning, emphasizing the comprehensive understanding and transfer of knowledge, is a critical indicator of learning quality among college students. Generative artificial intelligence (AI), through its support for efficient feedback and personalized learning, offers a new technological approach to fostering deep learning. This paper, grounded in Activity Theory, presents a deep learning activity model enhanced by generative AI technology. A quasi-experimental study was conducted over a semester, using the "Modern Educational Technology and Informatization Practice" course as a case study to validate the model's effectiveness. The study found that the model positively contributes to learners' learning process performance, knowledge acquisition, cognitive development, and emotional experience. This paper provides empirical evidence supporting the practical application of generative AI in promoting deep learning among college students, highlighting the need for continuous evaluation and refinement to fully harness its potential in advancing the technological transformation of higher education.

Keywords: Generative AI, Deep learning, Empirical study, Activity Theory

Introduction

Higher education faces new opportunities and challenges due to the advanced application of artificial intelligence (AI), particularly with the emergence of generative AI, exemplified by ChatGPT. The *2023 EDUCAUSE Horizon Report: Teaching and Learning Edition* (EDUCAUSE, 2023) identifies generative AI as a pivotal technology for higher education over the next five years. Amid rapidly growing public interest, its potential impacts have sparked intensive debate among education scholars (Qin et al., 2023). In examining generative AI's role in higher education, scholarly perspectives remain divided, with both positive and negative outlooks. Is it a modern-day Aladdin's lamp or a Pandora's box (Wang, Wang et al., 2023)? Some researchers contend that ChatGPT may undermine students' creativity and critical thinking skills (Yang, Liu et al., 2023). Conversely, other scholars argue that human–AI interactive learning activities enabled by generative AI surpass the "search is learning" approach of traditional internet use, enhancing students' learning motivation and engagement (Xia et al., 2023). Despite these differing perspectives on AI's educational applications, its reasonable use to support talent cultivation in higher education has become an unavoidable reality.

Deep learning advocates active, critical, and meaningful learning, emphasizing the learner's role in constructing a personal knowledge system and effectively transferring it to real-world contexts for solving complex problems (Zhang & Wu, 2012). Existing studies have adopted proactive strategies to address such challenges (Ashraf & Ahmed, 2020). However, traditional instructional activities typically adhere to a teacher-centered approach, which limits effective knowledge transfer and application and thus restricts the achievement of deep learning (Li et al., 2023). In contrast, generative AI, with its powerful natural language understanding and conversational capabilities, facilitates a Socratic, dialogic approach that gradually guides students to think autonomously and understand independently. This interactive dialogue stimulates cognitive depth and creativity, supporting learners in constructing meaningful understanding through inquiry and reflection (Chen et al., 2023). Furthermore, generative AI is capable of providing positive feedback to learners, which enhances motivation and strategy use, fostering deeper thought and reflection conducive to deep learning (Leenknecht et al., 2019). Additionally, students must apply deep reflection and judgement to evaluate generative AI outputs, which may not always be accurate or scientifically valid due to their generation from extensive training data. Therefore, from a theoretical perspective, the appropriate integration of generative AI into learning activities has the potential to facilitate deep learning.

Existing research has widely discussed the potential applications of generative AI in education, but empirical studies examining its role in promoting deep learning remain limited. This study seeks to investigate whether generative AI can enhance university students' academic performance and whether instructional activities that incorporate it can effectively guide learners toward deep learning. Adopting an activity theory perspective, this research compares learning activities that integrate generative AI with traditional learning activities, aiming to address these questions through empirical investigation.

Literature review

Research on generative AI in education and teaching

Since its emergence in 2022, generative AI has garnered sustained attention from researchers in higher education. Generative AI, exemplified by tools like ChatGPT, is driving transformative changes within the educational application ecosystem (Wu, Li et al., 2023), significantly advancing the reform of teaching models, instructional content, learning methods, and educational philosophies (Yang, Wang et al., 2023). In the context of school education, the appropriate use of generative AI can offer various forms of support and assistance to both teachers and students, ultimately enhancing the effectiveness of learning and teaching (Jiao, 2023).

Generative AI holds substantial potential for educational applications due to its powerful natural language understanding and content generation capabilities. Studies have highlighted promising applications of generative AI, such as ChatGPT, in areas including cultivating top-tier innovative talent (Wang & Li, 2023), training in cybersecurity workforce skills (Wang, Xu et al., 2023), professional development for educators (Wu, Wu et al., 2023), and enhancing academic performance (Alshater, 2022). Researchers have further explored generative AI's applications within educational settings. For example, Dai et al. (2023) investigated a new dialogic learning model based on ChatGPT, while Dong et al. (2023) proposed specific pathways for ChatGPT to empower student learning from a human–AI collaborative learning perspective.

Additionally, researchers have actively examined the use of generative AI in teaching. For instance, Zhai et al. (2023) developed a human–AI collaborative learning model that combines "generative AI and the metaverse," which has been shown to significantly improve learning outcomes. Wu, Zhou et al. (2024) demonstrated that generative AI-assisted oral language instruction positively affects students' lexical and syntactic complexity as well as fluency. Wu, Li et al. (2024) designed a ChatGPT-supported Course-Based Undergraduate Research Experience model, helping to foster students' research competencies by enhancing their knowledge, skills, and attitudes toward research. Similarly, Rad (2024) found that AI applications based on Wordtune can significantly improve learners' writing outcomes, engagement, and feedback literacy.

However, while generative AI presents new opportunities for higher education, it also introduces associated risks and challenges. These include threats to educational subjectivity (Zhang et al., 2023), ethical disruptions, risks to the sustainable development of education, and dilemmas around appropriate compensation (Zhao & Yan, 2023). Additional concerns involve the dilution of teacher and student autonomy, distortion of knowledge content, compromises in security and inclusivity, and the alienation of talent cultivation (Huang et al., 2024). Furthermore, generative AI raises issues related to academic integrity (Rahman

& Watanobe, 2023) and threatens educational equity, among other concerns (Emenike & Emenike, 2023).

