Original Research Article

The impact mechanism of generative AI-assisted learning on college students' deep learning: The mediating role of learning flow

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Abstract: Against the backdrop of the digital transformation of higher education, generative artificial intelligence (AI) has become an important support for college students' autonomous learning. Based on flow theory and deep learning theory, this study constructed a theoretical model of "generative AI-assisted learning—Learning flow—Deep learning" and conducted an empirical analysis on 426 undergraduate students. The results showed that generative AI-assisted learning significantly and positively predicted college students' deep learning; learning flow played a significant partial mediating role between them, accounting for 37.9% of the total effect. Generative AI can not only directly promote deep learning but also indirectly improve learning quality by activating learning flow. This study reveals the psychological path through which intelligent technology empowers deep learning, providing references for universities to optimize smart learning environments.
Keywords: generative artificial intelligence; deep learning; learning flow; mediating role; college students

1. Introduction

With the rapid popularization of large model technology, generative AI has been fully integrated into college students' learning processes such as knowledge exploration, assignment completion, and research projects, leveraging its advantages in natural interaction, content generation, and personalized adaptation. As a high-order learning form, deep learning emphasizes critical understanding, knowledge integration, and transferable application, serving as the core goal of undergraduate talent cultivation. Current research mainly focuses on the direct impact of AI on learning outcomes, with insufficient analysis of the transmission chain of "technology use—Psychological experience—Deep learning" from a psychological mechanism perspective. Flow, as a positive psychological state characterized by intense engagement and absorption, has formation conditions highly consistent with the functional features of generative AI and is closely related to the sustained engagement required for deep learning[1].

Based on this, this study takes learning flow as a mediating variable to systematically explore the impact mechanism of generative AI-assisted learning on college students' deep learning, clarifying the key role of psychological paths in technology-enabled learning. It aims to provide theoretical basis and practical solutions for universities to scientifically promote the educational application of generative AI and facilitate the occurrence of deep learning.

2. Theoretical basis and research hypotheses

2.1. Definition of core concepts

Generative AI-assisted learning refers to college students using tools such as DeepSeek and ERNIE Bot to conduct knowledge inquiry, idea development, simulation exercises, and reflective optimization. It features real-time feedback, personalized adaptation, and situational immersion, which can reduce cognitive load and enhance learning autonomy.

Deep learning is a learning method where students critically absorb new knowledge, integrate cognitive structures, and transfer skills to solve complex problems on the basis of understanding. It includes three dimensions: Knowledge integration, critical thinking, and transferable application, distinguishing itself from rote memorization as a high-order learning form[2].

Proposed by Mihaly Csikszentmihalyi, learning flow is a psychological state of focused engagement and integration of action and consciousness when individuals face clear goals, receive immediate feedback, and experience a balance between challenges and skills. It can effectively enhance intrinsic motivation and concentration, serving as a key psychological condition for promoting deep learning.

2.2. Research hypotheses

Generative AI reduces cognitive barriers through real-time feedback, improves learning efficiency via personalized adaptation, and stimulates active construction through situational immersion, directly promoting knowledge integration and transferable application. Therefore, the following hypothesis is proposed: H1: Generative AI-assisted learning has a significant positive predictive effect on college students' deep learning.

The real-time feedback, clear goals, and dynamic difficulty adjustment provided by generative AI align with the core conditions for flow generation, effectively enhancing concentration and engagement[3]. Thus: H2: Generative AI-assisted learning has a significant positive predictive effect on college students' learning flow.

The high concentration and intrinsic motivation brought by flow encourage students to actively engage in deep processing and meaning construction, acting as a psychological bridge connecting AI use and deep learning. Hence: H3: Learning flow plays a mediating role between generative AI-assisted learning and deep learning.

3. Research design

3.1. Research objects

Using stratified cluster sampling, college students from 3 undergraduate universities in Shanxi Province were selected. A total of 472 questionnaires were distributed, with 426 valid responses recovered, resulting in an effective recovery rate of 90.3%. Among the respondents, 189 were male and 237 were female; 165 were liberal arts students, 182 were science and engineering students, and 79 were art students; 112 were freshmen, 108 were sophomores, 125 were juniors, and 81 were seniors, with a balanced sample distribution.

3.2. Research instruments

All scales adopted a 5-point Likert scoring system. The Generative AI-Assisted Learning Scale was adapted from Ma et al., including 3 dimensions (real-time feedback, personalized adaptation, situational immersion) with 12 items, and a Cronbach's α coefficient of 0.872. The Learning Flow Scale used the revised version by Shao, consisting of 3 dimensions (focused engagement, action fusion, autonomous control) with 9 items, and a Cronbach's α coefficient of 0.856. The Deep Learning Scale was adapted from Han[4], covering 3 dimensions (knowledge integration, critical thinking, transferable application) with 10 items, and a Cronbach's α coefficient of 0.881.

3.3. Data processing

SPSS 26.0 was used for common method bias test, descriptive statistics, and correlation analysis. AMOS 24.0 was employed for confirmatory factor analysis, and the Bootstrap method (5,000 samplings) was applied to test the mediating effect.

