

A Model of Factors Influencing Learning Outcomes Based on Artificial Intelligence: Perspectives of Chinese University Students

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Abstract. In recent years, artificial intelligence (AI) technology garnered widespread attention and applied to various aspects of human life. Supported by Internet technology, AI transformed traditional problem-solving methods by utilizing information as a medium for sharing and communicating. It has significantly streamlined information processing, playing a crucial role in promoting the economic development of society and driving technological progress. This study aimed to investigate the relationship between self-efficacy, learning attitudes, learning behaviors, and learning outcomes among university students in China who have integrated artificial intelligence (AI) technology in their education. A total of 1865 participants completed a questionnaire that measured the variables of the model. The findings from the path analysis revealed that self-efficacy had a positive impact on both learning attitudes and behaviors, which in turn positively influenced learning outcomes. The mediation model accounted for 54.17% of the total effect. These results provide empirical evidence supporting the notion that students' self-efficacy, attitudes, and behaviors play a significant role in their academic achievement when utilizing AI technologies in education. Additionally, the model contributes new insights into the mechanisms underlying the effectiveness of AI-integrated education for university students. The study also discusses practical implications for the development of personalized education systems that leverage AI technology.

Keywords: AI Application; Self-efficacy; Learning Performance; Learning Attitude; Learning Behavior

1. Introduction

Currently, AI Generated Content (AIGC), gradually matured and ushered in comprehensive digital transformation across various fields. According to the forecast data from Tractica, the global AI software market is expected to generate \$126 billion by 2025, and have a 41.02% compound annual growth rate (CAGR) from 2021 to 2025 (as shown in Figure 1). An analysis by McKinsey in 2018 also predicted that by 2030, 70% of global enterprises will use at least one kind of artificial intelligence technology. Collaborating with artificial intelligence, humans can significantly enhance productivity. Also, Accenture, a well-known information technology company, estimated that organizations investing in human-AI collaboration can raise their revenue by 38% and boost employment by 10% from 2018 to 2022. Additionally, the pace of automation accelerated due to the COVID-19 pandemic. More workers need to accept job retraining and the demands for jobs requiring medium and low skills are expected to further decrease (Lund et al.,2021). Not only limited to the workforce, artificial intelligence technology significantly influences culture, diversity, education, scientific knowledge, communication, and information (Gan et al.,2019). In the realm of education, recent research focused extensively on the profound application of intelligent technology. There are three levels of its application: superficial "computational intelligence + education" application, intermediate "perceptual intelligence + education" application, and deep "domain-specific cognitive intelligence + education" application. These levels emphasize that intelligent technology can improve educational transformation (Figure 2 and Figure 3). The application scenario of AI in education includes aided instruction of teachers and enabling students' autonomous learning. During the learning process, AI technology can construct students' persona by continuously analyzing data through AI algorithms. From the teacher's perspective, collecting student feedback information can enhance teaching quality and refine teaching details, making instruction more targeted. From the student's perspective, it can help to analyze students' learning abilities, preferences, and subject proficiency across multiple dimensions. All of these can help to handle comprehensive assessments of students' overall abilities, identify weak points in students' knowledge, formulate optimal learning paths, provide personalized solutions, and aid in improving learning patterns, thereby realizing the principle of "teaching according to student's ability."