In summary, the academic community has engaged in theoretical discussions on the educational applications of generative AI, establishing a basis for understanding its multi-dimensional impact on education. However, there is a lack of empirical research in real classroom settings, particularly regarding the effects of generative AI on students' deep learning.

Research on deep learning empowered by technology

Deep learning is a significant branch within the learning sciences. Since its introduction in 1976, it has attracted considerable attention from researchers both domestically and internationally. However, a consensus on a definitive concept of deep learning has yet to be reached in academia, with three main perspectives prevailing: learning as a way, learning as a process, and learning as an outcome. Despite these differences, existing research reveals that all three perspectives emphasize learners' active engagement and problem-solving abilities within specific contexts, aligning with the cultivation of higher-order skills. According to Chen et al. (2023), deep learning is a form of understanding-based learning that underscores learners' critical thinking and creative application of knowledge. It involves connecting new knowledge with existing cognitive frameworks and developing strategies and solutions for problem-solving within defined thinking paradigms. Only through deep learning can students effectively apply knowledge to resolve real-world problems. It is widely recognized that deep learning is not a fixed or inherent mode of learning but can be cultivated through the design of specific instructional systems (Entwistle, 2000).

Technology-enabled deep learning primarily focuses on constructing and applying deep learning models from a technological perspective, as well as on the design, implementation, and outcomes of deep learning activities. Conducting deep learning activities in technology-supported environments—such as flipped classrooms, blended learning, smart classrooms, and MOOC platforms—has been shown to effectively promote learners' deep learning. Studies indicate that flipped classrooms facilitate deep learning and foster higher-order thinking skills in learners (Danker, 2015). Visualizing complex learning processes within virtual environments can significantly improve students' programming performance, deepen their understanding of subject content, and effectively stimulate intrinsic motivation, thereby achieving deep learning (Peng et al., 2017). Additionally, blended learning models designed for deep learning have been shown to significantly enhance learners' knowledge acquisition, deep learning capabilities, and overall learning satisfaction (Huang et al., 2019; Shen et al., 2022).

Existing research has developed practical application models of deep learning within various technological environments and verified their effectiveness in promoting deep learning. This study integrates generative AI technology into the current mainstream blended learning environment in higher education institutions. Guided by Activity Theory, it constructs a deep learning activity model based on generative AI and verifies its practical effectiveness. The generative AI used in this study is Wenxin Yiyan 4.0, which is built on the PaddlePaddle deep learning platform and the Wenxin knowledge-enhanced large model.

Construction of a deep learning activity model supported by generative AI

Activity Theory and related research

Activity Theory originates from Hegel's classical philosophy and Marx's dialectical materialism, both of which consider activity a foundational standpoint for analyzing human development (Lv et al., 2007). Later, through Lev Vygotsky's mediation theory and further refinement by psychologists such as Leontiev, Finnish scholar Yrjö Engeström developed the "triangular model" of Activity Theory, establishing it as a philosophical and interdisciplinary framework for analyzing various forms of human activity (Sun & Liu, 2015). The third-generation activity theory focuses on analyzing the process by which individuals complete activities through interaction and collaboration with others. It emphasizes the interplay among various elements within socially collective activities in a specific sociocultural context, providing theoretical support for technology-enhanced learning.

Related studies have demonstrated the suitability of using Activity Theory to analyze teaching activities supported by new technologies, such as digital reading analysis (Wu et al., 2022), and the exploration of socialized interactive learning in the metaverse (Han et al., 2023).

A deep learning activity model supported by generative AI

Activity Theory emphasizes the active role of learners, advocating for the use of tool mediation to help learners perceive and understand course content and construct knowledge through task completion, facilitating integration between learners and the learning community. This aligns with the concept that deep learning is grounded in learners' comprehension (Du & Gu, 2022). Grounded in the framework of activity theory, this study reconstructs the mechanism by which generative artificial intelligence (GAI), through its intelligent mediation characteristics, facilitates students' deep learning. This reconstruction leads to the development of an extended model, the generative activity system (GAS). The model comprises six fundamental elements: subject, object, tools, community, rules, and division of labor. The following discussion elucidates how GAI fosters deep learning by reconfiguring these six elements.

The reconfiguration of the six elements of Activity Theory by generative AI

Reconstruction of subject relationships: From binary division to ternary collaboration

In traditional educational settings, the teacher–student duality establishes a unidirectional and linear knowledge transmission structure. The teacher, as the authoritative source of knowledge, predominantly directs the instructional process, leaving students in a passive role that hinders active knowledge construction, which is essential for deep learning. The integration of GAI transforms this dynamic, creating a collaborative ecosystem among teachers, students, and machines. By transcending the limitations of a mere tool—through core capabilities such as text generation, language comprehension, and logical reasoning—GAI takes on "quasi-subject" attributes, functioning as a cognitive partner that dynamically adapts to diverse instructional scenarios. For example, GAI can support students' conceptual understanding by generating relevant case studies. In this restructured framework, teachers evolve into learning designers, regulators, and metacognitive coaches, focusing on advanced objectives and providing emotional support. Concurrently, students become active participants in knowledge construction, engaging in continuous and in-depth dialogue with GAI to foster cognitive development and encourage higher-order thinking.

Reconstruction of object attributes: A dual breakthrough in dynamic generation and embodied cognition

As objects within an activity system serve as both the target and the subject of cognitive processing, their attributes directly influence the depth of learners' cognitive engagement. Traditional learning activities typically feature objects characterized by static, homogeneous course content, linear knowledge presentation, and delayed feedback, which confines learning to shallow memorization. In contrast, deep learning activities supported by GAI reconfigure object attributes along two dimensions. The first dimension is dynamic generation: GAI analyzes dialogue logs to construct individualized cognitive maps in real time, ensuring that learning content aligns precisely with each learner's zone of proximal development. The second dimension is embodied cognition: Leveraging its multimodal generation capabilities, GAI creates immersive cognitive environments that facilitate bidirectional conceptual construction through situational dialogue, guiding learners to construct meaning through embodied experiences.

