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Using Generative Artificial Intelligence to Improve Chinese College Student Learning Outcomes: Self-determination Theory and Self- Efficiency Theory Perspectives

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Generative Artificial Intelligence (GAI) tools have shocked the world with their unprecedented functionality and have created a huge buzz in the field of education. Due to the personalized and real-time interactive nature of GAI tools, we believe that students' interactions with GAI will influence their learning outcomes through the impact of motivational factors. Despite the advantages of these tools in the field of higher education, there is still a lack of research on the specific mechanisms of integrating this technology into the learning process. Therefore, this study used self-determination theory and self-efficacy theory to investigate the relationship between GAI interactions and student learning outcomes to fill this gap. The results of this study, through an empirical study of college students in a second-tier city in China, suggest that GAI interactions can positively influence student learning outcomes through academic self-efficacy (ASE), creative self-efficacy (CSE), creativity, and motivation to learn. This study creatively added the creativity factor into the integration of GAI and learning, providing students with empirical evidence for using GAI tools to improve their academic performance, and informing the further integration of GAI into academic life in the future.

Keywords: Generative artificial intelligence, Higher education, GAI interaction, Learning outcomes, Creativity

1. Introduction

Artificial Intelligence (AI) traces its origins to early computation theories and the 1956 Dartmouth conference, which coined the term "Artificial Intelligence". Since then, developments like neural networks, deep learning, and reinforcement learning have driven AI's evolution. Landmark advancements include OpenAI's ChatGPT, Google's Gemini, and Anthropic's Claude, which have revolutionized generative AI by enabling tasks such as dialogue creation, image recognition, and translation. Generative AI, characterized by its ability to create novel content, is reshaping industries and societies by driving innovation while posing ethical challenges like misuse for fraud and misinformation. Researchers and organizations highlight opportunities, from economic growth to transformative education and software development, and emphasize improvements needed in model control, training efficiency, and interpretability.

Market analysts predict that by 2025, generative AI will generate 10% of human data, amplifying its societal impact. However, challenges persist in addressing safety, data privacy, and ethical concerns. Efforts, like Alex Engler's proposals for regulating generative AI, aim to mitigate risks and enhance its beneficial uses.

Generative AI is advancing rapidly, reshaping industries and workforce roles while posing new risks and opportunities. A June 2023 McKinsey report highlights the swift development of large-scale language models (LLMs) after ChatGPT, demonstrating their transformative capabilities in text, images, audio, and code. Generative AI enhances workflows by automating tasks like summarizing, drafting, and categorizing, with significant potential across sectors such as banking, healthcare, and education. However, McKinsey's survey reveals that fewer than half of organizations effectively manage AI risks like inaccuracies. In August 2023, McKinsey's "State of AI" survey emphasized generative AI's breakthrough year and its role in transforming business models. A key insight was the uneven adoption of risk mitigation strategies among companies worldwide, underscoring the nascent state of AI governance.

UNESCO issued guidelines in September 2023 for integrating generative AI into education responsibly. The document urges labeling AI-generated content, upholding ethical principles, and increasing human oversight. UNESCO envisions AI facilitating personalized learning, supporting students with impairments, and providing emotional guidance. Director-General Audrey Azoulay stressed the importance of public participation and robust regulations to harness AI's benefits while minimizing harm.

Generative AI’s potential is vast, from improving education to revolutionizing business. However, effective governance and ethical applications are critical to mitigate challenges and maximize its societal impact. The Horizon Report 2024, by Educause, identifies trends shaping higher education across six dimensions: social, technological, economic, environmental, political, and AI. For the first time, AI trends are spotlighted, underscoring its transformative role in pedagogy, learning personalization, and administrative efficiency. However, challenges such as data privacy, misinformation, and ethical risks persist. AI literacy is increasingly essential, enabling critical thinking, diversity, and equity in education.

China's proactive AI policies focus on intelligent education platforms, ethical AI norms, and international collaboration. Reports like Best Application Practices of Generative AI in China 2024 emphasize generative AI's potential in upgrading teaching methods, optimizing resources, and fostering innovation while cautioning against risks like quality concerns and fairness.