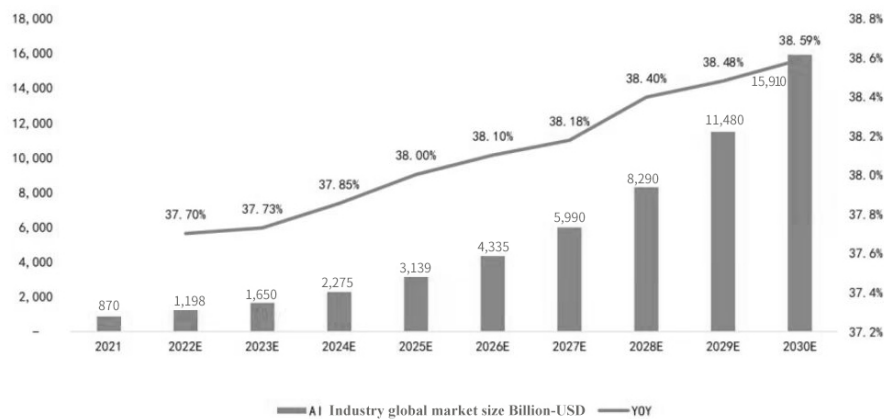


Fig.1: Global AI Software Market Scale

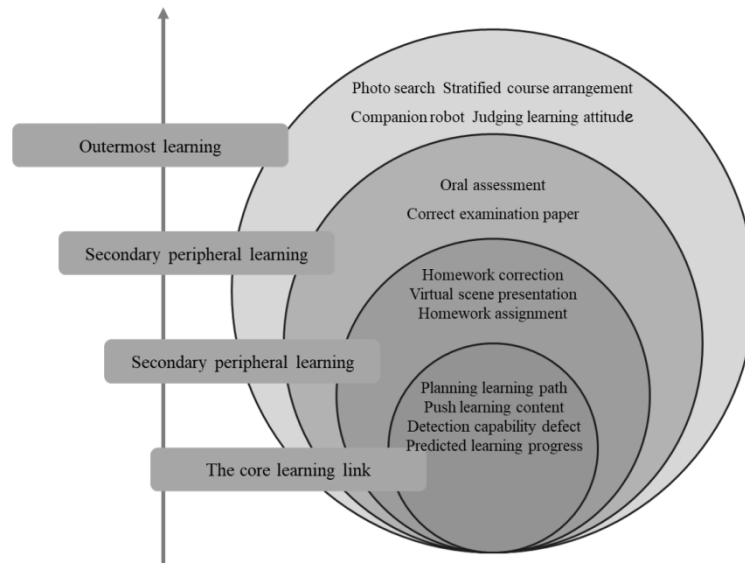


Fig. 2: The flow diagram of AI empowering education process

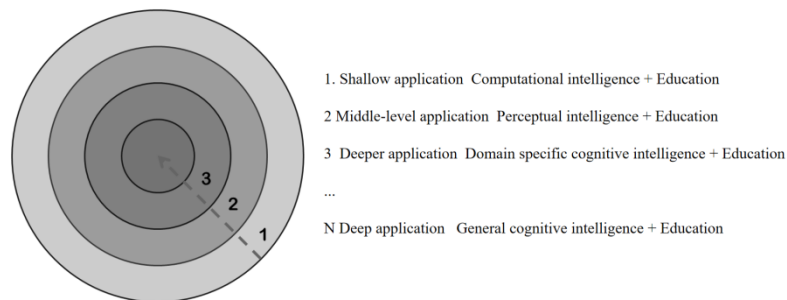


Fig. 3: Hierarchical division of intelligent educational applications

In the past decade, there has been a sharp increase in the application of artificial intelligence in education (Figure 4). In response to the new changes in the educational environment, EDUCAUSE, the American higher education IT association, released Horizon Report 2023 (Teaching and Learning Edition) on May 8, 2023. This report particularly focused on AI-generated content's impact on higher education, listing it as one of the six key technologies and practices. At the same time, the Online Education Market 2023 report showed that the global online education market grew from approximately \$190 billion in 2017 to over \$560 billion in 2023. This trend highlights the significant role of AI technologies like ChatGPT in higher education. Some relevant research finds that AI applications in higher education can provide personalized learning experiences, satisfying the diverse needs of students. ChatGPT, a natural language processing technology, can offer customizable learning resources and feedback to support students' academic growth (Bozkurt & Sharma, 2020). It can also provide real-time online tutoring and Q&A service, to provide immediate assistance and solutions to students (Roumeliotis & Tselikas, 2023). Additionally, ChatGPT can assist higher education teachers in automated assessment and feedback, using AI-generated feedback to guide students' learning and offer targeted suggestions and improvement strategies (Abbasnejad et al., 2020). However, it is not clear enough how combining AI with higher education has a specific impact on student learning outcomes. Also, there are lack of relevant theoretical and empirical research. Therefore, this study takes "AI application supporting prediction and personal learning" as an entry point. It examines whether the application of AI technologies in the education industry positively affects teaching quality and student learning performance. Also, by constructing a factor model influencing learning performance, the research aims to explore the factors affecting student learning performance.

