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AI Use and Learning Outcomes Among Undergraduate Students: The Mediating Role of Learning Motivation, Locus of Control, and Learning Preferences

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ABSTRACT

Background. The growing use of artificial intelligence (AI) in higher education has created new opportunities for personalized learning, although its contribution to student achievement remains theoretically and empirically contested.

Purpose. This study examined the direct and indirect effects of AI use on conceptual understanding and problem-solving ability through learning motivation, locus of control, and learning preferences.

Method. A quantitative explanatory design was employed with 88 pre-service teachers enrolled in an Instructional Media course at a teacher education institution in Central Java, Indonesia. Data were collected using validated questionnaires and cognitive assessments. Preliminary analyses were conducted using SPSS, while the measurement and structural models were evaluated through PLS-SEM with 5,000 bootstrap subsamples.

Novelty. This study simultaneously tested three psychological and learning-related mediators within a single structural model, thereby extending previous research that primarily examined the direct relationship between AI use and academic performance.

Results. AI use significantly predicted learning motivation and locus of control but did not significantly influence learning preferences. Learning motivation significantly predicted learning outcomes and mediated the relationship between AI use and learning outcomes. In contrast, locus of control and learning preferences showed no significant mediating effects. The direct effect of AI use on learning outcomes was also nonsignificant.

Conclusion. AI contributes to student learning primarily by strengthening learning motivation rather than through direct technological exposure. Effective AI integration should therefore emphasize reflective, autonomous, and cognitively engaging learning activities.

KEYWORDS : Artificial Intelligence; Conceptual Understanding; Learning Motivation; Learning Preferences; Locus Of Control; Problem-Solving Ability.

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INTRODUCTION

The emergence of generative artificial intelligence (AI) technology in recent years has triggered significant changes in the education sector globally. Since the launch of ChatGPT in late 2022, the use of generative AI has rapidly become a phenomenon that has not only captured public attention but also generated mixed reactions among

educational institutions worldwide This widespread adoption has outpaced regulatory and (Lim et al., 2023; Watson, 2025).

Institutional policy readiness: a UNESCO global survey of over 450 schools and universities found that fewer than 10% had formal policies or guidelines regarding the use of generative AI (Singh & Kaur, 2024; Symeou et al., 2025). This gap between the pace of technology adoption and governance readiness underscores that AI is no longer just a passing technological trend, but part of a fundamental transformation in how students learn and educational institutions operate worldwide.

This global phenomenon is similarly reflected within the higher education landscape in Indonesia, particularly in the Central Java region. Research conducted among students in Surakarta indicates that the integration of generative AI tools, such as ChatGPT and similar platforms, has become a routine component of students' academic endeavors, ranging from drafting assignments and preparing presentations to composing theses (Erwin et al., 2026; Monib et al., 2025; Rahman & Watanobe, 2023). Nevertheless, the same study also revealed a concerning shift in AI's function, evolving from a mere learning aid to a substitute for students' independent thought processes. This transformation carries the potential to diminish cognitive engagement and critical thinking abilities if its application is not adequately balanced with sufficient digital literacy and self-regulation (Faza & Lestari, 2025; Lazou & Tsinakos, 2023). These findings underscore that amidst the rapid adoption of AI by students in Central Java, individual student characteristics-such as learning motivation and self-regulation capabilities-emerge as crucial determinants influencing whether AI utilization positively impacts learning outcomes or, conversely, leads to detrimental effects.

The use of Artificial Intelligence in the context of learning can be explained through the Technology Acceptance Model (TAM) proposed (Kong et al., 2024; Sánchez Prieto et al., 2020; Talledo Monroy et al., 2026). This theory explains that a person's intention to use a technology is determined by two main factors: perceived ease of use and perceived usefulness. In the context of students, the higher the perception that AI is easy to use and provides real benefits in completing academic tasks, the greater the intensity and frequency of use in the learning process (Banat et al., 2024; Erwin et al., 2023; Erwin & Dakhalan, 2024; Hermansyah et al., 2025). This framework is relevant to use as a basis for understanding how the use of AI can be a starting point that influences other psychological variables in students' learning processes.

Learning motivation in this study was examined using Self-Determination Theory (SDT) developed by Deci and Ryan (1985). This theory explains that a person's motivation, both intrinsic and extrinsic, is influenced by the fulfillment of three basic psychological needs: autonomy, competence, and relatedness (Ryan & Deci, 2020a). The use of AI in learning has the potential to fulfill students' need for competence through easy access to information and instant assistance in understanding the material, as well as their need for autonomy through the transmission of the learning methods offered. Therefore, learning motivation is positioned as the variable theoretically most likely to change due to experience using AI, making it worthy of testing as a mediator between AI use and learning outcomes.