Technologies like ChatGPT facilitate personalized, interactive, and innovative learning experiences, boosting student engagement and research productivity. The GAI tool fulfills the need for students' performance expectations (Strzelecki, 2023). It stimulates them to utilize their time to deal with a wide variety of academic challenges, which ultimately increases their motivation and research productivity. Yet, effective use hinges on prompt quality and teacher guidance. While ChatGPT offers many benefits such as increased efficiency, improved accuracy, and cost savings, concerns about security and limited functionality have also been raised (Maheshwari, G, 2024), students value AI tools for motivation and task support, though concerns about security and functionality remain. Further studies are needed to explore the broader impact of GAIs on learning outcomes and educational behaviors. The academic discourse on GAI in higher education is promising but still in its early stages, with limited empirical research on its consequences. Much of the previous research has focused on the technical attributes of GAI tools, but there is a lack of observable associations between learning activities and GAI tool use. Although many studies have demonstrated that GAI tools have great potential to assist in research, its efficacy depends on how students interact with it; the interaction, if effective, can be beneficial to students' performance and competence, but if misused, it may lead to dependency and impede the development of basic skills.

To address these research gaps, this study constructed a model to understand the impact of GAI interaction on student learning outcomes. The fundamentals used in this study are self-determination theory and self-efficacy theory. Self-Determination Theory (SDT) views motivation as a continuum, driven by intrinsic and extrinsic factors. Intrinsic motivation arises from personal satisfaction, while extrinsic motivation stems from external rewards or outcomes (Ryan& Deci, 2000). SDT, widely studied in education, highlights its influence on learning outcomes, persistence, creativity, and emotional well-being. Based on self-determination theory, individuals exhibit self-determined behaviors when they perceive certain activities as favorable opportunities. Students immersed in an AI-integrated educational experience tend to exhibit higher perceptions of motivation, including desire to learn, self-efficacy, and beliefs about the future, which correlate with improved academic performance (Gao, Z. et al., 2024). Self-determination theory helps to understand the factors that influence intrinsic and autonomous extrinsic motivation and ultimately learning outcomes. Considering the link between student engagement and motivation, student-GAI interactions are seen as determinants that influence student motivation and learning outcomes. However, China's research on SDT focuses mainly on theory, with limited empirical studies integrating it into education. Self-efficacy, defined by Bandura, refers to confidence in one's ability to complete tasks. It impacts activity choice, persistence, attitudes toward challenges, and emotional responses. High self-efficacy boosts engagement, learning interest, and academic success. When interacting with AI, students can feel that they are in a tailored and personalized learning environment (Mollick, 2023; Wongmajarapinya et al., 2023) and can access and understand complex knowledge more easily (Peres et al., 2023). As a result, students may feel more confident in their learning, as evidenced by higher levels of self-efficacy. Meanwhile, self-efficacy has been shown to influence students' effort, persistence, interest, and achievement in learning activities (Schunk, 1995). Integrating SDT and self-efficacy into AI-enhanced education shows promising links between tailored AI environments, motivation, and learning outcomes. This study explores these interactions in higher education.

This study also explores the mediating role of creativity, and that enhancing the level of interaction between the GAI and students can fully utilize students' creativity and improve their integrative and logical thinking skills, which help students to keep exploring, focusing, and persevering in learning tasks (Cheng, 2023). Coming up with different conjectures or solutions, adopting novel approaches, making unusual connections, or changing the prevailing viewpoints are necessary in different disciplines (Iannello et al., 2020), all of which contribute to the improvement of learning outcomes.

According to the research objectives, this study proposes three research questions:

Q1: How do Chinese college students currently use GAI in their studies?

Q2: How do current GAI tools affect Chinese college students' learning?

Q3: How can GAI tools further help Chinese college students improve their learning outcomes in the future?

To address these issues, we collected data on college students' use of GAI for learning in Taiyuan, Shanxi Province, China, while we proposed three research objectives:

O1: To identify current GAI tools and GAI functions commonly used by Chinese college students, and to explore the tendency of college students to use them in the learning process.

O2: To model the relationship between GAI interactions and college students' learning outcomes, and to explore the influencing factors.

