Research on the Impact of Artificial Intelligence-Assisted Learning Environments on Students' Learning Motivation

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Abstract. This article, based on the Self-Determination Theory, uses questionnaire surveys, behavioral log analysis, and semi-structured interviews to study the impact of AI-assisted learning environments on intrinsic motivation, extrinsic motivation, and amotivation levels. The study employed an AI system based on adaptive learning algorithms, which can analyze students' learning behaviors and mastery of knowledge points in real-time, generating personalized learning paths, providing immediate feedback, and presenting multimodal resources. The experimental results indicate that the AI system significantly enhances the level of learning motivation, while also improving learning efficiency, task completion rates, and knowledge retention rates.

Keywords: Artificial Intelligence; Learning Motivation; Educational Innovation

1 Introduction

Artificial intelligence (AI)-assisted learning environments, with their powerful data processing capabilities and adaptive learning features, provide precise learning support for students. However, learning motivation, as a core factor affecting students' learning performance and sustained learning ability, requires further study regarding its change mechanisms within AI environments. Based on Self-Determination Theory, this paper combines quantitative analysis and behavioral tracking data to explore how AI-assisted learning environments affect students' intrinsic motivation, extrinsic motivation, and amotivation levels, offering theoretical support and practical references for the design and optimization of intelligent education systems. Nevertheless, AI-assisted learning environments face challenges in terms of fairness and accessibility, including uneven resource allocation, technological disparities, and differences in students' digital skills, which may prevent some students from fully benefiting. The applicability and effectiveness of AI learning environments may have inherent limitations across different educational levels and social contexts.

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2 The Impact of AI-Assisted Learning Environments

2.1 Increased Learning Motivation

AI-assisted learning environments effectively enhance students' motivation to learn through personalized learning, immediate feedback, and interactive experiences. AI utilizes deep learning algorithms to analyze students' learning habits, mastery of knowledge points, and behavioral patterns, generating targeted learning paths and resource matching to better meet individual student needs and stimulate their interest and initiative in learning [1]. AI systems can provide real-time data monitoring, offering specific learning suggestions and result analysis to students, helping them understand their current learning status. Through real-time encouragement, these systems can enhance students' sense of achievement and form a positive motivational loop. Interactive experiences increase the fun and immersion of learning.

2.2 Improved Learning Outcomes

AI systems can dynamically analyze students' learning behaviors and knowledge mastery, customizing personalized learning paths and avoiding ineffective learning phenomena common in traditional teaching. The theoretical relationship of this effect can be described by the mathematical model (1):

$$LM = \alpha \cdot IM + \beta \cdot EM + \gamma \cdot F \tag{1}$$

LM represents the overall level of learning motivation, IM is intrinsic motivation, EM is extrinsic motivation, and F is the intensity of feedback provided by the AI environment. α, β, γ are weight coefficients that reflect the impact of each factor on learning motivation.

During the learning process, the system provides real-time analysis of correctness and suggestions for improvement based on students' responses and task completion. Artificial intelligence optimizes the allocation of learning resources and helps students understand complex abstract concepts more intuitively through multimodal presentation methods [2]. In STEM courses, AI-driven experimental simulations can provide students with a learning experience close to real situations, enhancing the ability to apply knowledge.

2.3 Enhanced Interactivity

Artificial intelligence systems have achieved personalized interactive communication, enhancing the learning experience for students. Based on natural language processing technology, AI can engage in real-time conversations with students, answering questions, providing learning advice, and even offering emotional support. AI-driven intelligent tutoring systems can adjust the depth of responses based on students' questions and help students understand complex knowledge points more easily through voice and text interaction [3]. This flexible interaction replaces the time and space constraints of traditional teacher-student communication, making the learning process more humanized. The AI-enhanced real-time feedback mechanism further increases interactivity during learning. AI can generate feedback immediately after students' operations or answers, motivating them to continue participating in learning. In mathematics learning, AI systems can analyze students' problem-solving steps, point out problems in real-time, and provide specific suggestions for improvement [4].

3 Research Design

3.1 Research Methodology

The research employs a questionnaire survey method, designing a questionnaire that includes a learning motivation scale and user experience evaluation to collect and statistically analyze students' learning behavior data [5]. The subjects of the study are 150 students from middle schools and universities, with an experimental period of 8 weeks. In-depth semi-structured interviews are conducted to understand students' subjective feelings and motivational changes during the use of AI-assisted learning environments, while experimental log data analysis is used to track students' behavioral trajectories on the learning platform. The above methods are used to comprehensively evaluate the actual effect of AI on enhancing learning motivation and its mechanism of action.