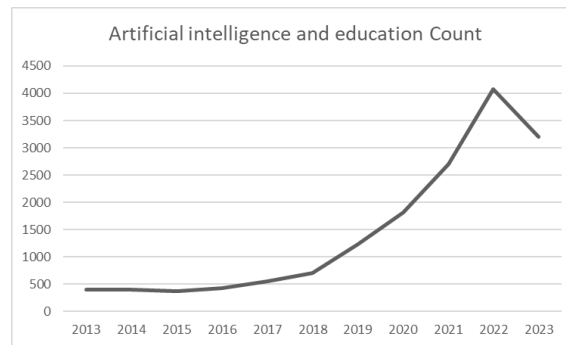


Fig. 4: Research on AI applications in education in the last decade (data from PubMed)

During the COVID-19 outbreak, online learning systems saw widespread use, and AI technology had an unprecedented impact on students' learning performance (Khan & Jawaid, 2020). In the academic community, there are two main viewpoints regarding the influence of artificial intelligence technology on students' learning outcomes. Some scholars have conducted experiments that prove the significant impact of AI technology on students' learning outcomes. For instance, Christudas et al. utilized Compatible Genetic Algorithm (CGA) to offer personalized learning content to students based on their preferred learning objects. The results showed that students' grades and satisfaction improved in the online learning environment (Christudas et al., 2018). Another example is the CARAMBA system developed by Cárdenas-Cobo et al., which provides appropriate learning exercises for students in scratch programming. The results confirmed that the CARAMBA system enhanced students' programming abilities (Cárdenas-Cobo et al., 2020). Some studies have shown that artificial intelligence technology does not improve students' learning outcomes. For instance, a study by Calvo-Ferrer examined the effects of intelligent educational games on vocabulary acquisition and perceived learning gains. The results indicated that these games had no impact on students' learning outcomes. The author suggested that these games might overly excite students and distract them from educational content (Calvo-Ferrer, 2017). Similarly, Zheng et al. compared the effects of a virtual class using an intelligent program and a traditional class on learning outcomes. The results revealed no significant difference between the two types of classes (Zheng et al., 2021). Overall, research on the relationship between artificial intelligence and learning outcomes is extensive but contentious. Neglecting other factors like self-efficacy, learning attitudes, and behaviors might contribute to these controversies (Sukestiyarno et al., 2021).

The learning outcomes refers to the changes in learners' knowledge, skills, values, and emotions that occur after learning activities. It is mainly evaluated based on indicators such as academic performance, learning ability, satisfaction, and interest (Zhang, 2023). The influencing factors mainly include the following aspects: Firstly, self-efficacy. Aluthman developed an automated essay evaluation (AEE) system that provides instant assessment, feedback, and automated scoring for students in online English learning environments. The results showed that the immediate assessment and feedback from the AEE system can enhance students' self-efficacy, making them more willing to face challenges and believe in their own success, which has a positive effect on writing performance (Aluthman, 2016). Secondly, learning attitude. Ijaz et al. created a virtual reality (VR) tool that applies artificial intelligence technology to history learning. The virtual reality tool immerses students in a virtual city environment, where they learn through browsing and interacting with virtual citizens. The results confirm that compared to simply reading history textbooks or watching educational videos, this artificial intelligence-based virtual learning mode is easier for students to develop a positive learning attitude and good learning behavior, which leads to better learning performance (Ijaz, 2017). Thirdly, learning behavior. Hsiao et al.'s research showed that students with higher frequencies of online learning behavior tend to have higher academic performance, and students' online learning behavior has a positive impact on future learning outcomes (Hsiao et al., 2019). In conclusion, the application of

artificial intelligence technology can help us evaluate and improve learning effects. One possible pathway to improving learning effects is that timely feedback and assessment technologies provided by artificial intelligence contribute to enhancing students' self-efficacy. Students with high self-efficacy are more willing to face challenges and believe in their ability to succeed, which leads to adopting positive learning attitudes and good learning behavior, ultimately improving learning effects. Therefore, by integrating the evidence from the above empirical studies, this study proposes the following research hypotheses:

H1: There is a positive correlation between students' self-efficacy and learning effects under artificial intelligence technology.