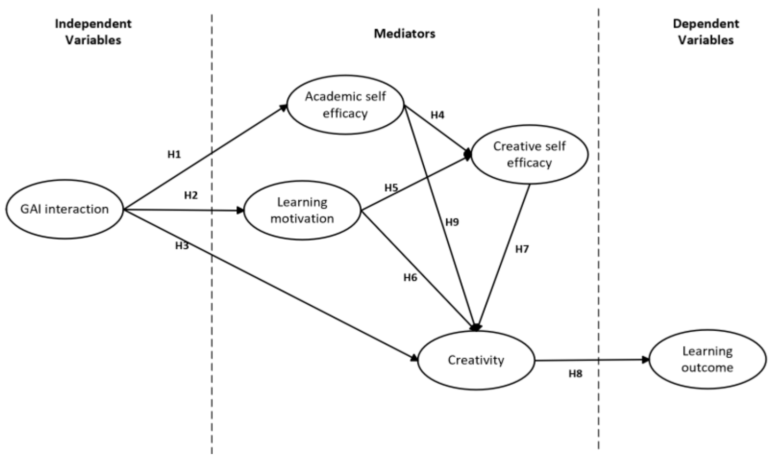
O3: To propose more suggestions for how to use GAI tools to improve learning outcomes in the future.

2. Literature review

This study takes college students' GAI interactive learning behaviors as the research object. In order to further understand the topic and establish a framework for the study, a review of relevant literature was conducted, including academic journal articles, books, texts, statistical data, and past studies. GAI tools have developed very rapidly in recent years and are increasingly used in education. Motivation plays a key role in the adoption and continued use of educational technology, and understanding the factors that drive learners' use of GAIs in learning can provide valuable insights into users' behavioral intentions and actual use of GAI applications. By interacting with these technologies, students may realize that they can use GAI tools to create exciting and satisfying content or solve more difficult tasks. They may have a higher assessment of their ability to achieve their goals with the help of GAI. In other words, students' interactions with GAI can increase their self-efficacy. Given the novelty of GAI in educational settings, few studies have investigated learners' motivation to use this technology for educational purposes. This research gap emphasizes the importance of exploring how learners' motivation aligns with the unique characteristics and capabilities that GAI brings to learning. On the other hand, higher self-efficacy to improve academic performance has been extensively studied in the existing educational literature (Schunk, 1995), Self-efficacy has been shown to influence students' effort, perseverance, interest, and achievement in learning activities (Schunk, 1995). Students with higher self-efficacy are more engaged, work harder, persist longer, show greater interest in learning, and achieve higher grades (Schunk, 1995). Therefore, this study applies self-determination theory and self-efficacy theory to the integration of higher education and GAI, and the research question focuses on the impact of learning with GAI tools on students' self-efficacy, and thus whether it promotes better learning outcomes in learning activities.

This study focuses on the mechanism of college students' GAI interactive learning behaviors on their learning outcomes. There are six variables in this study, in which the independent variable is GAI interaction, and the mediating variables are academic self-efficacy, learning motivation, creative self The dependent variable is learning outcome. We explore the correlations among these variables in order to be able to make some new discoveries about the mechanism of the influence of GAI interactive learning on college students' learning outcomes and to add to the literature in this field. We drew the conceptual model diagram which contains six variables and their relationships The model diagram is shown in Figure 1.

Figure 1 Conceptual Framework



Based on the conceptual model of the study, eight hypotheses were formulated in this study as shown in Table 1

Table 1 Research Hypothesis

NO.	Hypothesis
H1	GAI interaction positively affected academic self-efficacy.
H2	GAI interaction positively affected learning motivation.
H3	GAI interaction positively affected creativity.
H4	Academic self-efficacy positively affected creative self-efficacy.
H5	Academic self-efficacy positively affected learning motivation.
H6	Learning motivation positively affected creativity.
H7	Creative self-efficacy positively affected creativity.
H8	Learning motivation positively affected creative self-efficacy.
H9	Creativity positively affected learning outcome.
H10	Academic self-efficacy mediates the effect of GAI interaction on learning motivation.
H11	Learning motivation mediates the effect of GAI interaction on creativity.
H12	Learning motivation mediates the effect of academic self-efficacy on creative self-efficacy.