Locus of control refers to a concept described by Rotter (1966), which explains an individual's belief regarding the source of control over events they experience-whether it originates from within themselves (internal locus of control) or from external factors such as luck or other people (external locus of control) (Giovanelli et al., 2026). Students with an internal locus of control tend to believe that their academic success is determined by their own efforts and abilities, while students with an external locus of control are more likely to believe that their learning outcomes are influenced by factors beyond their control. In the context of this research, the use of AI is considered to influence students' perceptions of their locus of control-for example, excessive

reliance on AI could potentially shift the perception of learning control from internal to external, as students perceive their success as being due to the AI's abilities rather than their own efforts.

Learning outcomes in this study were measured through two dimensions based on the revised Bloom's Taxonomy developed (Anderson & Krathwohl, 2001). Conceptual understanding represents basic cognitive abilities (C2 -understanding), namely students' ability to explain, interpret, and classify a concept. Meanwhile, problem solving represents higher cognitive abilities (C4-C6 -analyzing, evaluating, creating), which involve the processes of analysis, evaluation, and synthesis in solving complex and unstructured problems. Distinguishing between these two dimensions is important because they represent different cognitive levels, thus allowing this study to analyze whether the influence of AI use (through the mediators of learning motivation, locus of control, and learning style) has a different impact on students' basic cognitive abilities compared to their higher cognitive abilities.

Based on the description above, it appears that extensive research has been conducted on the use of AI in learning, both globally and in the context of higher education institutions in Indonesia, including in Central Java. Most of this research tends to focus on two areas: first, research that highlights the direct influence of AI use on student learning effectiveness or outcomes (e.g., research on economics and business students); second, research that highlights the negative impacts and inhibitions of AI in the academic realm, as found among students in Surakarta (Rina et al., 2024). However, research that specifically examines why and through what mechanisms AI use can affect learning outcomes-taking into account student psychological characteristics such as learning motivation, locus of control, and learning style as mediators-is still relatively limited, particularly in the context of courses that require application skills, such as learning media.

However, understanding these mechanisms is crucial, given that the effectiveness of AI in improving learning outcomes is likely not uniform across all students, but rather depends on individual characteristics, as explained in the Aptitude-Treatment Interaction framework (Cronbach & Snow). This gap is increasingly relevant considering that instructional media courses require students not only to understand concepts theoretically but also to be able to apply them in real-world problem-solving-two dimensions of learning outcomes that have the potential to be differentially influenced by the use of AI. Therefore, this research is crucial to fill this gap by simultaneously examining the role of learning motivation, locus of control, and learning styles as mediators between AI use and student learning outcomes in instructional media courses.

This study employed a quantitative approach with a survey method, aiming to empirically test the relationships between variables based on data collected from the research sample (Cindy et al., 2022). Data analysis in this study was conducted in two stages using different statistical tools according to their functions. The first stage used SPSS to conduct data collection tests, including normality and homogeneity tests, as well as descriptive analysis of respondent characteristics. Given that the research sample came from four classes taught by the same lecturer but with different meeting schedules, a one-way ANOVA test was also conducted at this stage to ensure there were no significant differences between class groups in the main research variables, thus ensuring that the data from the four classes were appropriately combined into a single sample.

The second stage used the Partial Least Squares Structural Equation Modeling (PLS-SEM) approach through SmartPLS to examine the structural relationships between AI use, learning motivation, locus of control, learning styles, and student learning outcomes. This approach was chosen because it is capable of simultaneously testing complex structural models, including mediating relationships between latent variables, while also being suitable for moderate sample sizes and not requiring strict assumptions of data normality (Khatun, 2021). The combination of

these two analytical tools allows the study to produce data that has been statistically verified for its validity before being further tested using a structural model, thereby increasing the methodological validity and originality of this study's contribution to higher education studies in Indonesia, particularly in Central Java.