4. Empirical results and analysis

4.1. Common method bias test

The Harman's single-factor test was conducted. Exploratory factor analysis without rotation showed that the variance explained by the first common factor was 18.64%, lower than the critical value of 40%, indicating no severe common method bias.

4.2. Reliability and validity tests

The Cronbach's α coefficients of all scales exceeded 0.8, and the composite reliability and average variance extracted met the standards. The results of confirmatory factor analysis were: $\chi^2/df=2.314$, RMSEA=0.058, CFI=0.936, TLI=0.917, indicating a good model fit and satisfactory reliability and validity in line with academic standards.

4.3. Descriptive statistics and correlation analysis

The mean values of all variables ranged from 3.56 to 3.71, showing a medium to high level. Correlation analysis revealed that generative AI-assisted learning was significantly positively correlated with learning flow (r=0.582**) and deep learning (r=0.615**); learning flow was significantly positively correlated with deep learning (r=0.653**), laying the foundation for mediating effect testing.

Table 1. Means, standard deviations, and correlation coefficient matrix of variables.

Variables	Mean	Standard Deviation	1	2	3
1. Generative AI-Assisted Learning	3.56	0.59	1		
2. Learning Flow	3.62	0.57	0.582**	1	
3. Deep Learning	3.71	0.54	0.615**	0.653**	1

Note: **p<0.01.

4.4. Mediating effect test

Bootstrap test results showed that the total effect of 0.525 was significant; the direct effect of AI on deep learning (0.326) and the indirect effect (0.199) were both significant, with 95% confidence intervals excluding 0. Learning flow played a partial mediating role, accounting for 37.9% of the total effect, confirming H1, H2, and H3.

Table 2. Results of mediating effect test.

Path	Effect Value	Standard Error	95% Confidence Interval	Effect Type
AI→Deep Learning	0.326	0.051	[0.231, 0.415]	Direct Effect
AI→Flow→Deep Learning	0.199	0.036	[0.145, 0.262]	Indirect Effect
Total Effect	0.525	0.054	[0.423, 0.618]	Total Effect

5. Interpretation of the impact mechanism

The impact of generative AI-assisted learning on deep learning is jointly achieved through direct driving and mediating transmission.

The direct impact is reflected in the systematic optimization of the learning process through technological empowerment. Real-time feedback helps students quickly correct cognitive biases, avoiding stagnation at the shallow understanding stage; personalized adaptation matches learning rhythm and ability levels, reducing cognitive load; situational immersion stimulates inquiry motivation, promoting knowledge transfer and problem-solving, directly acting on the core dimensions of deep learning[5].

The mediating impact manifests as the psychological activation effect of learning flow. The interactive design of generative AI meets the conditions for flow generation, enabling students to enter a state of focused engagement. In flow, with highly concentrated attention and fully activated intrinsic motivation, students actively engage in deep processing and meaning construction, transforming technical support into stable deep learning qualities and completing the transmission of "technical support—Psychological activation—Learning upgrading."

Overall, the impact of generative AI on deep learning is the result of the synergistic drive of technological tool empowerment and positive psychological experience. The direct effect highlights the value of tools, while the indirect effect emphasizes psychological value. Together, they form a stable mechanism of "technical adaptation—Flow activation—Deep learning," revealing the inherent laws of intelligent technology empowering higher education.

6. Conclusions and educational recommendations

6.1. Research conclusions

This study draws three main conclusions through empirical analysis. First, generative AI-assisted learning can significantly and positively predict college students' deep learning, and the rational use of intelligent technologies contributes to the occurrence of higher-order learning. Second, generative AI-assisted learning can significantly improve college students' learning flow experience, as its interactive characteristics are highly consistent with the conditions for flow emergence. Third, learning flow plays a significant partial mediating role between generative AI-assisted learning and deep learning, with approximately 37.9% of the effect mediated by flow. The findings reveal the internal mechanism of generative AI in influencing deep learning and provide empirical evidence for the empowerment of higher education by intelligent technologies.

6.2. Educational recommendations

First, optimize the design of generative AI learning tools and strengthen flow-oriented functions. Focus on real-time feedback, personalized pathways, and situational inquiry, and reasonably set difficulty gradients to prevent tools from becoming mere answer generators.

Second, strengthen flow-oriented learning guidance and improve focused engagement capabilities. Teachers should clarify learning goals, design stepwise tasks, and provide process feedback to guide students in maintaining reflection during AI-assisted learning and avoiding shallow dependence.

Third, enhance college students' AI learning literacy and strengthen critical thinking. Offer relevant guidance courses to help students use AI as an inquiry tool, distinguish information, conduct independent reasoning, and uphold critical thinking and innovative awareness.

Fourth, construct a synergistic ecology of technology—Psychology—Teaching. Integrate generative AI into the entire teaching process, combining flow stimulation strategies with deep learning goals to form a trinity support system, promoting students' transition from shallow learning to deep learning.

7. Research limitations and prospects

This study has limitations: the sample is concentrated in universities in Shanxi Province, with limited geographical coverage; only the mediating role of learning flow was examined, without including moderating variables such as major and learning style. Future research can expand the sample scope, introduce moderating variables to construct a more comprehensive model, and conduct longitudinal tracking studies to reveal the long-term impact of generative AI on deep learning, providing more solid support for the digital transformation of higher education.

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