3.2 Participants and Sample Selection

The research participants included 150 students from middle schools and colleges, with the sample distribution covering three stages: junior high, high school, and university. To enhance the general applicability of the research results, the sample considered the educational background and socioeconomic conditions of the participants, including students from urban, rural, and marginalized areas. The sample included students from regions with relatively abundant educational resources as well as underdeveloped areas to assess the potential differences in AI learning environments across different backgrounds. Stratified random sampling was used for sample selection, stratifying based on factors such as gender, grade level, and academic performance to ensure the comprehensiveness and balance of the data. Participants were required to have basic computer operation skills and no significant changes in their learning environment in the past year, to exclude external interference factors. All participants signed informed consent forms to ensure the ethical compliance of the study.

3.3 Data Collection

Three methods are used to collect data: questionnaire survey, behavioral log analysis, and semi-structured interviews, to comprehensively assess the impact of AI-assisted learning environments on students' learning motivation [6]. The learning motivation scale (based on self-determination theory) is used to collect students' intrinsic motivation, extrinsic motivation, and amotivation scores. The questionnaire is conducted once before and once after the experiment to obtain data on changes in motivation. Quantitative data such as learning duration, task completion rate, feedback response time, and error correction frequency are collected from the AI learning platform's behavior logs to analyze learning behavior characteristics and their association with motivation. Fifteen students are selected for interviews to obtain detailed descriptions of their subjective experiences and the impact of motivation in AI learning environments.

4 Results Analysis and Discussion

4.1 Experimental Results

The experiment utilized a learning motivation scale based on the Self-Determination Theory to measure students' intrinsic motivation, extrinsic motivation, and amotivation levels before and after the experiment. The specific data are shown in Table 1:

Table 1. Learning Motivation Scores Comparison (Pre and Post Experiment)

Motivation Type	**Pre-Experiment Average Score**	**Post-Experiment Average Score**	**Improvement (%)**
Intrinsic Motivation	62.3	79.8	28.1
Extrinsic Motivation	68.5	81.2	18.6
Amotivation	21.4	12.7	-40.6

As can be seen from Table 1, intrinsic motivation scores increased from 62.3 to 79.8, a rise of 28.1%; extrinsic motivation scores went up from 68.5 to 81.2, an increase of 18.6%; while amotivation scores decreased by 40.6%, indicating that the AI learning environment significantly stimulated learning motivation. Interviews revealed that most students felt that personalized learning paths and immediate feedback enhanced their interest and sense of achievement in learning. A sophomore student stated, "AI tasks are both fun and match my level, and I feel a great sense of accomplishment with each task completed." Another graduate student mentioned that real-time progress analysis helped him plan his learning goals more clearly, significantly increasing his focus.[7].

To further analyze the correlation between changes in learning motivation and characteristics of learning behavior, the Pearson correlation coefficient was used for calculation:

$$r=\frac{\sum(X_i-\overline{X})\sum(Y_i-\overline{Y})}{\sqrt{\sum(X_i-\overline{X})^2\cdot\sum(Y_i-\overline{Y})^2}} \tag{2}$$

Xi is the value of the first variable, Yi is the value of the second variable, and the sum is the mean of X and Y. The Pearson correlation coefficient r is calculated through equation (2) to analyze the correlation between motivational changes and behavioral characteristics, with specific results shown in Table 2.

Table 2. Correlation Analysis of Motivation Changes and Learning Behavior Features

Variable Pair	Correlation Coefficient (r)	Significance Level (p-value)
Intrinsic Motivation - Study Time	0.67	< 0.01
Intrinsic Motivation - Task Completion Rate	0.72	< 0.01
Extrinsic Motivation - Error Corrections	-0.65	< 0.05
Extrinsic Motivation - Feedback Response Time	-0.58	< 0.05