3. Methodology

This study uses questionnaires to conduct quantitative research. Firstly, we choose a reference scale according to the previous related research and design the initial questionnaire according to the reference scale, we design a Likert-type five-point questionnaire, from 1 “strongly disagree” to 5 “strongly agree”. Five experts (two management and three computer science associate professors) evaluated the questionnaire for relevance and language. Items were revised, optimized, or deleted based on their feedback. A pilot test analyzed reliability and validity, leading to further refinement. An IOC test ensured content validity, finalizing the questionnaire. The modified and optimized questionnaire was divided into two parts, the first part being the personal information of the participants and the second part being the use of generative AI techniques and their impact. The second part contains 6 subscales, which are GAI interaction, learning motivation, academic self-efficacy, creative self-efficacy, learning outcomes, creativity.

The questionnaire was formally conducted. The purpose sampling method was used in this study and the research sample was identified as college students enrolled in Taiyuan City, Shanxi Province, China, and purposive sampling was used for sample sampling, with a total of 703 people participating in the survey, and 410 pieces of valid data remaining after data validity screening were analyzed.

Finally, data analysis was carried out. The collected sample data were analyzed to verify whether the research hypotheses were valid. This paper mainly uses SPSS and AMOS software for data analysis. We used the following seven main data analysis programs. First, SPSS was used for reliability analysis, validity analysis, and exploratory factor analysis (EFA) to test the quality of the data, as well as descriptive statistics to analyze and summarize the distributional status and characteristics of the data. AMOS was then used as a validation factor analysis (CFA) and structural equation modeling (SEM) to test the research hypotheses.

4. Expected Finding and Discussion

4.1 Participant Demographic Profile Analysis

Firstly, we analyzed the data of 410 samples with descriptive statistics, including frequencies and percentages. Secondly, reliability, validity analysis and validation factor analysis (CFA) were performed, where the analyzed indicators were factor loadings, composite reliability (CR), variance mean extraction (AVE), and model fit indices, and the research hypotheses were tested utilizing bootstrap estimation method to construct the SEM. Lastly, hypotheses testing was summarized and discussed based on the results obtained.

There was a total of 410 valid respondents in this study, of which 304 were males, representing 74.1% of the total. The rest were females, totaling 106 or 25.9% of the total. The largest number of participants was in the first year of university, with a total of 161 students taking part in the survey, accounting for 39.3% of the total number. The next highest number was in the second year of university with 142 students or 34.6% of the total. The remaining participants were college juniors and seniors, totaling 26.1% of the total. The majors of the students who participated in the survey were mainly engineering majors (62.7%), while the rest of the majors had fewer participants (no more than 10%). In addition, the study found that among all the participating generative AI tools, ChatGPT was the most selected, with 67.8% of the students having used it, while the other tools accounted for a smaller percentage. The most interesting GAI features were information search and text generation, with 71.2% and 4.6% of respondents reporting this, respectively. As shown as cross-tabulation of participants' most frequently used GAI tools with their most frequently used GAI functions, based on the statistical analysis, it can be concluded that participants using ChatGPT most frequently used the Text Generation and Information Search functions, and the inclination towards these two functions was also reflected in the use of participants using other tools.

4.2 Reliability and Validity Assessment

Item Cronbach's α reliability analysis was conducted. The alpha coefficients of the subscales should be greater than 0.7 ($\alpha>0.7$), and the coefficients of the total scale should be greater than 0.6 ($\alpha>0.6$), at which point the reliability of the sample data is acceptable (Cronbach, 1951). The scale reliability in this study is shown in Table 2. According to the data analysis of this study, it can be concluded that the Cronbach alpha coefficients of the subscales are all greater than 0.8, and the Cronbach alpha coefficients of the total scale are greater than 0.9, which are in accordance with the criteria, then the sample data are reliable and can be used for the study.

Table 2 Reliability Test Results of Sample Data

Scale	Number of Items	Cronbach alpha
GAI interaction scale	3	0.885
Creativity scale	3	0.802
Learning motivation scale	5	0.915
Academic self-efficacy scale	4	0.909
Creative self-efficacy scale	4	0.903
Learning outcomes scale	3	0.892
Total	22	0.925

On the basis of literature review and self-efficacy theory research, the questionnaire validity analysis was conducted by five experts, while checking the questionnaire language expression to see if it is reasonable, the questionnaire was designed and modified to ensure the content validity of the measurement items. Now the main test is structural validity.