The rapid advancement of Artificial Intelligence (AI) has reshaped teaching and learning practices worldwide, with adoption accelerating markedly since the emergence of generative AI tools in late 2022 (Kumar et al., 2026). Despite this rapid uptake, institutional governance has lagged behind: a global UNESCO survey of over 450 schools and universities found that fewer than 10% had established formal policies on generative AI use (UNESCO, 2023). This trend is similarly evident in Indonesian higher education, including in Central Java, where students increasingly rely on AI tools such as ChatGPT for academic tasks ranging from assignment completion to thesis writing-though not without risks of overdependence and reduced critical engagement (Rahiem, 2026).

While prior studies have examined either the direct benefits of AI on learning effectiveness or its potential for academic misuse, limited attention has been paid to the psychological mechanisms through which AI use translates into learning outcomes. Drawing on the Aptitude-Treatment Interaction framework (Cronbach & Snow), the effectiveness of AI is unlikely to be uniform across students but contingent on individual characteristics. This study addresses this gap by examining learning motivation, locus of control, and learning style as mediating variables linking AI use to learning outcomes-operationalized as conceptual understanding and problem-solving ability-among students enrolled in an Instructional Media course. The proposed model integrates the Technology Acceptance Model (Davis, 1989) to explain AI adoption, Self-Determination Theory (Deci & Ryan, 1985) to explain motivational change, Rotter's (1966) locus of control theory, Kolb's (1984) experiential learning theory, and the revised Bloom's Taxonomy (Anderson & Krathwohl, 2001) to distinguish lower- and higher-order learning outcomes.

Using a quantitative survey design with a sample of 98 students across four intact classes, this study employs Partial Least Squares Structural Equation Modeling (PLS-SEM) to test the hypothesized mediation model, given its suitability for testing complex structural relationships with moderate sample sizes and without strict normality assumptions (Hair et al., 2019). This study aims to examine the direct effect of AI use on learning outcomes and to test the mediating roles of learning motivation, locus of control, and learning style in this relationship, thereby contributing both theoretically-by extending the Aptitude-Treatment Interaction framework to AI-mediated learning contexts-and practically, by informing evidence-based strategies for integrating AI into instructional design courses.

RESEARCH METHODOLOGY

Research Design

This study employs a quantitative research design with a cross-sectional survey approach, aimed at examining the causal relationships among variables at a single point in time rather than tracking change over an extended period (Van der Stede, 2014). This design was selected because the study seeks to test a hypothesized structural model-linking AI use, learning motivation, locus of control, learning style, and learning outcomes-through statistical inference rather than descriptive exploration. The population consists of students enrolled in the Instructional Media course, drawn from four intact classes taught by the same lecturer to control for instructor-related variance, with a total sample of 98 students (Class A = 25, Class B = 24, Class C = 25, Class D = 24). Data were collected at the eighth meeting across all four classes to ensure equivalent exposure to course

content prior to measurement. Given the presence of latent constructs measured through multiple indicators, this study adopts Partial Least Squares Structural Equation Modeling (PLS-SEM) as the primary analytical technique, given its suitability for testing complex mediation models with moderate sample sizes and without requiring multivariate normality.

Research Subjects

The participants in this study were active students enrolled in the Instructional Media course during the semester in which the study was conducted. Participant recruitment employed total population sampling, whereby all members of the accessible population were initially considered for inclusion because the population was relatively small and could be reached in its entirety (Sugiyono, 2022).

The initial population consisted of 98 students distributed across four intact classes taught by the same lecturer. Class A consisted of 25 students, Class B of 24 students, Class C of 25 students, and Class D of 24 students. The four classes had relatively homogeneous characteristics in terms of the course instructor, learning objectives, instructional materials, and stages of course completion. Data collection was conducted concurrently during the eighth meeting in each class to minimize differences in participants' exposure to the course content.

Inclusion criteria required participants to be actively enrolled in the Learning Media course and to have used the artificial intelligence (AI) platform during the learning process. After eligibility screening, six students were excluded for not meeting the inclusion criteria. The excluded participants consisted of three students from Class A, four students from Class B, two students from Class C, and one student from Class D. Consequently, the final analytical sample consisted of 92 students, with 23 participants from each class. Students who did not meet the inclusion criteria were not included in the statistical analysis.

Inclusion criteria required participants to be actively enrolled in the Instructional Media course and to have used artificial intelligence (AI) platforms during the learning process. After eligibility screening, ten students were excluded for not meeting the inclusion criteria: three students from Class A, four students from Class B, two students from Class C, and one student from Class D. Consequently, the final analytical sample consisted of 98 students, distributed unevenly across the four classes as a result of the screening process. Students who did not meet the inclusion criteria were not included in the statistical analysis.