Transformation of the community's essence: From interpersonal collaboration to a human–AI symbiotic ecosystem

The community, as a social network within learning activities, plays a crucial role in shaping the depth of collaboration and the quality of meaning construction. Traditional learning communities focus primarily on binary interactions—either between teachers and students or among peers—constrained by temporal and spatial limitations, fixed roles, and homogeneous resources. The integration of GAI transforms this dynamic by reconstructing a core mechanism of constructivism—contextualized social negotiation.

First, by integrating into the community as a "cognitive partner," GAI establishes a dynamic quaternary structure comprising teachers, students, AI, and peers. This structure enables real-time cross-domain collaboration that transcends the cognitive limitations inherent in traditional interpersonal knowledge construction. Second, by leveraging multimodal interaction to create a blended virtual–physical negotiation space, GAI generates heuristic question chains in real time when learners experience cognitive stagnation. This process advances dialogue from simple factual reporting to critical deliberation. Third, through algorithmically adapting negotiation strategies, GAI provides visual cognitive scaffolds for learners with weaker conceptual foundations while designing ethical debate tasks for advanced learners.

Evolution of tools: From static carriers to intelligent mediators

Tools serve as mediators connecting subjects and objects, with their level of intelligence directly influencing the scope of effective knowledge construction. Traditional learning tools, limited by the static properties of physical media, restrict cognitive processing to superficial symbolic manipulation. In contrast, GAI, acting as an intelligent mediator, reconfigures the regulatory mechanisms underpinning cognitive development. It transcends the expressive limitations of conventional learning materials—such as text, images, and videos—by dynamically generating personalized cognitive scaffolds for learners.

Through generative dialogue and multimodal interaction, learners are encouraged to engage in higher-order thinking. In authentic problem-solving scenarios, they utilize mechanisms such as cognitive conflict activation and multi-perspective argumentation facilitated by GAI to construct meaning. This process promotes metacognitive development, leading to the cross-contextual transfer of knowledge.

Rules form: From rigid institutions to flexible contracts

Rules function as a regulatory system that coordinates teacher-prescribed learning guidelines, learner interaction protocols, human–machine collaboration agreements, and learning assessment criteria. Traditional learning rule frameworks are often constrained by fixed procedures devised by teachers, uniform standards, and limited peer interactions. This rigidity can lead learners to become trapped in a state where strict rule compliance suppresses cognitive innovation. In contrast, GAI—by analyzing dialogue to discern students' cognitive styles—dynamically adjusts both problem difficulty and explanation modes, precisely aligning task complexity with the learner's zone of proximal development. Additionally, flexible contracts empowered by GAI enable dynamic role allocation, stimulating cognitive conflict and shifting the learning community from low-level information sharing to high-level conceptual negotiation. This transition ultimately facilitates the meaningful construction of knowledge.

Intelligent division of labor: From fixed roles to dynamic collaboration

Division of labor involves assigning roles and responsibilities within a learning community based on specific learning objectives. GAI reconstructs the allocation of learning tasks, overcoming the traditional challenge of "role fixation and fragmented tasks." By leveraging contextual awareness, it dynamically assigns tasks, employs interactive analysis to identify individual learner characteristics, and promotes role fluidity—such as transitioning from executors to conceptual integrators. Furthermore, through the intelligent analysis of each learner's contributions, GAI enhances transparent accountability within collaborative learning.

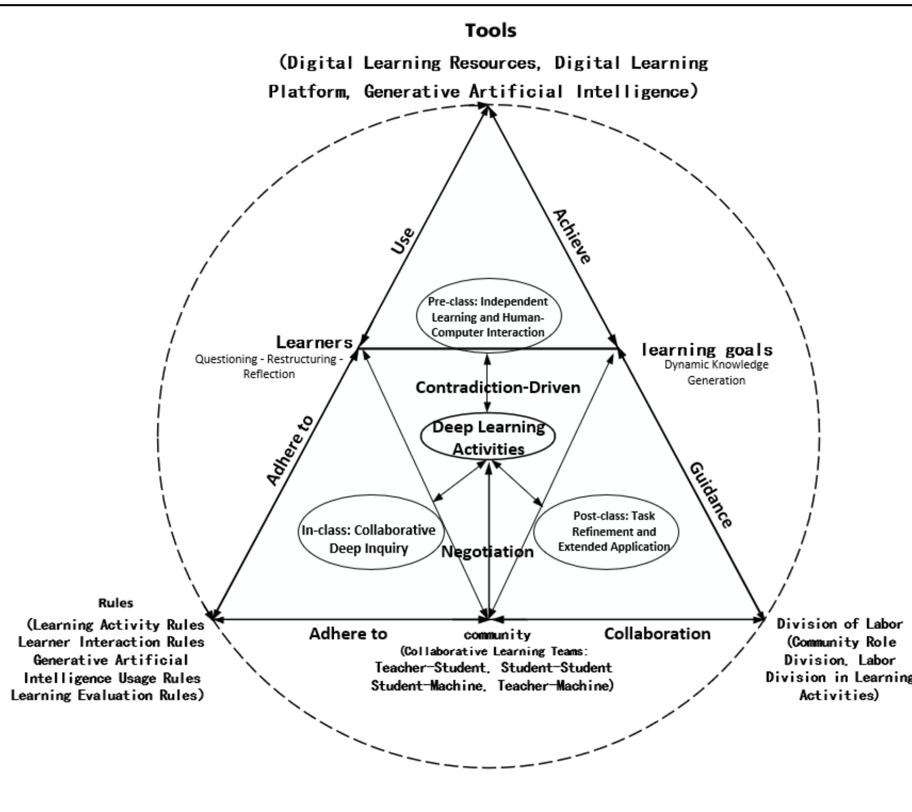

Fig. 1 Model of deep learning activities supported by generative artificial intelligence

The internal and external contradictions of the generative activity system and their role in driving learners' deep learning

The activity theory emphasizes that contradictions are the core driving force behind system transformation. When GAI is integrated into the learning activity system, the original structure—comprising subject, tools, object, community, rules, and division of labor—undergoes reconfiguration. The resulting internal and external contradictions prompt learners to move beyond superficial knowledge acquisition and transition toward a deep learning paradigm characterized by metacognitive regulation, cross-context transfer, and problem-solving.