For the scale, KMO test and Bartlett's test of sphericity were used to indicate the degree of correlation between variables. If the correlation is good (KMO>0.7, Bartlett Sig.<0.01) (Hair et al., 2010), then further principal component analysis is performed, indicating that the structural validity of the questionnaire is ensured. According to the results of KMO and Bartlett's test in this study, it can be obtained that KMO=0.908, Bartlett Sig.<0.001, which means that the scale correlation of this study is good and it is suitable for factor analysis.

Harman's single factor test was used in this study. According to the test results, it can be concluded that the first common factor explains 39.513% of the total variance, which is less than the critical value of 40% (Harman, 1976), therefore, there is no serious common method bias problem in this study, and the factor analysis can be continued.

4.3 Analysis of Control Variables

Three control factors were included in this study, i.e., gender, grade, and major. According to Spearman's correlation analysis, it can be obtained that the Spearman's analysis Sig. (2-tailed) of all control variables (i.e., gender, grade, and major) on learning outcomes is greater than 0.1, which means that none of the results are significant. That is, all control variables (i.e., gender, grade, and major) have no significant correlation on learning outcomes, and the control variables set in this study are negligible.

4.4 Confirmatory Factor Analysis (CFA)

According to the data analysis, it can be concluded that the factor loading of all items is greater than 0.8, the CR of the subscales is greater than 0.8, and the AVE of the subscales is greater than 0.6(Fornell & Larcke, 1981). All of them are in line with the index requirements, and it can be concluded that the data have good convergent validity.

We performed a path analysis for each variable using AMOS based on structural equation maps to investigate their effects. During the analysis, maximum likelihood estimation was used, and 2000 bootstrap runs were performed to establish 95% confidence intervals. Where the path relationship is significant when P<0.05, path coefficient values between 0.1 and 0.3 indicate a low level of influence, 0.3 to 0.5 indicate a moderate level of influence, and 0.5 to 1.0 indicate a high level of influence (Suhr, 2006). The results of the analysis in this study are shown in Table 3.

Table 3 Regression Weights

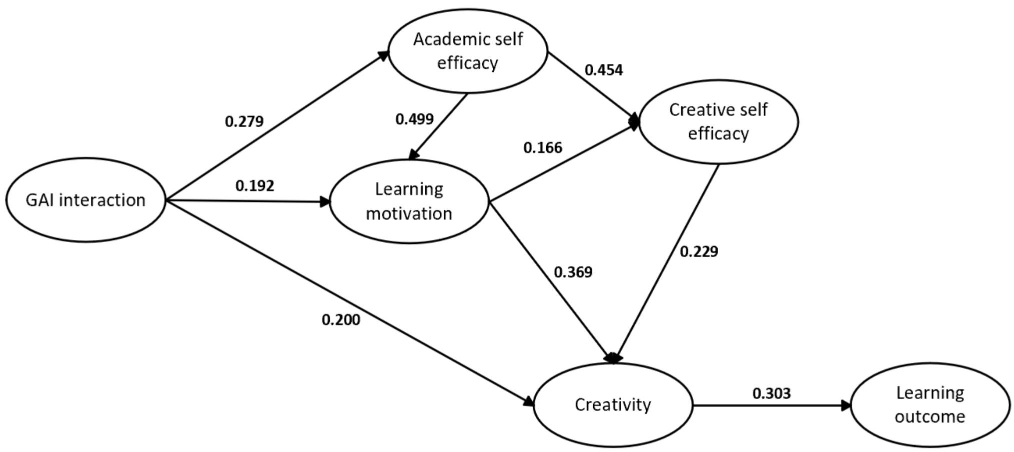
Relation between variables			Estimate	P
academic_self_efficacy	<--	GAI_interaction	.279	***
learning_motivation	<--	academic_self_efficacy	.499	***
learning_motivation	<--	GAI_interaction	.192	***
creative_self_efficacy	<--	learning_motivation	.166	.005
creative_self_efficacy	<--	academic_self_efficacy	.454	***
creativity	<--	learning_motivation	.369	***
creativity	<--	creative_self_efficacy	.229	***
creativity	<--	GAI_interaction	.200	***
learning_outcomes	<--	creativity	.303	***