Table 1. Distribution of the Initial Population, Excluded Participants, and Final Analytical Sample by Class

Class	Initial Population	Excluded	Final Sample	Percentage of Final Sample (%)
A	25	3	22	25.0
B	24	4	20	22.7
C	25	2	23	26.1
D	24	1	23	26.1
Total	98	10	88	100.0

Research Instruments

Data were collected using four self-report questionnaires and two cognitive assessment instruments. The questionnaires measured artificial intelligence use, learning motivation, locus of control, and learning preferences, whereas the cognitive instruments assessed conceptual understanding and problem-solving ability in the Instructional Media course.

All questionnaire items were rated using a five point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). Higher scores indicated a stronger level of the respective construct.

The conceptual-understanding test was scored dichotomously, while the problem-solving test was evaluated using an analytic scoring rubric.

Table 2. Summary of the Research Instruments

Instrument	Theoretical Foundation	Dimensions	Number of Items	Response Format
Artificial Intelligence Use	Technology Acceptance Model	Perceived ease of use, perceived usefulness, and intensity of use	10	Five-point Likert scale
Learning Motivation	Self-Determination Theory	Autonomy, competence, and relatedness	12	Five-point Likert scale
Locus of Control	Locus of Control Theory	Internal and external locus of control	12	Five-point Likert scale
Learning Preferences	Experiential Learning Theory	Diverging, assimilating, converging, and accommodating	12	Five-point Likert scale
Conceptual Understanding	Revised Bloom's Taxonomy	Explaining, interpreting, classifying, and comparing	15	Multiple-choice test
Problem-Solving Ability	Revised Bloom's Taxonomy	Analyzing, evaluating, and creating	5 cases	Case-based essay test

Artificial intelligence use was measured using a 10 item questionnaire developed with reference to the Technology Acceptance Model proposed by Davis (1989). The questionnaire comprised four items measuring perceived ease of use, four items measuring perceived usefulness, and two items measuring intensity of use. Learning motivation was measured using a 12-item questionnaire developed with reference to Self-Determination Theory Deci & Ryan (1985). The instrument consisted of three dimensions: autonomy, competence, and relatedness, with four items representing each dimension.

Locus of control was assessed using a 12 item questionnaire developed with reference to Rotter's (1966) theoretical framework and indicators adapted for the context of university students. Six items measured internal locus of control, while the remaining six measured external locus of control. Learning preferences were measured using a 12 item questionnaire developed with reference to Kolb's Experiential Learning Theory (Kolb, 1984). The instrument included four dimensions: diverging, assimilating, converging, and accommodating, with three items representing each dimension. Conceptual understanding was measured using 15 multiple-choice questions developed according to the understanding level, or C2, of the revised Bloom's taxonomy (Anderson & Krathwohl, 2001). The test assessed four cognitive indicators: explaining, interpreting, classifying, and comparing.

Problem-solving ability was assessed using five case-based essay tasks developed according to the analyzing, evaluating, and creating levels of the revised Bloom's taxonomy (Anderson & Krathwohl, 2001). The tasks required students to identify instructional problems, analyze the factors contributing to those problems, compare alternative instructional media, evaluate their advantages and limitations, and design appropriate media-based solutions. The cases were contextualized within realistic teaching and learning situations.

Before hypothesis testing, the questionnaire measurement models were evaluated for indicator reliability, internal consistency, convergent validity, and discriminant validity. Indicator reliability was assessed using outer loadings, internal consistency using Cronbach's alpha and composite reliability, convergent validity using the average variance extracted, and discriminant validity using the heterotrait-monotrait ratio. The conceptual-understanding test was evaluated using item difficulty, item discrimination, corrected item-total correlations, and test reliability. The problem-solving test was examined through content validation, corrected item-total correlations, internal

consistency, and inter-rater reliability. The numerical results of these evaluations are presented in the Results section.

Data Analysis

Statistical analyses were performed using IBM SPSS Statistics and SmartPLS software. Preliminary investigations encompassed descriptive statistics, data screening, and an assessment of normality conducted through the Shapiro-Wilk test. A one-way analysis of variance (ANOVA) was conducted to investigate potential differences in the principal study variables across Classes A, B, C, and D. The assumption of homogeneity of variances was evaluated using Levene's test. In cases where this assumption was violated, Welch's ANOVA was subsequently employed. The four classes were consolidated into a single analytical sample when no statistically significant group differences and no meaningful effect sizes were identified.