The correlation between learning duration and intrinsic motivation is significantly positive ($r=0.67$, $p<0.01$), indicating that as intrinsic motivation increases, the average learning duration of students in the AI learning environment significantly increases [8]. This suggests that the AI environment, by providing personalized tasks and adaptive resources, motivates students to focus on learning for longer periods. The correlation coefficient between task completion rate and intrinsic motivation is $r=0.72$, indicating that the higher the intrinsic motivation, the higher the efficiency with which students complete tasks. The negative correlation between the number of error corrections and extrinsic motivation ($r=-0.65$, $p<0.05$) suggests that an increase in extrinsic motivation is accompanied by a decrease in the number of error corrections, indicating that the AI system reduces obstacles in the learning process through precise error diagnosis and immediate suggestions. The significant negative correlation between feedback response time and extrinsic motivation ($r=-0.58$, $p<0.05$) indicates that the response time required for students to complete tasks in the AI environment is shortened, reflecting that the feedback mechanism of the AI system enhances the smoothness of the learning process[9].

4.2 Performance Evaluation

Through the analysis of students' learning performance before and after the experiment, the AI-assisted learning environment significantly improved students' learning outcomes, efficiency, and engagement [9].

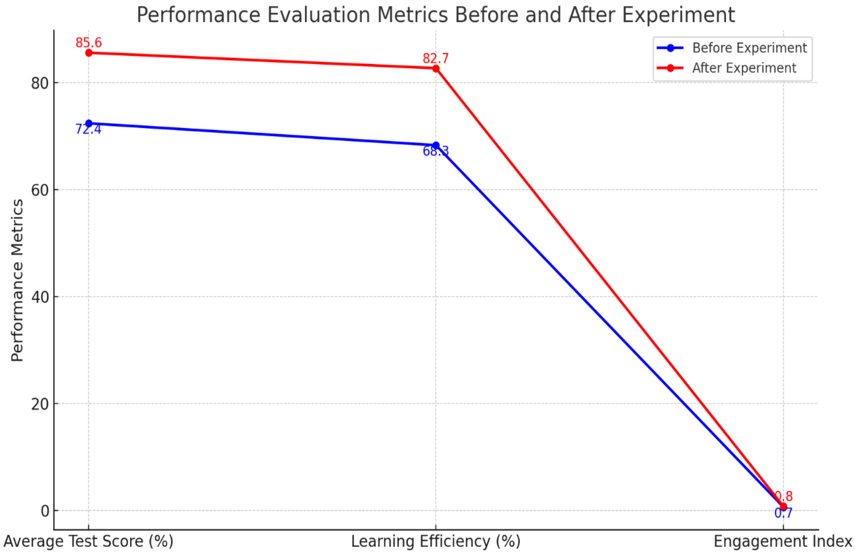

Fig. 1. Comparison of Student Performance Indicators Before and After the Experiment

As can be seen from Figure 1, the average test score of students increased from 72.4% before the experiment to 85.6%, an increase of 18.2%; learning efficiency increased from 68.3% to 82.7%, an increase of 21.1%; and the engagement index increased from 0.65 to 0.78, an increase of 20.0%, indicating that the AI-assisted learning environment has a significant promoting effect on students' learning outcomes.

The interview revealed that students with scarce educational resources feel unfamiliar with operating AI systems, often due to outdated equipment, unstable internet connections, or insufficient digital skills, leading to discomfort. A high school student from a rural area fell behind in learning because of lagging simulation functions; a university student experienced stress from frequent feedback, resulting in decreased interest and motivation. This indicates that disparities in educational resources and technological adaptability significantly affect the fairness of AI learning environments.

4.3 Application Effectiveness Evaluation

To comprehensively evaluate the application effectiveness of the AI-assisted learning environment, this study conducted a quantitative analysis from three key indicators: student satisfaction, knowledge retention rate, and task completion success rate, and displayed the changes in each indicator before and after the experiment through Figure 2.