*p<0.1, **p<0.05, ***p<0.01.t-value of fixed-parameter items is empty

According to previous studies, P<0.05 is considered significant for path. Path coefficient values between 0.1 and 0.3 indicate a low level of influence, 0.3 to 0.5 indicate a moderate level of influence, and 0.5 to 1.0 indicate a high level of influence (Owusu, E.K.; Chan, A.P.; Hosseini, M.R. 2020). Specifically, GAI interaction had a significant effect on college students' academic self-efficacy with a low level of influence (Estimate =0.279, P<0.001); college students' academic self-efficacy had a significant effect on their motivation to study with a moderate level of influence (Estimate =0.499, P<0.001); and GAI interaction had a significant effect on college students' motivation to study with a low level of influence (Estimate =0.499, P<0.001). (Estimate =0.192, P<0.001); college students' motivation to study had a significant effect on their creative self-efficacy, with a moderate effect (Estimate =0.166, P=0.005); college students' academic self-efficacy had a significant effect on their creative self-efficacy, with a moderate effect (Estimate =0.454, P<0.001); and college students' motivation to study had a significant effect on their creative self-efficacy, with a moderate effect (Estimate =0.499, P<0.001); college students' academic motivation had a significant and moderate effect on their creativity (Estimate =0.369, P<0.001); college students' creativity self-efficacy had a significant and low effect on creativity (Estimate =0.229, P<0.001); and GAI interaction had a significant and low effect on college students' creativity (Estimate =0.200, P<0.001); college student creativity has a significant effect on learning outcomes with a moderate level of influence (Estimate =0.303, P<0.001).

After analyzing our model diagram and path coefficients are shown in Figure 2

Figure 2 Model Analysis



Note: The path correlation coefficient is marked on the graph.

The biased confidence intervals indicate significant mediating effects: (1) the effect of GAI interaction on learning_ motivation, the mediating effect transmitted through Academic self-efficacy is significant (0.114–0.225); (2) the mediating effect of GAI interaction on creativity, transmitted through learning motivation, was significant (0.122–0.222); (3) the mediating effect of Academic self-efficacy on Creative self-efficacy that the mediating effect transmitted through learning motivation is significant (0.027–0.153).

At the same time, we calculated the fitting index of the model graph. While the absolute model fit index SRMR = 0.124 does not meet the criteria, the rest of the model fit indices c2/df = 1.884, RMSEA = 0.046, GFI = 0.925, AGFI = 0.905, TLI = 0.968, IFI = 0.972, CFI = 0.972, and NFI = 0.942 all reach the satisfactory standard. Therefore, this paper concludes that the model is well fitted.

4.5 Discussion

By integrating Self-Determination Theory and Self-Efficacy Theory, the results of this study highlight that GAI interactions can influence student learning outcomes through academic self-efficacy, creative self-efficacy, motivation to learn, and creativity.

GAI interactions in this study were not directly related to college students' learning outcomes but were significantly related when mediated through academic self-efficacy, creative self-efficacy, learning motivation, and creativity. Specifically, GAI interaction had a positive effect on college students' academic self-efficacy (H1), GAI interaction had a positive effect on college students' motivation to learn (H2), GAI interaction had a positive effect on college students' creativity (H3), academic self-efficacy had a positive effect on creative self-efficacy (H4), academic self-efficacy had a positive effect on college students' motivation to learn (H5), motivation to learn has a positive effect on college students' creativity (H6), creative self-efficacy has a positive effect on college students' creativity (H7), academic motivation has a positive effect on creative self-efficacy (H8), and college students' creativity has a positive effect on learning outcomes (H9).