Internal contradictions within the system are reflected in the conflict between tools and rules, as well as between the division of labor and objects. One significant tension arises between the efficiency of content generation enabled by GAI and the academic ethical risks it poses, such as the convenience of automatically generated text versus the norms of academic integrity. Learners must navigate the balance between the practicality of AI tools and the constraints imposed by ethical regulations, engaging in an iterative knowledge construction process of generation–questioning–reconstruction. This process fosters metacognitive monitoring abilities. Moreover, AI integration drives a dual transformation in teaching roles: Teachers shift from knowledge transmitters to learning designers, while students evolve from information recipients to AI collaborators. Throughout this process, the boundaries of responsibility between teachers and students must be renegotiated, promoting students' active participation in collaborative dialogue and knowledge co-construction.

External contradictions arise from the conflict between the traditional knowledge transmission model and the dynamic knowledge network driven by GAI. For instance, GAI transcends the static knowledge frameworks of textbooks by creating an open and multimodal system of knowledge representation. This shift compels learners to establish critical connections between standardized knowledge systems and generative knowledge networks, such as verifying the reliability of AI-generated content through cross-context comparisons. This process not only involves adaptive adjustments to cognitive structures but also requires learners to confront the value tensions between academic norms and practical demands. As GAI bridges the school system with real-world contexts, students must navigate discrepancies between academic conventions and practical applications, fostering their ability to solve authentic problems and engage in critical value reflection.

Based on the above analysis of contradictions, four key pathways can be identified through which the GAS promotes deep cognitive development:

Cognitive conflict: Breaking the "correct answer dependence"

GAI may produce inaccurate or biased information, requiring students to identify contradictions through multi-source verification and logical reasoning. This process encourages students to actively construct their own knowledge networks.

Identity negotiation: From "learner" to "AI collaborator"

Students must navigate their role positioning between technological dependence and cognitive autonomy, cultivating self-determination and ethical responsibility in AI-mediated learning environments.

Rule evolution: From technological exclusion to AI literacy development

Learning regulations should evolve from restricting AI use to guiding effective AI integration, providing learners with a framework for critically engaging with AI. This transition fosters higher-order thinking skills such as analysis, evaluation, and creation.

Community collaboration: Embodied practice of distributed cognition

Within human–AI collaborative knowledge production communities, learners engage in a functional division of labor—for example, AI handles information retrieval while students focus on value judgment. This redistribution of cognitive load enhances their ability to systematically understand and develop innovative solutions to complex problems.

Research design

Research course and participants

To investigate the application effects of generative AI-supported deep learning activities, this study conducts empirical research using the "Modern Educational Technology and Informatization Practice" course at University A during the spring semester of 2024 as a case example. This course is a mandatory teacher education course for teacher training students, focusing on thematic learning across six units centered around "smart classroom teaching design." It comprises a total of 36 hours, with 12 hours online and 24 hours offline. The course adopts a blended teaching model, emphasizing the enhancement of students' deep learning quality through task-driven, inquiry-based learning.

This study targeted two natural classes from the 2021 cohort of chemistry majors (experimental group: N=54; control group: N=55), with group assignment determined by lottery. Both groups participated in a 15-week comparative experiment (from the 2nd to the 16th teaching week) conducted in a standardized smart classroom environment. The experimental group implemented a deep learning model supported by generative AI, while the control group followed a conventional blended teaching model.

Experimental controls were maintained across three dimensions: (1) consistency of the instructional agent (both groups were taught by the researcher); (2) task isomorphism (pre-class, in-class, and post-class tasks were identical); and (3) environmental constancy (the same smart classroom and online learning platform were used). Baseline equivalence was confirmed via independent samples t-tests, which showed no statistically significant differences between the groups in terms of prior course foundation ($t=-0.452$, $p=0.652 > 0.05$, learning motivation ($t=0.181$, $p=0.858 > 0.05$), or learning engagement ($t=0.840$, $p=0.403 > 0.05$), thus satisfying the requirement for experimental group homogeneity. Throughout the experiment, potential confounding factors—such as teacher behavior (including body language and verbal expression) and environmental disturbances—were rigorously controlled.

Research implementation process

The experimental study spanned 15 weeks and was divided into six thematic stages. The first week was dedicated to an overview of the course and introduction, while weeks 2 to 16 focused on the experimental research of the six major themes.

Within the experimental group, students employed generative AI as an intelligent learning assistant, completing their learning tasks through dialogic interaction with the AI and collaborative human–machine engagement. To generate high-quality interactive content, the instructor provided specialized guidance to the students in the experimental group on how to engage in effective dialogue with generative AI before the experiment began and required students to adopt a questioning format of "role + task + requirements + explanation." All participants in the experimental group signed written informed consent forms and were required to strictly adhere to the rules for using generative AI, prohibiting the direct citation of AI-generated content. Additionally, students were asked to meticulously document their generative AI exploration learning reports, including descriptions of command language, AI responses, evaluations of AI-generated results, and content reconstruction based on evaluations of AI-generated results. In the control group, students employed traditional learning methods to complete identical learning tasks. Each participant signed an academic integrity agreement stipulating that only conventional search engines were to be used for independent study. Participants were required to submit complete search history records and were strictly prohibited from using AI tools during the tasks. For students in the control group, the same learning tasks were completed using traditional online learning methods. They were required to sign an academic integrity agreement, which stipulated that only conventional search engines could be used for self-directed learning. Additionally, they were required to submit a complete record of their search history, and the use of generative AI tools during the task was strictly prohibited.

Pre-class learning phase: Independent study and human–computer interaction

Teachers arrange pre-class independent study activities according to the syllabus, publish learning videos, papers, cases, and other resources through the learning platform, and set related learning tasks and assessments. Students log in to the learning platform to complete the study of foundational knowledge and produce corresponding learning outcomes. In the experimental group, when students encountered doubts or required a deeper understanding of complex concepts during their learning process, they engaged in multi-turn interactive dialogues with generative AI. Through these interactions with an AI assistant, students obtained detailed analyses of specialized knowledge points and received immediate feedback. They were also required to document the entire human–AI interaction process—including query prompts, AI responses, evaluations, and subsequent content reconstructions based on feedback—thereby promoting iterative knowledge comprehension and internalization. In contrast, students in the control group relied on traditional online search methods to resolve their queries and were required to submit a complete record of their search history.