The research hypotheses were empirically examined using partial least squares structural equation modeling (PLS-SEM), following a two-stage procedure (Hair et al., 2019). The measurement model's robustness was evaluated by examining outer loadings, average variance extracted (AVE), Cronbach's alpha, composite reliability (CR), and the heterotrait-monotrait (HTMT) ratio. Subsequently, the structural model was assessed using the variance inflation factor (VIF), the coefficient of determination (R^2), effect size (f^2), and predictive relevance (Q^2). Statistical significance was determined through a bootstrapping procedure employing 5,000 subsamples. Both direct and indirect effects were considered statistically significant if their p-values were below 0.05 and their 95% bootstrapped confidence intervals did not include zero.

Research Procedures

The study was conducted in four stages: instrument preparation, data collection, data screening, and data analysis. The instruments were developed based on the Technology Acceptance Model (Davis, 1989), Self-Determination Theory (Deci & Ryan, 1985), locus of control theory (Rotter, 1966), experiential learning theory (Kolb, 1984), and the revised Bloom's taxonomy (Anderson & Krathwohl, 2001). Content validity was assessed through expert judgment, followed by pilot testing with students outside the target population. Ethical approval was obtained from the relevant institutional authority, and informed consent was secured from all participants.

Data were collected during the eighth course meeting across four intact classes within the same academic week. Participants completed self-report questionnaires measuring AI use, learning motivation, locus of control, and learning preferences, as well as written assessments of conceptual understanding and problem-solving ability. Of the initial 98 students, 10 were excluded because they did not meet the eligibility criteria, resulting in a final analytical sample of 88 participants. The data were screened for incomplete responses, missing values, and potential outliers before analysis.

Preliminary analyses were conducted using SPSS and included descriptive statistics, normality and homogeneity tests, and one-way ANOVA to examine differences across the four classes. The hypothesized relationships were subsequently tested using PLS-SEM in SmartPLS. The analysis involved evaluation of the measurement and structural models, followed by hypothesis testing through bootstrapping with 5,000 resamples.

RESULT AND DISCUSSION

Table 2 presents the descriptive statistics for the study variables. Among the questionnaire-based variables, AI use had the highest mean score (M = 3.72, SD = 0.58), followed by learning motivation (M = 3.65, SD = 0.52), learning preferences (M = 3.55, SD = 0.49), and locus of control

(M = 3.41, SD = 0.61). The mean scores for conceptual understanding and problem-solving ability were 72.40 (SD = 11.30) and 68.15 (SD = 12.85), respectively. These results indicate moderately high levels of AI use, learning motivation, locus of control, and learning preferences among the participants.

Table 3. Descriptive Statistics of the Study Variables (n = 88)

Variable	Minimum	Maximum	Mean	SD
AI Use	2.10	4.90	3.72	0.58
Learning Motivation	2.30	4.80	3.65	0.52
Locus of Control	2.00	4.70	3.41	0.61
Learning Preferences	2.40	4.60	3.55	0.49
Conceptual Understanding	45.00	95.00	72.40	11.30
Problem-Solving Ability	40.00	92.00	68.15	12.85

The Kolmogorov-Smirnov tests produced nonsignificant results for all variables ($p > 0.05$), indicating no substantial departures from normality. The homogeneity-of-variance assumption was also satisfied, as the Levene's test results were nonsignificant, with p-values of at least 0.214. A series of one-way ANOVAs was conducted to determine whether the main study variables differed across Classes A, B, C, and D. As shown in Table 3, no statistically significant differences were found in AI use, learning motivation, locus of control, learning preferences, or overall learning outcomes. The effect sizes were small, with η^2 values ranging from 0.026 to 0.056.

The absence of significant class differences, combined with the small effect sizes and similarities in course instructor, instructional content, course progression, and data-collection period, supported the decision to combine the four classes into a single analytical sample of 88 students.

Table 4. One-Way ANOVA Results Across the Four Classes

Variable	F	df	p-value	η^2	Decision
AI Use	1.42	3, 84	0.242	0.048	Not significant
Learning Motivation	0.98	3, 84	0.406	0.034	Not significant
Locus of Control	1.67	3, 84	0.180	0.056	Not significant
Learning Preferences	0.75	3, 84	0.525	0.026	Not significant
Overall Learning Outcomes	1.29	3, 84	0.283	0.044	Not significant

The measurement model was evaluated by examining indicator loadings, average variance extracted, Cronbach's alpha, composite reliability, and discriminant validity. Two learning-preference indicators with outer loadings below 0.60 were removed before estimating the final model. As presented in Table 5, the outer loadings of the retained indicators ranged from 0.65 to 0.89. Several indicators with loadings between 0.60 and 0.70 were retained because of their theoretical relevance and because their respective constructs met the required AVE and composite reliability criteria.

