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ARTIFICIAL INTELLIGENCE IN THE CLASSROOM: EFFECTS ON MOTIVATION, SELF-EFFICACY, AND STUDENT ACHIEVEMENT

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Abstract: As artificial intelligence (AI) becomes increasingly embedded in educational settings, understanding its psychological and academic impacts on learners has become critical. This study investigates the effects of AI-assisted instruction on university students' learning motivation, self-efficacy, and academic performance. Adopting a quasi-experimental design, 120 undergraduates were divided into two groups: one received AI-supported instruction using an intelligent learning platform, while the other followed a traditional teacher-led approach. Participants completed standardized questionnaires assessing learning motivation and academic self-efficacy, and final course scores were used as performance indicators. Independent samples t-tests revealed that the AI-assisted group outperformed the traditional group across all outcome measures, with statistically significant improvements in motivation, self-efficacy, and academic achievement. Multiple regression analysis further showed that AI instruction, motivation, and self-efficacy were all significant predictors of learning outcomes, jointly explaining over 33% of the variance in final scores. These results highlight the psychological mechanisms through which AI can enhance student learning and suggest that AI technologies, when pedagogically aligned and psychologically supportive, can significantly improve both engagement and performance.
Keywords: Artificial Intelligence, Motivation, Academic Self-Efficacy, AI-Assisted Instruction

1. INTRODUCTION

In recent years, artificial intelligence (AI) has been increasingly adopted in educational settings to improve teaching efficiency, personalize learning experiences, and support administrative decision-making (Ahmad et al., 2022). Among these applications, AI-assisted instruction—particularly in the form of intelligent tutoring systems, automated feedback, and adaptive learning platforms—has emerged as a promising tool for enhancing student learning (Nguyen et al., 2024). With the rapid advancement of machine learning algorithms and natural language processing, AI systems are now capable of dynamically responding to learners' individual needs, adjusting instructional content in real time, and providing personalized feedback at scale. As such, AI is reshaping not only pedagogical methods but also the psychological processes that underpin effective learning (Yue et al., 2022).
While considerable attention has been paid to the technical performance of AI tools in education, less is known about their psychological and affective impacts on students (Shum & Luckin, 2019; Ali & Abdel-Haq, 2021). Specifically, the extent to which AI-assisted learning environments influence students' learning motivation and self-efficacy remains underexplored. Learning motivation refers to the internal drive that directs and sustains learning behaviors, while self-efficacy reflects a learner's belief in their capability to succeed in academic tasks. Both constructs are widely recognized as key predictors of academic performance and student engagement (Bandura, 1997; Pintrich & De Groot, 1990). As AI increasingly mediates the learning process, understanding its role in shaping these psychological outcomes becomes essential for evaluating its broader educational value.
Previous studies have demonstrated mixed results. Some research suggests that AI tools can enhance motivation and reduce anxiety by offering timely support and personalized feedback (Holstein et al., 2019), while others caution that overreliance on automation may diminish learners' agency or sense of competence (Luckin & Cukurova, 2019; Cukurova, 2025). Moreover, many existing studies emphasize learning outcomes (e.g., grades,

completion rates) without fully considering the psychological mechanisms that mediate these effects (Pedro et al., 2019). There is a clear need for empirical studies that examine how AI-based instruction influences not only what students learn, but how they feel and think during the learning process.
To address this gap, the present study investigates the effects of AI-assisted instruction on university students' learning motivation, self-efficacy, and academic performance. Adopting a quasi-experimental design, we compare students who received AI-supported teaching with those who experienced traditional instruction, and analyze both psychological and academic outcomes. By integrating cognitive psychology, educational technology, and quantitative evaluation, this study contributes to a more holistic understanding of AI's role in shaping effective learning environments. Our findings have implications for the design of intelligent instructional systems, the psychological support structures surrounding their implementation, and the future of AI-integrated pedagogy in higher education.

2. METHODS

This study employed a quasi-experimental to examine the effects of AI-assisted instruction on students' learning motivation, self-efficacy, and academic performance. Two instructional modes were compared: an experimental group that received AI-supported teaching and a control group that received traditional instruction. The independent variable was the type of instruction (AI-assisted vs. traditional), and the dependent variables were student learning motivation, self-efficacy, and learning outcomes. The design aimed to capture group-level differences while controlling for key demographic covariates.

2.1 Participants

Participants were undergraduate students (N = 120) enrolled in introductory courses at a public university in China. A convenience sampling strategy was adopted. Students were assigned to either the AI-assisted group (n = 60) or the traditional instruction group (n = 60), based on their class enrollment.
Demographic information including age, gender, major, and year of study was collected to ensure baseline comparability. Participants provided informed consent and were assured of the confidentiality and voluntary nature of their involvement.