In-class learning phase: Collaborative deep inquiry

During the in-class learning phase, learners (subjects), generative AI (quasi-subjects), and teachers form multiple learning communities that facilitate the construction of knowledge through teacher–student interaction, student–student interaction, and human–computer interaction. Groups engage in intra-group discussions based on their inquiry needs, break down learning tasks, and collaborate with generative AI for cooperative inquiry. Students utilize generative AI to generate multimodal digital resources, such as text, images, and videos, related to the inquiry questions. In this process, generative AI acts as a resource-generation assistant, scriptwriting assistant, and instructional-design assistant, supporting groups in completing learning activities. It also provides feedback and evaluation on students' phased learning outcomes, promoting self-reflection, guiding them to optimize learning strategies, and forming final learning outcomes. During the group inquiry learning process, teachers carefully observe the depth of students' inquiry and the presentation of outcomes, actively encouraging and guiding more group members to participate in problem inquiry. In the group presentation and sharing segment, generative AI serves as an evaluator of learning results, assisting teachers in assessing group projects and supporting students in reflection and iteration. In contrast, the control group students acquired information using conventional learning tools (e.g., web search engines) and engaged in group discussions to carry out task decomposition and inquiry.

Post-class learning phase: Task refinement and extended application

In the post-class learning phase, student learning activities encompass task refinement, learning reflection, and the application of knowledge transfer. In the experimental group, students engaged in sustained interactions with generative AI, continually identifying and analyzing shortcomings in their learning outputs. Through multi-turn dialogues, the AI not only provided immediate feedback but also assisted students in reflecting on issues from multiple perspectives and adjusting their strategies, thereby enabling refined improvements in their work. This process required students to document the details of their interactions and analyze the AI feedback, thereby deepening their understanding of the subject matter through iterative revisions and fostering both critical thinking and problem-solving skills. Furthermore, students can utilize generative AI to conduct research-oriented learning activities, broaden their knowledge structures, and apply the acquired knowledge to practical contexts, thereby achieving the transfer and application of knowledge. In contrast, the control group students primarily relied on traditional resources and self-reflection to refine their tasks.

Research methods and tools

This study adopts a mixed-methods research paradigm, combining quantitative and qualitative research. The empirical study collected data on four dimensions: learners' performance during the learning process, knowledge mastery, cognitive levels, and affective experiences. The specific research methods and instruments are as follows.

Survey method

The survey method is used for pre- and post-tests. The pre-test aims to assess students' learning status at the beginning of the course, focusing on their motivation and engagement, which serve as baseline measures for the intervention. The post-test is conducted to evaluate students' performance following the intervention, including their engagement and learning satisfaction.

As an important measure of learner involvement, learning engagement reflects the depth of students' participation in learning. It primarily refers to the behavioral intensity of students' participation in learning activities, the use of cognitive strategies, and the quality of emotional engagement. The Learning Engagement Scale is adapted from the scale developed by Shen (2021) and includes three dimensions: behavioral engagement, cognitive engagement, and emotional engagement. The scale uses a 5-point Likert scale, with 1 representing "completely disagree" and 5 representing "completely agree," and consists of 20 items. The total score of each measurement dimension represents the degree of students' learning engagement. The Cronbach's α value for the Learning Engagement Scale is 0.938, and the Cronbach's α values for the three dimensions—behavioral engagement, cognitive engagement, and emotional engagement—are 0.896, 0.884, and 0.737, respectively, all of which are greater than 0.7, indicating good reliability. The overall KMO coefficient for the scale is 0.869, and the significance of Bartlett's test of sphericity is less than 0.001, indicating that the scale data meet the basic KMO and Bartlett's test requirements, demonstrating good structural validity.

The learning motivation scale was adapted from Wang (2020) and consists of 10 items, measuring learning motivation across three dimensions: cognitive intrinsic drive, self-improvement intrinsic drive, and affiliative intrinsic drive. A 5-point Likert scale was used for responses. The Cronbach's α value of the course learning motivation scale was 0.91 (greater than 0.7), indicating good internal consistency reliability of the questionnaire. The KMO value was 0.886, and Bartlett's Test of Sphericity yielded a significance level below 0.05, confirming that the data met the criteria for KMO and Bartlett's test, demonstrating good structural validity. The Learning Satisfaction Questionnaire is adapted from the blended learning satisfaction scale developed by Wang (2020), which includes two dimensions: perceived quality and perceived expectations, consisting of a total of 8 items. The Cronbach's α value is 0.969, indicating good reliability. After the experimental intervention, a learning satisfaction survey was conducted with both the experimental and control groups.

Content analysis

This method was employed to evaluate the quality of students' learning outcomes systematically. To leverage the advantages of performance assessment in monitoring higher-order thinking skills and complex cognitive processes (Zhou, 2019), this study selected an information-based instructional design as the foundation for performance assessment and applied a structured analytical framework to systematically examine students' knowledge transfer ability and the quality of deep learning.

The development of the research instruments incorporated the cognitive developmental dimensions of the SOLO taxonomy, which deconstructs learners' problem-solving processes into their underlying mental structures and cognitive levels, providing theoretical support for assessing deep learning quality and higher-order thinking skills (Zhang et al., 2014). Specifically, this study adopted the five-level cognitive-developmental model of the SOLO taxonomy—pre-structural (P), uni-structural (U), multi-structural (M), relational (R), and extended abstract (E)—in conjunction with the assessment scale developed by Chen and Deng (2016), to construct a quantitative coding system comprising five levels. This system translates students' cognitive levels into observable hierarchical characteristics through structured indicators, maintaining the integrity of the theoretical model while enhancing the practical utility of the assessment tool.