H2: Students' learning attitude mediates the relationship between self-efficacy and learning effects under artificial intelligence technology.

H3: Students' learning behavior mediates the relationship between self-efficacy and learning effects under artificial intelligence technology.

H4: Students' self-efficacy has an indirect effect on learning effects through the parallel mediation of learning attitude and learning behavior under artificial intelligence technology.

2. Research Design

With the outbreak of COVID-19, online learning systems were widely used, and AI technology exert unprecedented impact on students' learning performance (Khan & Jawaid, 2020). However, when comparing the effect of virtual classes and traditional classes on learning performance, Zheng et al. found no significant difference between them (Zheng et al., 2021). So, there is controversy in the research results that AI technology will influence learning outcomes. It may be primarily due to the oversight of other factors, such as self-efficacy, learning attitudes, and learning behaviors (Sukestiyarno et al., 2021). Therefore, based on the deficiencies in previous researches, this study aims to investigate and discuss the influence of self-efficacy, learning attitudes, and learning behaviors of students in Chinese higher education institutions on their learning performance based on artificial intelligence technology.

2.1. Sampling method

This study used convenience sampling method to select students from five universities in the provinces of Henan, Jiangsu and Shanxi in China as a survey sample to investigate the actual situation of students' self-efficacy, learning attitudes, learning behaviors, and learning effects in the context of artificial intelligence technology application. After obtaining verbal informed consent from the students, the main test used the same instructions and distribution process, asking the subjects to carefully read and fill out the questionnaire as required. A total of 1950 questionnaires are distributed and collected. After excluding invalid questionnaires with excessively short response time and unreasonable answers, 1865 valid questionnaires remain (with an effective rate of 95.64%). Among the participants, there are 479 males and 1386 females, with an average age ranging from 18 to 25 years old ($M_{age} = 20.04 \pm 1.48$ years). Since all of the universities participants are from are the second batch of normal universities for students to apply to, the total data of females is more than males. In subsequent analyses, we will further examine the impact of gender ratio differences on the study. For detailed information on other variables related to the participants, please refer to Table 1.

Table 1. Other variables associated with subjects

Variable	Category	Frequency	Percentage
Gender	Man	479	25.70%
	Female	1386	74.30%
Nation	the Han nationality	1740	93.30%
	Other	125	6.70%

Grade	Freshman	832	44.60%
	Sophomore	636	34.10%
	Junior	191	10.20%
	Senior	206	11.00%
Subject	Natural science	194	10.40%
	Medical science	6	0.30%
	Agricultural science	52	2.80%
	Humanities and society	1064	57.10%
Origin of student	Engineering and technology	549	29.40%
	East	1670	89.50%
	Midland	132	7.10%
	West	62	3.30%
	Country	1223	65.60%
	Towns and villages	321	17.20%
	City	321	17.20%

2.2. assessment tools

In this study, the Self-Efficacy Scale developed by Peng Huamao (Peng Huamao, 2016) the Learning Attitude Scale, Learning Behavior Scale, and Learning Outcome Scale developed by Wang Gaihua are used as a testing tool (Wang Gaihua, 2020). The whole questionnaire is divided into four parts, totaling 47 items. In it, demographic questions include five items: gender, ethnicity, grade, major, and students' origin. The Self-Efficacy Scale consisted of two dimensions: general self-efficacy and specific self-efficacy. The Learning Attitude Scale contained 10 items. The Learning Behavior Scale consisted of 24 items, organized into five dimensions: learning participation, learning perseverance, learning focus, learning interaction, and learning flexibility. The Learning Outcome Scale includes 12 items. Except for demographic questions, all items were rated on Likert scale ("1" = strongly disagree, "5" = strongly agree). The higher the score, the better the performance.