2.2 Instruments

2.2.1 Learning Motivation

Learning motivation was measured using the Motivated Strategies for Learning Questionnaire (MSLQ), specifically the Motivation section (Pintrich et al., 1993). This subscale contains 31 items, rated on a 7-point Likert scale (1 = not at all true of me, 7 = very true of me). The instrument includes subdimensions such as intrinsic goal orientation, task value, and control of learning beliefs. The Cronbach's α in this study was 0.89, indicating high internal consistency.

2.2.2 Self-Efficacy

Academic self-efficacy was assessed using the General Academic Self-Efficacy Scale (Nielsen et al., 2018), consisting of 8 items on a 5-point Likert scale (1 = strongly disagree, 5 = strongly agree). The Cronbach's α in this study was 0.85.

2.2.3 Learning Outcomes

Learning performance was evaluated through students' final course scores, which were based on a combination of classroom assessments, assignments, and final exam results. Scores were standardized on a 100-point scale for comparative purposes.

2.3 Data Analysis

Data analysis was conducted using IBM SPSS (Version 28.0). Prior to hypothesis testing, descriptive statistics including means, standard deviations, skewness, and kurtosis were computed for all major variables to examine their distributional properties. Reliability coefficients (Cronbach's alpha) were also calculated to assess the internal consistency of each scale. No major violations of normality were observed, and all variables were deemed suitable for parametric analysis.
To examine group differences between the AI-assisted instruction group and the traditional instruction group, independent samples t-tests were employed on three dependent variables: learning motivation, self-efficacy, and final academic performance. These tests aimed to determine whether exposure to AI-based instruction significantly enhanced students' psychological and academic outcomes compared to conventional teaching.
In addition, one-way analysis of variance (ANOVA) was used to explore whether any demographic factors (e.g., gender, year of study) significantly affected the outcome variables. Where significant effects were found, post hoc analyses using Tukey's HSD were conducted to locate specific group differences.

3. RESULTS

3.1 Descriptive Data

Descriptive statistics were computed to summarize the central tendencies and dispersions of the main variables, including learning motivation, self-efficacy, and academic performance, for both the AI-assisted instruction group and the traditional instruction group. As shown in Table 1, students in the AI-assisted group reported higher mean scores across all three variables. Specifically, the average learning motivation score in the AI group was M = 5.63, SD = 0.71, compared to M = 5.21, SD = 0.69 in the traditional group. For self-efficacy, the AI group averaged M = 4.22, SD = 0.61, whereas the traditional group reported M = 3.87, SD = 0.59. Regarding academic performance, measured by final course grades, the AI-assisted group achieved a higher mean score (M = 84.6, SD = 6.3) compared to the traditional group (M = 78.9, SD = 6.9).

Table 1. Descriptive Statistics and Reliability Coefficients for Key Variables

Variable	Group	Mean (M)	SD	Cronbach's α
Learning Motivation	AI-assisted	5.63	0.71	0.89
	Traditional	5.21	0.69	0.88
Self-Efficacy	AI-assisted	3.22	0.61	0.85
	Traditional	3.07	0.59	0.84
Learning Outcomes	AI-assisted	84.6	6.3	—
	Traditional	78.9	6.9	—

3.2 Group Comparisons

To examine the effects of AI-assisted instruction on students' psychological and academic outcomes, independent samples t-tests were conducted to compare the AI-assisted group and the traditional instruction group on three key dependent variables: learning motivation, self-efficacy, and learning outcomes.

The results revealed statistically significant differences between the two groups across all measures. In terms of learning motivation, students in the AI-assisted group (M = 5.63, SD = 0.71) reported significantly higher motivation than those in the traditional group (M = 5.21, SD = 0.69), t(118) = 3.34, p = .001. The effect size, measured by Cohen's d, was 0.61, indicating a moderate practical impact. Similarly, for self-efficacy, the AI-assisted group (M = 4.22, SD = 0.61) outperformed the traditional instruction group (M = 3.87, SD = 0.59), with a statistically significant difference, t(118) = 3.01, p = .003, and a Cohen's d of 0.55, also reflecting a moderate effect size.

Most notably, there was a substantial difference in learning outcomes, as measured by final course scores. Students in the AI-assisted group achieved higher academic performance (M = 84.6, SD = 6.3) compared to those in the traditional group (M = 78.9, SD = 6.9). The difference was highly significant, t(118) = 4.67, p < .001, with a large effect size (d = 0.86). These findings suggest that AI-based instructional methods contribute not only to enhanced psychological factors such as motivation and self-efficacy, but also lead to measurable improvements in students' academic achievement.

Table 2. Group Differences in Learning Motivation, Self-Efficacy, and Learning Outcomes

Variable	*t*(df)	*p*	Cohen's *d*
Learning Motivation	3.34(118)	.001	0.61
Self-Efficacy	3.01(118)	.003	0.55
Learning Outcomes	4.67(118)	<.001	0.86

Note. AI-assisted group consistently outperformed the traditional group. All comparisons were statistically significant.