Results and discussion

Analysis of the learning process

Level of learning engagement

An independent samples t-test was conducted to analyze the learning engagement scale data from the experimental group (N=54) and the control group (N=55). Levene's test for equality of variances indicated no significant difference between the two groups (F=0.279, p=0.598). The results demonstrated that the experimental group exhibited a significantly higher level of learning engagement (M=74.00, SD=11.50) compared to the control group (M=66.64, SD=12.09), t(107)=3.257, p=0.002. The effect size analysis revealed a Cohen's d of 0.624, indicating a medium effect. Learning activities supported by generative AI significantly improved students' overall learning engagement, indicating that technology-enhanced learning environments can effectively stimulate students' interest and participation (Serrano et al., 2019).

A comparative analysis was further conducted between the experimental and control groups across three dimensions of learning engagement: behavioral engagement, cognitive engagement, and emotional engagement.

In the dimension of behavioral engagement, a significant difference was observed between the experimental group (M=30.31, SD=4.84) and the control group (M=26.76, SD=5.08), t(107)=3.735, $p < 0.001$. The effect size, as measured by Cohen's d, was 0.716, indicating a medium effect. This may be due to the ability of generative AI to generate personalized resources based on students' learning needs and progress, thereby increasing student engagement (Ellis & Slade, 2023) and demonstrating a higher level of behavioral engagement.

In the dimension of cognitive engagement, the experimental group (M=21.69, SD=4.36) demonstrated a significant difference compared to the control group (M=19.91, SD=4.21), t(107)=2.163, p=0.033. The effect size, as measured by Cohen's d, was 0.414, indicating a small effect. This result may be attributed to the strong situational comprehension and continuous conversation capabilities of generative AI technology, which can provide timely interactive feedback and personalized guidance to students. This helps students better understand their learning progress and areas for improvement, allowing them to adjust their learning strategies and exhibit a higher level of cognitive engagement.

In the dimension of emotional engagement, the experimental group (M=22.00, SD=3.22) exhibited a significant difference compared to the control group (M=19.96, SD=3.80), t(107)=3.020, p=0.003. The effect size, represented by Cohen's d, was 0.578, indicating a medium effect. This suggests that learning activities supported by generative AI can effectively stimulate students' emotional connections. This may be because generative AI

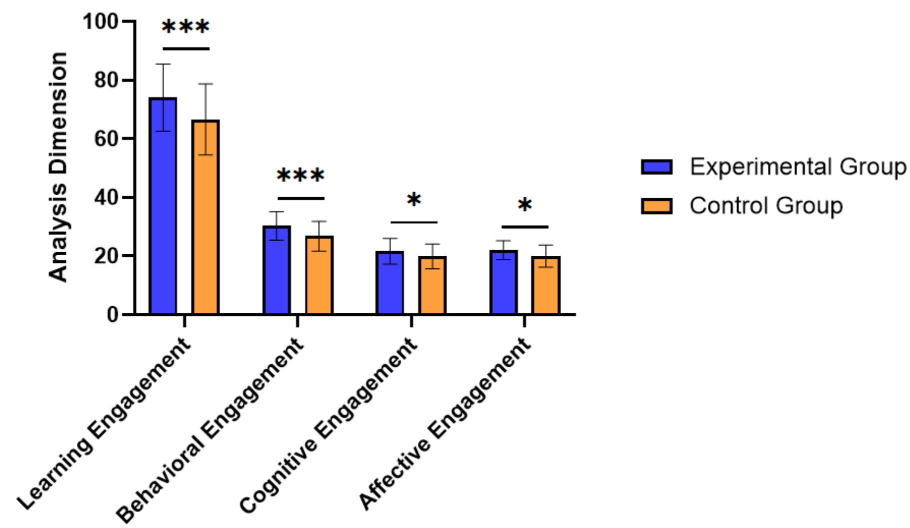

Fig. 2 Results of the independent samples t-test for post-learning engagement

contributes to creating immersive learning environments and providing personalized feedback (Wang, Lund et al., 2023), thereby stimulating students' interest and emotional engagement.

The experimental group exhibited statistically significant superiority across the three dimensions of engagement: behavioral, cognitive, and emotional. Effect size analysis revealed medium effects for behavioral and emotional engagement, and a small effect for cognitive engagement, indicating a pattern of behavioral engagement > emotional engagement > cognitive engagement. This phenomenon may be attributed to the fact that behavioral and emotional engagement are more directly influenced by external environments and tasks, whereas cognitive engagement relies more on learners' intrinsic cognitive strategies and abilities, which are less likely to improve over a short-term learning period. It is recommended that teachers, when designing learning activities, pay special attention to elements that can enhance students' behavioral participation and emotional connections, such as interactive learning, situational simulations, and gamified learning. Additionally, it is suggested that more higher-order thinking tasks and complex real-world problem scenarios be integrated into the curriculum design, utilizing generative AI to provide personalized feedback and support, thereby further enhancing students' cognitive engagement.

Analysis of classroom interaction participation

Students' classroom interaction behaviors serve as a direct reflection of the deep learning process and its behavioral characteristics. This study extracted data on students' interaction participation frequency recorded by the course platform and conducted an independent samples t-test to compare the classroom interaction behaviors between the experimental and control groups. The results indicated a significant difference between the experimental group ($M=21.63$, $SD=2.095$) and the control group ($M=18.20$, $SD=1.919$) in terms of classroom interaction behavior ($t(107)=8.916$, $p < 0.001$). The effect size, Cohen's $d=2.008$, suggests a substantial practical significance. These findings further support the conclusions regarding behavioral engagement in the learning engagement scale and confirm the positive impact of the experimental intervention on enhancing students' learning engagement.