The scales used in this study have good reliability and validity. The overall internal consistency coefficient of the Self-Efficacy Scale is 0.889, with internal consistency coefficients of 0.865 and 0.877 for general self-efficacy and specific self-efficacy dimensions, respectively. The Learning Attitude, Learning Behavior, and Learning Effectiveness Scales were adapted from previous studies by Wang Gaihua et al. The original internal consistency coefficient of the Learning Attitude Scale was 0.934, which was 0.924 in this study. The original internal consistency coefficient of the Learning Behavior Scale was 0.912, with internal consistency coefficients ranging from 0.754 to 0.880 for each sub-dimension. In this study, the internal consistency coefficient was 0.931, with internal consistency coefficients ranging from 0.832 to 0.893 for each sub-dimension. The original internal consistency coefficient of the Learning Effectiveness Scale was 0.935, which was 0.937 in this study.

2.3. Model

Based on the hypothesis of this study, this study builds the theoretical hypothesis model (Figure 5). The hypothesis points out that under the background of artificial intelligence education, the self-efficacy of university students affects learning outcomes through the parallel mediating effects of learning attitudes and learning behaviors. In other words, students with high self-efficacy believe in their ability to have better learning outcomes, and then stimulate positive learning attitudes, adopting proactive learning behaviors, such as active participation in classroom activities, setting reasonable learning goals, and engaging in active review and practice. Ultimately, these positive attitudes and behaviors lead to good learning outcomes and higher academic achievements.

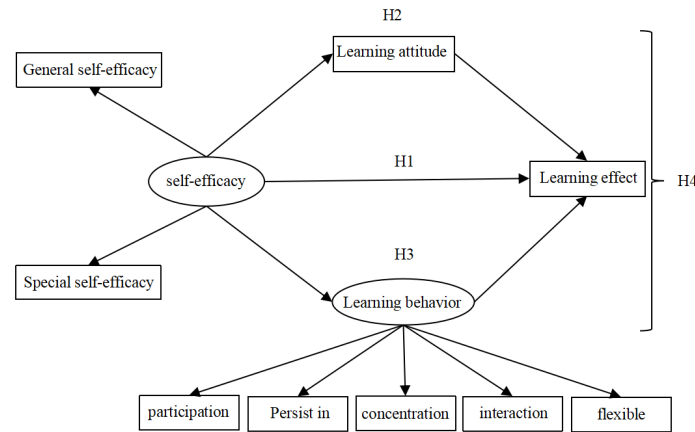


Fig. 5: Model of the mediating role of learning attitudes and learning behaviors between self-efficacy and learning outcomes

2.4. Statistical analysis

In this study, SPSS 25.0 and Mplus 8.3 software are utilized for data entry, organization, and correlation analysis, as well as model fitting and path analysis. The research discusses the impact of self-efficacy on learning outcomes, as well as the mediating roles of learning attitudes and learning behaviors. At the same time, it analyzes results integrated data and summarizes the research findings in the report.

2.5. Common methods bias test

This study collects data by self-report questionnaire, which might be affected by common method bias. To soften its potential influence, some procedural controls, such as emphasizing anonymity and confidentiality, are applied during the data collection process. In addition, Harman single-factor test is conducted in the subsequent data analysis to judge the presence of common method bias issues (Zhou Hao & Long Lirong, 2004). The result shows that the explaining rate of the first factor is 12.94%, which is well below the critical standard of 40% (Podsakoff et al., 2003). Therefore, there is no common method bias in this study.

3. Analysis of Research Results

3.1. Reliability analysis

This study tests the internal consistency using Cronbach's Alpha, and the results are presented in Table 2. The Cronbach's Alpha from all variables in the questionnaire exceeded 0.88, indicating high overall reliability.