The interactivity and real-time feedback brought about by AI applications can also provide personalized pacing and error correction, allowing students to experience their learning progress more quickly. This immediate feedback mechanism can enhance students' self-efficacy, thus increasing their motivation to learn. Especially in those environments that emphasize proactive and constructive learning methods, students show higher learning motivation when using GAI for interactive learning. Also, students with higher levels of creative self-efficacy showed more positive beliefs about their academic abilities in all subject areas and higher levels of participation in after-school group activities. When students are willing to actively participate in learning and classroom activities, they have stronger beliefs about organizing and executing actions to achieve desired academic outcomes (Wei, Y. et al., 2022). Taken together, the integration of GAI tools into learning activities is a key driver in increasing motivation while removing barriers that may hinder academic success（Gherghel et al,2023). Țală, M.L. et al., (2024) suggest that users who rate the quality of AI-generated texts positively perceive that the use of AI for academic purposes enhances creativity. There is a direct dependency between these two variables, i.e., users who have a favorable opinion of AI are more likely to believe that using AI for academic purposes improves their creativity. Previous research has shown a significant relationship between creativity and academic achievement. This was further validated in this study, where more creativity and creative thinking were stimulated when students thought about how to solve problems, which encouraged them to experiment more and achieve better learning outcomes. The learning environment enhanced by ChatGPT fostered specific motivations in students, which in turn influenced their learning behaviors and outcomes.

Some scholars have argued that the use of GAI tools can help students to better understand what they are learning and improve their mastery of knowledge, which in turn improves academic performance, while others have argued that GAI may lead to laziness and over-reliance, with little or no analytical skills, which in turn reduces academic performance. The results of this study provide some empirical evidence of the positive impact of using GAI for student learning. Using GAI tools as a learning scaffold may have a positive impact on motivation and learning outcomes.

At the same time, this study delved into the intricate relationships between various motivational elements, revealing unexpected patterns. Specifically, academic self-efficacy had a positive impact on creative self-efficacy, and learning motivation had a positive impact on creative self-efficacy. Numerous studies have pointed out that self-efficacy plays a mediating role in students' motivation, understanding, learning, and achievement. In addition, high self-efficacy is associated with superior academic performance, refined problem-solving skills, and greater resilience in the face of challenges. Following this lead, we complemented the positive affective relationship between creative self-efficacy, academic self-efficacy, and academic motivation in the context of students' use of GAI tools for learning.

As shown in Table 4, our hypotheses H1-H12 are all passed, which proves that our hypotheses and analysis are scientifically reliable.

Table 4 Hypothesis results

NO.	Relation between variables	Results
H1	GAI interaction→ Academic self-efficacy	Supported
H2	GAI interaction→ learning motivation	Supported
H3	GAI interaction→ creativity	Supported
H4	Academic self-efficacy→ Creative self-efficacy	Supported
H5	Academic self-efficacy→ learning motivation	Supported
H6	learning motivation→ creativity	Supported
H7	Creative self-efficacy→ creativity	Supported
H8	learning motivation→ Creative self-efficacy	Supported
H9	creativity→ learning outcomes	Supported
H10	GAI interaction→ Academic self-efficacy→ learning motivation	Supported
H11	GAI interaction→ learning motivation→ creativity	Supported
H12	Academic self-efficacy→ learning motivation→ Creative self-efficacy	Supported

5. Conclusion and Recommendation

5.1 Summary of Findings

This study aims to further explore the integration of GAI with higher education, and further investigate whether students' interactions with GAI are beneficial to their learning outcomes based on the visible learning experiences of university students, and what are the influencing factors involved. Based on the current status of the integration of GAI and higher education and the literature analysis, this study summarizes three questions: what is the current situation of Chinese college students' use of GAI in their learning? How do current GAI tools affect Chinese college students' learning? How can GAI tools further help Chinese college students improve their learning outcomes in the future? To address these questions, we integrated self-determination theory and self-efficacy theory and identified the research variables as: independent variables (GAI interaction), mediating variables (academic self-efficacy, learning motivation, creative self-efficacy, creative). creative). The dependent variable (learning outcome).