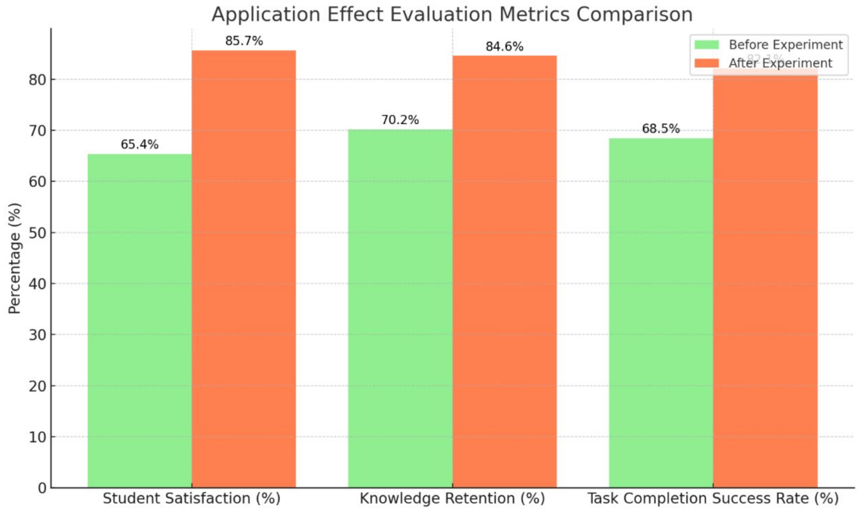

Fig. 2. Comparison of Application Effect Evaluation Indicators

Student satisfaction significantly increased from 65.4% to 85.7% after the experiment, with an increase of 31.0%. Interview results indicate that this improvement is mainly due to the personalized learning experience and immediate feedback mechanism provided by the AI learning environment. Knowledge retention rate increased from 70.2% before the experiment to 84.6%, with an increase of 20.6%. Through multimodal content presentation and personalized review functions, the AI learning environment significantly enhanced students' understanding and memory of knowledge. The success rate of task completion increased from 68.5% to 82.1%, with an increase of 19.9%. The AI system helped students complete learning tasks more accurately through immediate error analysis and feedback, reducing the occurrence of repetitive mistakes, indicating that the AI environment has significant advantages in optimizing the learning process and improving task completion efficiency.

5 Conclusion

Through quantitative analysis and experimental verification, this paper explores the impact of AI-assisted learning environments on students' learning motivation[10]. The results show that AI learning environments significantly enhance students' intrinsic and extrinsic motivation through personalized learning paths, immediate feedback mechanisms, and multimodal resource presentation. Data indicate that students' learning efficiency, test scores, and engagement have all significantly improved, and the improvement in task completion rate and knowledge retention rate further confirms the positive effect of AI environments on learning outcomes. Correlation analysis shows that there is a significant association between the improvement of motivation and the optimization of learning behaviors, particularly in enhancing learning duration and task completion efficiency.

References

1. Feng L .Investigating the Effects of Artificial Intelligence-Assisted Language Learning Strategies on Cognitive Load and Learning Outcomes: A Comparative Study[J].Journal of Educational Computing Research,2025,62(8):1961-1994.
2. Lee M ,Laureys S .Artificial intelligence and machine learning in disorders of consciousness.[J].Current opinion in neurology,2024,37(6):614-620.
3. Oluwaseyi A O ,Sumitha R ,Ling N C T , et al.Investigating student’s motivation and online learning engagement through the lens of self-determination theory[J].Journal of Applied Research in Higher Education,2024,16(5):2185-2198.
4. Hussain S ,Ahmad S ,Wasid M .Artificial intelligence-driven intelligent learning models for identification and prediction of cardioneurological disorders: A comprehensive study[J].Computers in Biology and Medicine,2025,184109342-109342.
5. Sameer A D ,Sunita J .Evolving needs of learners and role of artificial intelligence (AI) in training and development (T&D): T&D professionals' perspective[J].Journal of Management Development,2024,43(6):788-806.
6. Cohen R ,Katz I .Students’ academic competence beliefs as an antecedent of perceived teachers’ autonomy support and motivation: a longitudinal model[J].Current Psychology,2024,(prepublish):1-12.
7. Prakash S S ,Muthuraman N .Learning approaches, motivation, and specialty preference form a nexus: a cross-sectional study among preclinical medical students[J].Discover Education,2024,3(1):238-238.
8. Martin J A ,Bostwick P C K ,Durksen L T , et al.Teachers’ motivation to teach Aboriginal perspectives in the curriculum: links with their Aboriginal students’ academic motivation[J].The Australian Educational Researcher,2024,(prepublish):1-26.
9. Zehui Z ,Guoqing H ,Tingting L , et al.Effect of groups size on students' learning achievement, motivation, cognitive load, collaborative problem-solving quality, and in-class interaction in an introductory AI course[J].Journal of Computer Assisted Learning,2022,38(6):1807-1818.
10. Kang L .Determinants of College Students’ Actual Use of AI-Based Systems: An Extension of the Technology Acceptance Model[J].Sustainability,2023,15(6):5221-5221.