Table 2. Reliability analysis

	Cronbach's Alpha	Items No.
Self-efficacy	0.889	11
Learning attitude	0.924	10
Learning behavior	0.931	24
Learning effect	0.937	12

3.2. Correlation analysis

The means, standard deviations, and correlations for each variable are presented in Table 3. Gender shows a significant negative correlation with age ($r = -0.09, p < 0.01$). Age does not show any significant correlations with self-efficacy, learning attitudes, learning behaviors, or learning outcomes. Significant positive correlations are found among self-efficacy, learning attitudes, learning behaviors, and learning outcomes ($r = 0.34\sim 0.58, ps < 0.001$).

Table 3. Results of descriptive statistics and correlation analysis of variables (n = 2989)

变量	M	SD	1	2	3	4	5	6
1. Gender	1.74	0.44	1					
2. Age	20.04	1.48	-.088**	1				
3. Self-efficacy	39.66	6.15	.034	-.040	1			
4. Learning attitude	36.58	5.94	.013	.030	.469**	1		
5. Learning behavior	87.78	12.04	.028	.003	.512**	.583**	1	
6. Learning effect	43.14	7.72	-.005	-.014	.340**	.425**	.421**	1

Note: ***p < 0.001, **p < 0.01, *p < 0.05, same below.

3.3. Detection of mediating effects

Based on the descriptive statistical analysis, this study establishes a structural equation model to examine the mediating roles of learning attitudes and behaviors in the relationship between self-efficacy and learning outcomes utilizing Bootstrap(with 5000 times replicated samplings and 95% confidence intervals). The model demonstrates good fitting: $\chi^2/df = 5.292$, CFI=0.981, TLI = 0.972, RMSEA = 0.048, SRMR = 0.024. The standardized path analysis results reveal that self-efficacy can positively predict university students' learning attitudes ($\beta = 0.71$, $p < 0.001$), and learning attitudes, in turn, can positively predict students' learning outcomes ($\beta = 0.16$, $p < 0.001$). This indicates that higher self-efficacy levels among university students can lead to better learning attitudes and better attitudes results in higher learning outcomes. Additionally, self-efficacy can predict students' learning behaviors significantly and positively($\beta = 0.83$, $p < 0.001$), and learning behaviors can positively predict students' learning outcomes ($\beta = 0.18$, $p < 0.01$). All of these suggest that higher self-efficacy among students can lead to better learning behaviors which contribute to better learning outcomes. Furthermore, self-efficacy also has a positive predictive effect on students' learning outcomes significantly ($\beta = 0.22$, $p < 0.05$).

The results of the detection indicate that between self-efficacy and learning outcomes, the mediation effect of learning attitudes is 0.11, $p < 0.001$, with 95% confidence interval of [0.052, 0.164], confirming it is significant. Also, between self-efficacy and learning outcomes, the mediation effect of learning behaviors is 0.15, $p < 0.01$, with a 95% confidence interval of [0.033, 0.253], indicating a mediating effect. The mediation effect as a proportion of the total effect is $0.260 / (0.260 + 0.220) = 54.17\%$.