Based on the research questions and variables, we identified three research objectives: to find out what GAI tools and GAI functions are commonly used by Chinese college students, and to explore the tendency of college students to use them during the learning process; to model the relationship between GAI interactions and college students' learning outcomes, and to explore the influencing factors and mechanisms; and to make more suggestions for college students on how to use GAI tools to improve their learning outcomes in the future based on the results of the study. In the course of the study, we deeply explored the direct effects of GAI interaction on learning outcome, and their indirect effects through mediation, and finally proposed 12 research hypotheses and drew a conceptual framework diagram, of which nine hypotheses are direct relationship hypotheses and three hypotheses are mediated relationship hypotheses.

Notably, there are three innovations in this study.

1. This study creatively integrates creativity into the research to explore what role creativity plays in the impact of student interaction with GAI on learning outcomes. Most previous studies have focused more on technological development or learning motivation, analyzing user satisfaction and willingness to use. There is a gap in the involvement of creativity factors. Our study demonstrates that students' interaction with GAI can enhance students' learning outcomes by improving their creativity, which opens up a new way of thinking about the development of research in this area.

2. This study subdivided self-efficacy into academic self-efficacy and creative self-efficacy, and while most of the previous studies used self-efficacy as a whole as a mediating variable, this study further analyzed how different kinds of self-efficacy play a role in the impact of students' interactions with GAI on learning outcomes.

3. This study uses empirical research to analyze the specific mechanisms by which GAI interaction affects the enhancement of student learning outcomes. Most of the literature in this field consists of theoretical studies and literature meta-analyses, with fewer empirical studies. We further enrich the findings of empirical studies in this field to further consolidate the foundation for the development of the study.

5.2 Recommendation

5.2.1. This study focuses on integrating GAI tools into higher education, revealing their impact on tangible learning activities. Unlike prior studies that emphasize affective factors, it incorporates creative factors into motivational frameworks, using self-determination and self-efficacy theories to assess how GAI interactions influence motivation, academic and creative self-efficacy, creativity, and learning outcomes. The findings enrich academic research on AI in education, offering insights into the integration of GAI tools in diverse educational contexts. Unique to this study is its focus on university students in Tier 2 cities in China, contrasting with existing research on Tier 1 cities, and providing a foundation for expanding GAI tools into broader regions. Future studies should explore optimal contexts for using AI technologies like ChatGPT to enhance academic performance.

5.2.2. The findings demonstrate that ChatGPT effectively offers immediate feedback and personalized learning, advancing teaching practices by embedding technological support and fostering lifelong learning skills. AI-supported personalization enhances motivation, contributing to sustained learning and better outcomes. However, the benefits depend on the quality of user prompts, emphasizing the need for teacher guidance. To ensure ethical use and academic integrity, institutions must evaluate the risks and rewards, collaborate with AI developers and stakeholders, and establish clear policies. These measures will balance the advantages of GAI tools with responsible usage in higher education.

5.3 Future Research

However, this study also has its limitations, pointing to areas that need to be further explored.

First, the sampling location of this study was a second-tier city in China, and only current college students in one city were studied; although the purpose of this study was to make observations for GAI use in a second-tier city, this may limit the generalizability of the findings due to the fact that there are variations in the synergistic development of higher education and digitalization in different regions. Future research may need to validate the conceptual model in more second-tier cities in China, or even conduct further research in other cultural contexts and countries to obtain more generalizable findings.

Second, this study only examined and analyzed student learning in the current context, and although the data we collected are valuable, we acknowledge that they do not allow us to observe long-term trends. Future research could take a longitudinal approach to dynamically analyze the process of student learning using GAI tools. By examining changing patterns and trends, a deeper understanding of the long-term impact of GAI tools on student learning outcomes can be obtained.

Finally, there is a significant limitation to our research on integrating GAI tools into educational activities; the GAI tools' responses to the questions use data collected over a limited time frame. As a result, if the data is flawed in some way (e.g., the presence of false or incomplete messages), this could lead to ChatGPT providing biased, incorrect, or confusing answers. The current study uses only student self-assessments, which may be somewhat subjective, and it may be difficult for students to confirm whether the information they receive is actually correct and valid. As time progresses, the GAI tool database will be further optimized, and future research proposes GAI response evaluation criteria to gain a comprehensive understanding of how students interact with and assess AI-generated content, and to analyze the validity of the information obtained, in order to gain a deeper understanding of the pedagogical implications of generative AI in higher education settings.

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