3.3 Regression Analysis

To further examine the extent to which instructional method and psychological factors predicted students' academic performance, a multiple linear regression analysis was conducted. In this model, learning outcomes (final course scores) served as the dependent variable, while AI-assisted instruction (dummy coded: 1 = AI, 0 = traditional), learning motivation, and self-efficacy were included as independent variables.

Preliminary checks confirmed that the assumptions of linearity, normality, homoscedasticity, and absence of multicollinearity were met. The overall regression model was statistically significant, F(3, 116) = 19.54, p < .001, accounting for 33.6% of the variance in learning outcomes (R^2 = .336). As displayed in Table 3, all three predictors made significant contributions to the model. AI-assisted instruction emerged as the strongest predictor of academic performance (B = 4.91, p < .001), suggesting that students who received AI-supported teaching scored approximately 4.91 points higher on average than those in the traditional group. Both learning motivation (B = 2.33, p = .003) and self-efficacy (B = 2.78, p = .007) were also positively associated with academic achievement, indicating that psychological engagement and self-belief play important roles in student success.

These findings underscore the importance of integrating intelligent technology into instructional design while also fostering students' psychological readiness to learn. The combined influence of technological and psychological predictors offers a compelling model for understanding academic outcomes in AI-enhanced learning environments.

Table 3. Multiple Regression Predicting Learning Outcomes

Predictor	B	SE	β	*t*	*p*

AI Instruction	4.91	1.12	.37	4.38	<.001
Learning Motivation	2.33	0.78	.26	2.99	.003
Self-Efficacy	2.78	1.01	.21	2.76	.007

4. DISCUSSION

This study investigated the effects of AI-assisted instruction on students' learning motivation, self-efficacy, and academic performance within a university-level classroom setting. The results demonstrated that students who experienced AI-supported teaching reported significantly higher levels of motivation and self-efficacy and achieved better academic outcomes compared to those who received traditional instruction. Furthermore, multiple regression analyses revealed that both psychological constructs, along with AI instruction, were significant predictors of academic achievement, explaining over one-third of the variance in final course performance (Marques et al., 2011; Freire & Ferreira, 2020). These findings provide empirical support for the educational value of integrating artificial intelligence into pedagogical practices, particularly when coupled with attention to learners' psychological readiness.

The results of this study contribute to the growing body of literature that highlights the role of technology-enhanced learning environments in shaping students' affective and cognitive outcomes. From a social cognitive theory perspective (Bandura, 1997), AI-assisted learning environments may increase students' self-efficacy by offering personalized feedback, scaffolding difficult content, and reducing uncertainty during complex tasks. Likewise, the observed increase in learning motivation aligns with the self-determination theory (Deci & Ryan, 1985), as AI tools can foster learners' perceived autonomy and competence through adaptive pathways and goal-directed learning recommendations.

Moreover, this study reinforces the argument that AI systems do not merely serve as content delivery tools, but also as psychological support mechanisms capable of enhancing students' self-belief and engagement (Buschmeyer et al., 2023; Lutfiani et al., 2025). This extends prior research which often treated AI as a neutral medium, by emphasizing the emotional and motivational dimensions that are intertwined with AI-human interaction in educational contexts.

From an educational management perspective, these findings have several practical implications. First, institutions seeking to implement AI in teaching should not only consider the technological infrastructure, but also the psychological scaffolding that supports learners' adaptation to AI-enhanced environments. AI systems that integrate features to boost motivation and self-efficacy (Shi & Zhang, 2025)—such as adaptive goal-setting, real-time encouragement, and progress visualization—may yield more substantial academic benefits. Second, teacher training programs should emphasize AI-human collaboration, helping educators understand how to leverage AI tools without fully delegating instructional authority (Xu et al., 2025). Hybrid teaching models, where human teachers maintain relational and emotional support while AI handles adaptive feedback and pacing, may provide optimal learning experiences.

5. CONCLUSION

This study provides empirical evidence that AI-assisted instruction significantly enhances university students' learning motivation, self-efficacy, and academic performance. Compared to traditional teaching methods, AI-supported environments offer a more adaptive and engaging learning experience, leading to better psychological preparedness and improved academic outcomes. The findings highlight the intertwined roles of technological design and learner psychology in shaping effective educational experiences in the era of artificial intelligence.

The practical implications are equally important. For educational leaders and policy makers, these findings suggest that investments in AI-based educational technology should be accompanied by frameworks that support learner motivation and self-efficacy development. Simply deploying AI platforms is insufficient—successful integration requires careful attention to student perception, psychological safety, and adaptive feedback design. Institutions should prioritize teacher training programs that emphasize human-AI collaboration, helping educators blend relational, human-centered pedagogy with the strengths of algorithmic adaptivity.

Furthermore, the study calls for ethical and equitable implementation of AI in education. As AI technologies become more prevalent, issues of access, fairness, and psychological readiness must be addressed. Policymakers should develop guidelines that ensure inclusive AI integration, especially in resource-constrained settings.

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