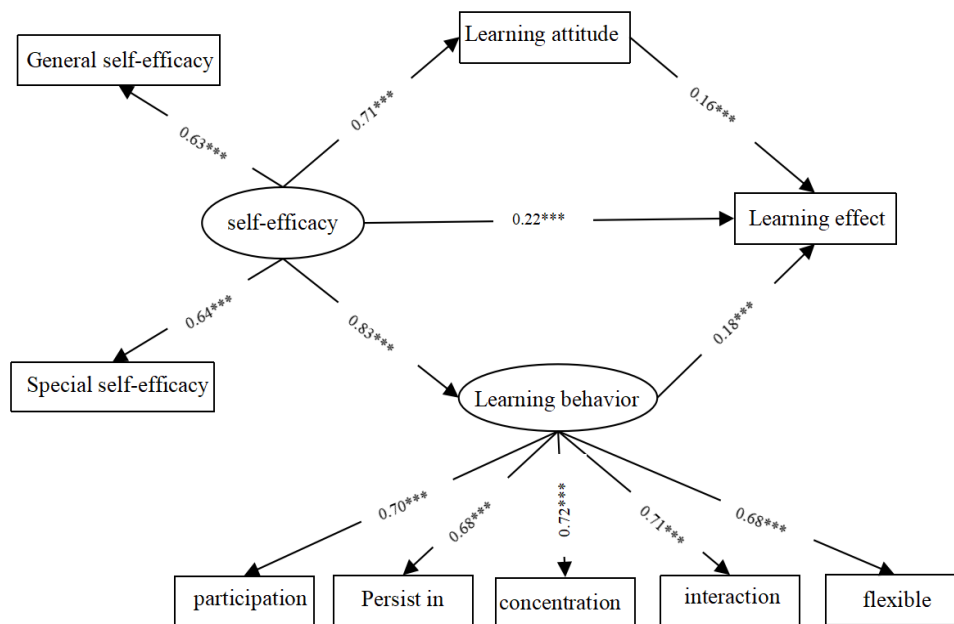


Fig.6: Analytical model of the mediating role of learning attitudes and learning behaviors between self-efficacy and learning effect

On the basis of descriptive statistical analysis, mediation effect tests were conducted separately using bias-corrected percentile Bootstrap (repeated sampling 5000 times) (Table 4). The results showed that the mediating effect value of learning attitude between self-efficacy and learning effectiveness was 0.11, $p < 0.001$, with a confidence interval of [0.20, 0.62], so the mediating effect of learning attitude between self-efficacy and learning effectiveness of college students was significant. The mediating effect of learning behavior between self-efficacy and learning effectiveness was 0.15, $p < 0.001$, with a confidence interval of [0.13, 0.94], thus learning behavior plays a mediating role between self-efficacy and learning effectiveness. Finally, the value of the parallel mediating effect of self-efficacy and learning effectiveness through learning attitude and learning behavior was 0.26, $p < 0.001$, with a confidence interval of [0.42, 1.48], so learning attitude and learning behavior play a parallel mediating role between self-efficacy and learning effectiveness of college students, and the ratio of its mediating effect to the total effect was $0.26 / (0.26 + 0.22) = 54.2\%$, the mediating effect of learning attitude is $0.11 / (0.11 + 0.22) = 33.3\%$, and the mediating effect of learning behavior is $0.15 / (0.15 + 0.22) = 40.5\%$ of the total effect.

Table 4. Mediation effects and 95% confidence intervals estimated by the Bootstrap approach

Model path Effect	Standardized estimates of indirect effects	95% CI	
		LLCI	ULCI
self-efficacy→Learning attitude→Learning effect	0.11	0.20	0.62
self-efficacy→Learning behavior→Learning effect	0.15	0.13	0.94
self-efficacy→Learning attitude→Learning behavior→Learning effect	0.26	0.42	1.48

4. Conclusions

This study’s proposed model elucidates important factors shaping students’ learning performance

when utilizing AI technologies in higher education. The results indicated self-efficacy has indirect positive effects on learning outcomes through its influence on students' learning attitudes and behaviors. This expands theoretical understanding of determinants of academic achievement in technology-enhanced learning environments.

The findings suggest educators should foster students' self-efficacy along with facilitating positive learning attitudes and productive behaviors to optimize outcomes. AI systems could be designed to provide personalized feedback to strengthen self-efficacy. The limitations of the study including the sample and self-report measures are acknowledged. Future research should validate the model across diverse contexts. Overall, this research takes initial steps toward unraveling the complex interplay of individual differences and AI-enabled education. Firstly, artificial intelligence brings great changes to education and learning (Guilherme, 2019). Through intelligent education platforms, students will have personalized learning plans, and they will be provided with teaching resources and guidance based on their learning situations and needs. Secondly, artificial intelligence promotes educational equity (El-Bishouty et al., 2019) and enhances teaching quality (Tan, 2020). Additionally, AI assists teachers in managing and organizing teaching resources, improving classroom efficiency and interactivity, tracking students' learning progress, and providing feedback, thus enhancing students' self-efficacy (Osetskyi et al., 2020). In summary, the application of artificial intelligence technology in the educational field has a positive impact on teaching quality and effectiveness, leading to innovations in teaching methods. We should continue to promote the integration of AI technology and education, providing students with high-quality, personalized educational resources and services, thus contributing to the development of the education sector as a whole.

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