Knowledge mastery analysis

The assessment tool for evaluating course knowledge mastery was a final examination, the test questions were selected from a standardized question bank and reviewed by four scholars in the field of educational technology, ensuring good validity. The test had a total score of 100 points and included both subjective and objective questions. The assessment of knowledge mastery was conducted by analyzing the test items based on Benjamin Bloom's Taxonomy of Educational Objectives. In this framework, the categories of 'Remember' and 'Understand' are considered as shallow learning, while 'Apply', 'Analyze', 'Evaluate', and 'Create' are regarded as deep learning. Analysis revealed significant differences between the experimental and control groups in overall knowledge mastery ($p < 0.001$), shallow learning scores ($p=0.041 < 0.05$), and deep learning scores ($p < 0.001$), with the experimental group outperforming the control group in all measures. The effect sizes (Cohen's d) for overall knowledge mastery, shallow learning scores, and deep learning scores were 0.732, 0.396, and 0.722, respectively, indicating medium, small to medium, and large effects. The results are shown in Figure 3. The findings indicate that learning activities supported by generative AI have a relatively pronounced positive impact on learners' mastery of course knowledge. However, the empowering effects of this support on learning activities at different cognitive levels are not uniform and exhibit distinct differences.

These findings suggest that generative AI-supported deep learning activities have a notable positive impact on learners' course knowledge mastery. Moreover, the varying effect sizes across different cognitive levels imply that behavioral and emotional engagement are more directly influenced by external environments and tasks, whereas cognitive engagement relies more on learners' intrinsic cognitive strategies and abilities, which are less likely to improve over a short-term learning period. Generative AI facilitates interactive learning scenarios, analyzes students' learning data to develop personalized content, and provides intelligent guidance (Kasneci et al., 2023), effectively promoting deep thinking and knowledge construction among students. Through continuous

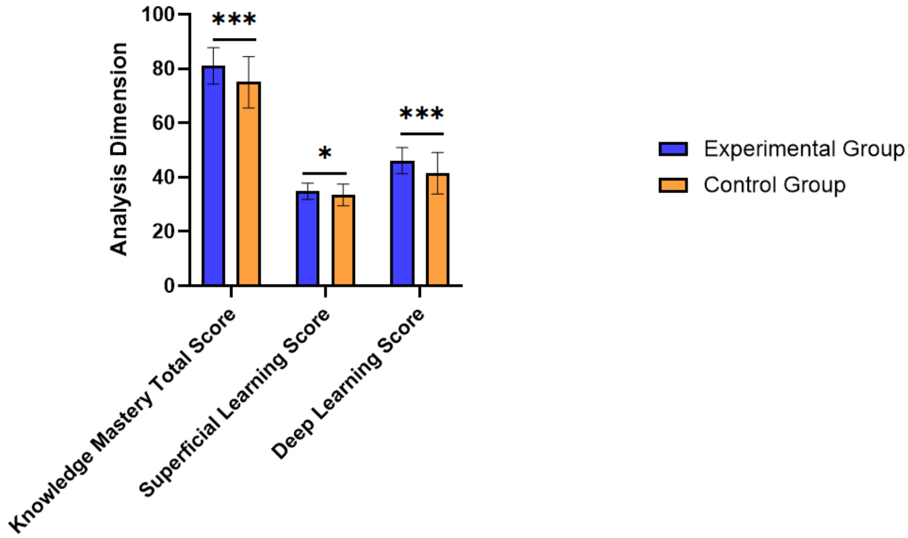

Fig. 3 The results of the independent samples t-test regarding the level of knowledge mastery

interaction with generative AI, students are more likely to develop a deep understanding and application of course content, leading to higher-quality learning outcomes.

Analysis of cognitive level

Based on the SOLO taxonomy, when learners' thinking levels are at the relational or extended abstract structures, it signifies that they have achieved deep learning. Utilizing the analytical framework of student thinking levels constructed in this study, we conducted a quantitative coding analysis of the submitted instructional design plans for information technology-enhanced teaching. The results for the experimental group were as follows: 44.44% of their instructional design plans were categorized under the relational structure, and 7.41% under the extended abstract structure, with a total of 51.85% reaching the level of deep learning. For the control group, the results were: 3.64% under the relational structure, and 32.73% under the extended abstract structure, with a total of 36.37% achieving deep learning. These findings suggest that generative AI has a positive impact on the development of higher-order thinking skills among college students, which is consistent with the research by Li et al. (2025).

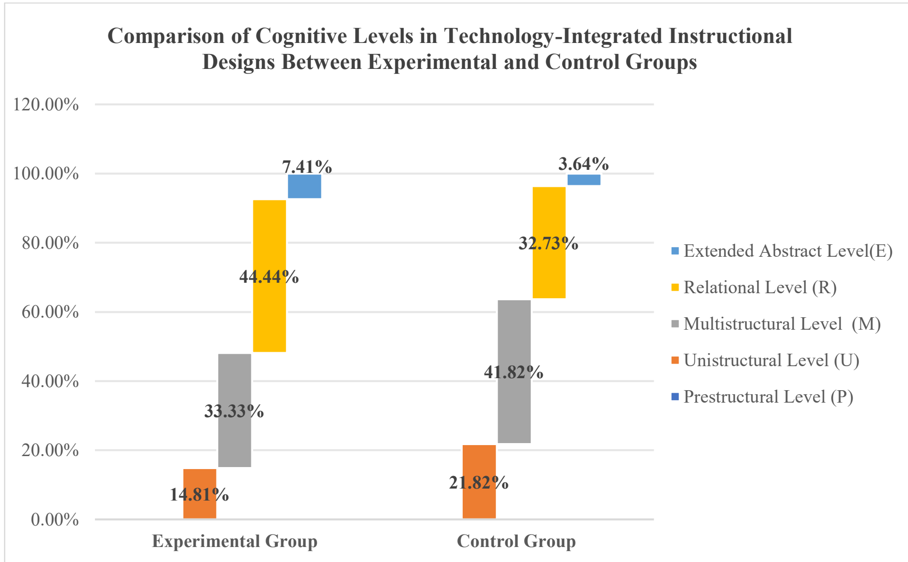

Fig. 4 Comparison of cognitive levels between the experimental group and the control group

Analysis of emotional experience

An integrative analysis of data derived from questionnaire surveys and in-depth interviews reveals that learning activities supported by generative AI exhibit a triple effect in the dimension of emotional experience. Specifically, these activities manifest as positive feedback in terms of cognitive satisfaction, as well as deep-seated facilitation of cognitive development. However, it is also necessary to be vigilant about the emotional risks associated with technological dependency.