All AVE values exceeded 0.50, ranging from 0.521 to 0.658, indicating satisfactory convergent validity. Cronbach's alpha coefficients ranged from 0.771 to 0.861, while composite reliability values ranged from 0.831 to 0.905. These results demonstrate satisfactory internal consistency across all constructs.

Table 5. Construct Validity and Reliability Results

Construct	Outer-Loading Range	AVE	Cronbach's Alpha	Composite Reliability
AI Use	0.71-0.86	0.612	0.834	0.887

Learning Motivation	0.74-0.89	0.658 0.861	0.905
Locus of Control	0.68-0.81	0.554 0.792	0.855
Learning Preferences	0.65-0.79	0.521 0.771	0.831
Conceptual Understanding	0.72-0.85	0.601 0.812	0.870
Problem-Solving Ability	0.70-0.83	0.589 0.798	0.862

Discriminant validity was examined using the heterotrait-monotrait ratio. As shown in Table 6, the HTMT values ranged from 0.361 to 0.719 and remained below the conservative threshold of 0.85. Therefore, the constructs demonstrated adequate discriminant validity and represented empirically distinct concepts.

Table 6. Discriminant Validity Based on the HTMT Criterion

Construct	AI Use	Learning Motivation	Locus of Control	Learning Preferences	Conceptual Understanding	Problem Solving
AI Use	-					
Learning Motivation	0.612	-				
Locus of Control	0.487	0.541	-			
Learning Preferences	0.398	0.463	0.512	-		
Conceptual Understanding	0.521	0.634	0.402	0.377	-	
Problem-Solving Ability	0.498	0.589	0.388	0.361	0.719	-

The final structural model is presented in Figure 1. AI use was specified as the exogenous construct, while learning motivation, locus of control, and learning preferences were specified as parallel mediators. Student learning outcomes were represented by conceptual understanding and problem-solving ability.

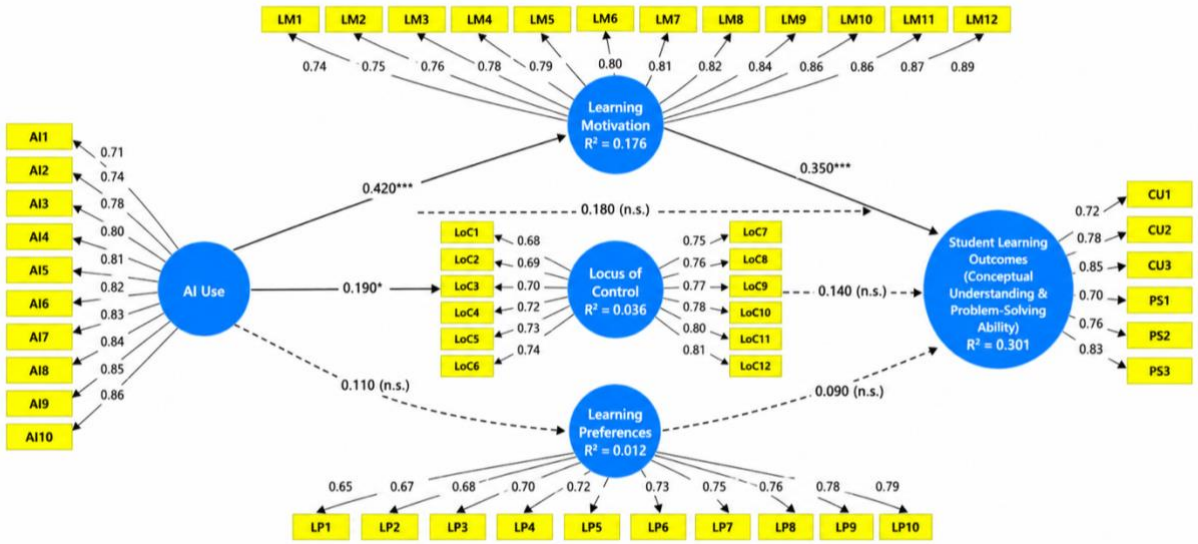

Figure 1. Structural model of AI use, mediating variables, and student learning outcomes.

The structural model was evaluated using the coefficient of determination and predictive-relevance values. AI use explained 17.6% of the variance in learning motivation, 3.6% of the variance in locus of control, and 1.2% of the variance in learning preferences. The model explained 31.2% of the variance in conceptual understanding and 28.9% of the variance in problem-solving ability. These values indicate moderate explanatory power for the two learning-outcome dimensions but weak explanatory power for locus of control and learning preferences.

All Q^2 values were positive, indicating that the model possessed predictive relevance for all endogenous variables. However, the predictive relevance for locus of control and learning preferences was relatively limited.

Table 7. Explanatory Power and Predictive Relevance of the Structural Model

Endogenous Variable	R^2	Q^2	Interpretation
Learning Motivation	0.176	0.142	Weak
Locus of Control	0.036	0.021	Very weak
Learning Preferences	0.012	0.006	Very weak
Conceptual Understanding	0.312	0.248	Moderate
Problem-Solving Ability	0.289	0.221	Moderate

The statistical significance of the structural relationships was evaluated through bootstrapping with 5,000 subsamples. The results are presented in Table 7. AI use had a significant positive effect on learning motivation ($\beta = 0.420$, $t = 5.812$, $p < 0.001$), indicating that greater use of AI was associated with stronger student motivation. AI use also had a significant positive effect on locus of control ($\beta = 0.190$, $t = 2.104$, $p = 0.036$), although the magnitude of this relationship was relatively small.

In contrast, AI use did not significantly affect learning preferences ($\beta = 0.110$, $t = 1.243$, $p = 0.214$). This result suggests that students' preferred ways of learning were relatively stable and were not substantially changed by their use of AI.Learning motivation had a significant positive effect on learning outcomes ($\beta = 0.350$, $t = 4.671$, $p < 0.001$). However, locus of control ($\beta = 0.140$, $t = 1.532$, $p = 0.126$) and learning preferences ($\beta = 0.090$, $t = 0.887$, $p = 0.375$) did not significantly predict learning outcomes. The direct effect of AI use on learning outcomes was positive but did not reach the conventional level of statistical significance ($\beta = 0.180$, $t = 1.897$, $p = 0.058$). Therefore, the relationship was interpreted as statistically nonsignificant rather than significant or marginally significant.

Table 8. Direct-Effect Testing Results

Structural Path	β	t-statistic	p-value	Decision
AI Use → Learning Motivation	0.420	5.812	<0.001	Significant
AI Use → Locus of Control	0.190	2.104	0.036	Significant
AI Use → Learning Preferences	0.110	1.243	0.214	Not significant
Learning Motivation → Learning Outcomes	0.350	4.671	<0.001	Significant
Locus of Control → Learning Outcomes	0.140	1.532	0.126	Not significant
Learning Preferences → Learning Outcomes	0.090	0.887	0.375	Not significant
AI Use → Learning Outcomes	0.180	1.897	0.058	Not significant

The mediating effects of learning motivation, locus of control, and learning preferences were evaluated using the specific indirect effects and bias-corrected 95% bootstrap confidence intervals. The indirect effect of AI use on learning outcomes through learning motivation was statistically significant ($\beta = 0.147$, 95% CI 0.081, 0.219). The confidence interval did not include zero, confirming that learning motivation significantly mediated the relationship between AI use and learning outcomes.

Because the indirect effect through learning motivation was significant while the direct effect of AI use on learning outcomes was nonsignificant, the result indicated an indirect-only mediation pattern. This means that AI use influenced learning outcomes primarily through its contribution to students' learning motivation rather than through a statistically significant direct pathway. The indirect effect through locus of control was not significant ($\beta = 0.027$, 95% CI -0.011, 0.068)

because the confidence interval included zero. Similarly, learning preferences did not significantly mediate the relationship between AI use and learning outcomes (β = 0.010, 95% CI -0.019, 0.041).

Table 9. Specific Indirect Effects

Mediation Path	Indirect Effect	95% Bootstrap CI	Decision
AI Use → Learning Motivation → Learning Outcomes	0.147	0.081, 0.219	Significant mediation
AI Use → Locus of Control → Learning Outcomes	0.027	-0.011, 0.068	No significant mediation
AI Use → Learning Preferences → Learning Outcomes	0.010	-0.019, 0.041	No significant mediation

The findings indicate that AI use improves student learning outcomes primarily through learning motivation rather than through a direct effect. AI use had a significant positive effect on motivation, and motivation subsequently predicted learning outcomes, producing a significant indirect effect. This pattern is consistent with Self-Determination Theory, which explains that learning environments supporting autonomy and competence can strengthen students' motivation, persistence, and academic performance (Ryan & Deci, 2020b). Generative AI may support these psychological needs by providing rapid feedback, personalized explanations, and opportunities for independent learning. Similar arguments have been advanced (Yan et al., 2024), who emphasized the potential of large language models to support personalized learning and immediate instructional assistance.