Firstly, the sense of learning presence empowered by technology significantly enhances students' cognitive satisfaction. The course satisfaction questionnaire results indicated that students in the experimental group were generally satisfied with the learning activities supported by generative AI, with an overall course satisfaction rate of 91.98%, which is higher than the control group's satisfaction rate of 82.26%. Specifically, in terms of perceived quality, the experimental group expressed satisfaction with teaching content, teaching activities, teaching evaluation, instruction quality, teaching interaction, and learning platform, all of which exceeded 90%. Satisfaction with instruction quality and teaching interaction exceeded 95%. Regarding perceived expectations, 86.6% of students believed that the course met their learning needs. This emotional identification was concretized in the interviews as follows: "Compared with traditional blended learning, especially during the online learning phase, it is very convenient to ask questions to generative AI when encountering doubts"; "The content generated by large language models is comprehensive and systematic, providing aspects that we might not have considered, which can offer ideas for further designing teaching activities and is very helpful for our practical projects." By constructing an emotional chain of "need-satisfaction-identification," generative AI effectively alleviates the sense of isolation in online learning and enhances emotional engagement in the learning process.

Secondly, critical interaction processes enhance deep-level cognitive satisfaction. Although some participants acknowledged the need for greater cognitive effort—"It requires more time to think about the content it generates and to judge whether the content is correct"—all students in the experimental group concurred that the interactive mode with large language models facilitated cognitive development. Typical expressions such as "The designed experimental steps were incorrect and needed to be adjusted by myself" reflect the learners' cognitive transition from technological dependence to self-awakening. This process of "questioning-validation-reconstruction" in thinking training enables students to achieve a sense of accomplishment in overcoming cognitive conflicts.

However, it is necessary to be vigilant about the potential risk of emotional alienation caused by technological mediation. Although 88.8% of the respondents expressed a strong willingness to promote its use, the 11.2% neutral stance reveals an underlying crisis: prolonged human–machine interaction may lead to "technological dependency" ("If used for a long time, it becomes very easy to rely on it completely and lose one's own thinking"). This ambivalent emotion suggests that teachers should meticulously design learning scenarios in which students utilize generative AI, organize challenging group inquiry tasks, and stimulate students' active thinking and deep cognition. Moreover, teachers need to constantly monitor students' initiative and depth in cognitive processing during human–machine interactions. Additionally, it is crucial to strictly enforce rules regarding students' use of generative AI to avoid technological dependency and cognitive inertia. These findings suggest that the learning activities supported by generative AI not only met students' learning expectations but also earned the recognition of the majority of students, providing a positive emotional experience.

Reflection and future prospects

This study, based on traditional activity theory, constructs a generative AI-integrated learning activity framework. It explains the restructuring mechanism of generative AI on the six elements of activity theory, analyzes the internal and external contradictions in the generative learning activity system, and explores its promoting effect on learners' deep-level cognitive development. This framework continues to emphasize the importance of mediated tools in activity theory and achieves a deep integration of human cognition and machine intelligence through Generative AI (GenAI). It provides a new analytical paradigm for understanding deep-learning mechanisms in the digital age. Through a 15-week empirical investigation, examined the impact of generative AI-based learning activities on college students' deep learning processes and outcomes. The data analysis reveals that deep learning activities based on generative AI have positive effects on learners' performance in the learning process, knowledge mastery, cognitive level, and emotional experience.

This study expands the research horizon of technology-enabled deep learning and enriches the application research of generative AI in education, providing practical references for the innovation of college course teaching models.

It is crucial to note that the dual-edged sword effect of technological tools demands our vigilance. Even though generative AI can offer personalized learning experiences, the risks associated with its application require special attention. In the first place, data ethics and privacy security are of great concern. The storage and use of sensitive information, such as conversation records and learning trajectories, can easily lead to data abuse if not regulated. Secondly, intelligent technology can alienate human self-development. If students do not follow AI usage rules and blindly trust AI-generated content, their thinking abilities will be weakened. It is recommended that education authorities develop generative AI usage guidelines to clarify ethical boundaries. At the same time, strengthening ethical education is essential to ensure that teachers and students understand ethical guidelines and use generative AI ethically. Integrating AI ethics into the digital literacy curriculum for teacher-trainees can cultivate students' critical review skills of AI-generated content, preventing over-reliance on tools and cognitive degeneration. In conclusion, using generative AI in education should focus on real-world educational issues, unlock its potential in teaching, highlight teachers' leading role, and emphasize their mission in cultivating students' higher-order thinking, emotions, attitudes and values.

However, this study also has the following limitations: (1) The small sample size and 4-month experiment period may affect the generalizability of the results. Future studies will expand the sample, lengthen the observation period, use longitudinal tracking, and apply multi-stage dynamic modelling to assess the sustained impact of generative AI. (2) This study specifically targeted junior college students in the course on modern educational technology and information practice for empirical research; future studies should explore its applicability across different subject courses and educational stages. (3) Deep learning is an extremely complex learning activity. Characterizing it solely based on learners' performance in the learning process, knowledge mastery, cognitive level, and emotional experience may not provide a comprehensive understanding. Future research should leverage learning capture and analysis technologies to collect multimodal learning data, thereby increasing the persuasiveness of research conclusions.

Abbreviations

AI: Artificial intelligence; GAI: Generative artificial intelligence; GAS: Generative activity system.

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Authors' contributions

Wenxin Zhang conceived and designed the study, acquired data, conducted data analysis and interpretation, drafted the manuscript, and revised it. Bo Chen was responsible for data collection, provided support for data analysis, edited the manuscript, and coordinated the review process. Ci Tang carried out the literature review, was in charge of visual design, and performed the final review of the manuscript. All authors read and approved the final manuscript.

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Availability of data and materials

The data that support this study's findings are available from the Course Teaching Survey, but restrictions apply to the availability of these data, which were used under license for the current study and so are not publicly available. However, the data are available from the authors upon reasonable request and with the permission of the Chengdu Normal University, China.

Declarations

Competing interests

The authors declare that they have no competing interests.

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