The nonsignificant direct effect of AI use on learning outcomes challenges the assumption that frequent use of AI automatically results in better academic achievement. AI is better understood as a learning scaffold whose effectiveness depends on the quality of students' engagement with the generated information. When students use AI to clarify concepts, explore alternative explanations, and evaluate possible solutions, it may facilitate deeper learning; however, passive dependence on generated answers may reduce independent reasoning and critical evaluation. Similarly noted that educational benefits coexist with risks related to overreliance, inaccurate information, and reduced intellectual effort. Therefore, the present findings support a conditional perspective in which AI contributes to learning only when it activates meaningful cognitive and motivational processes.

Locus of control and learning preferences did not significantly mediate the relationship between AI use and learning outcomes. Although AI use had a small positive association with locus of control, students' perceptions of personal control were insufficient to produce measurable improvements in academic performance. Learning preferences were also relatively unaffected by AI use, suggesting that the technology may accommodate existing approaches to learning rather than fundamentally transform them. These results strengthen the argument that motivational readiness is more influential than stable personal preferences in determining the educational value of AI. Accordingly, lecturers should design AI-supported tasks that encourage autonomy, reflection, verification, and independent problem-solving rather than merely increasing students' exposure to AI tools.

CONCLUSION

This study concludes that AI use contributes to student learning outcomes primarily through the strengthening of learning motivation. Although AI use did not exert a statistically significant direct effect on learning outcomes, it significantly increased students' motivation, which subsequently improved their conceptual understanding and problem-solving ability. This finding indicates that the educational value of AI depends less on the frequency of use and more on its capacity to stimulate active engagement, persistence, and meaningful learning.

Locus of control and learning preferences were not found to mediate the relationship between AI use and learning outcomes. These results suggest that relatively stable personal characteristics do not automatically translate AI use into better academic performance. Instead, motivational processes appear to play a more central role in explaining how AI supports learning. Therefore, lecturers should integrate AI into learning activities through tasks that promote reflection, verification, independent reasoning, and problem-solving rather than merely encouraging students to use AI tools.

The study is limited by its relatively small sample, single-course context, and cross-sectional design, which restrict causal interpretation and generalizability. Future research should involve larger and more diverse samples, employ longitudinal or experimental designs, and examine additional mediating variables such as self-regulated learning, critical thinking, AI literacy, and cognitive engagement. These directions may provide a more comprehensive understanding of the conditions under which AI can effectively improve student learning outcomes.

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ETHICAL STANDARDS

This study was conducted in accordance with ethical principles for educational research involving human participants. Permission to conduct the research was obtained from Universitas KH Abdul Chalim, Indonesia, prior to data collection. Participation was voluntary, and all participants were informed about the research objectives, procedures, confidentiality, and data usage. Informed consent was obtained from all participants, and all personal information was anonymized to protect participants' privacy and confidentiality.

AUTHORS' CONTRIBUTION

Author 1: Conceptualization; Methodology; Research design; Formal analysis; Interpretation of results; Writing -original draft; Writing -review and editing; Visualization; Project administration; Coordination of the research process.
Author 2: Conceptualization; Investigation; Data collection; Data curation; Instrument development; Validation; Literature review; Writing -review and editing.
Author 3: Investigation; Data collection; Data curation; Resources; Participant coordination; Research documentation; Preliminary data processing; Writing -review and editing.
Author 4: Methodology; Formal analysis; Statistical analysis; Validation; Supervision; Interpretation of findings; Writing -review and editing; Quality assurance of the manuscript.

DISCLAIMER REGARDING THE USE OF GENERATIVE TECHNOLOGIES AND AI-ASSISTED AI TECHNOLOGIES

During the preparation of this manuscript, the authors used Claude, developed by Anthropic, to assist in identifying potentially relevant literature and refining search terms. All AI-generated suggestions were independently reviewed and verified against the original scholarly sources. The

authors retained full responsibility for the selection, interpretation, accuracy, and presentation of the literature included in this manuscript.

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