



Artificial Intelligence and Academic Performance in Higher Education: The Mediating Role of Self-Regulated Learning and the Influence of Learning Motivation and Digital Literacy

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Abstract:

The integration of artificial intelligence (AI) in higher education has attracted growing scholarly attention; however, existing studies largely emphasize technology adoption while offering limited insight into the mechanisms through which AI influences academic performance. Addressing this gap, this study proposes and tests a mechanism-based model that examines the role of self-regulated learning (SRL) in mediating the relationship between AI usage and academic outcomes, while incorporating learning motivation and digital literacy as antecedent factors. Using survey data from 547 undergraduate students, the study employs structural equation modeling to analyze both direct and indirect relationships among the constructs. The findings reveal that AI usage has a significant positive effect on academic performance and SRL, with SRL emerging as the strongest predictor of academic outcomes and a key mediating mechanism. Learning motivation significantly drives AI usage, whereas digital literacy does not directly influence academic performance but operates indirectly through SRL. These results suggest that the effectiveness of AI is contingent upon students' ability to regulate their learning processes rather than the mere adoption of technology. This study contributes to the literature by extending technology adoption perspectives toward a process-oriented framework that integrates motivational, technological, and cognitive dimensions. The findings offer important implications for educators and policymakers, emphasizing that optimizing AI in education requires not only access to technology but also the development of students' self-regulatory capacities.

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Introduction

The rapid advancement of artificial intelligence (AI) has significantly reshaped the landscape of higher education, offering new opportunities to enhance teaching and learning processes. AI-powered systems, such as intelligent tutoring systems, generative AI tools, and adaptive learning platforms, enable personalized learning experiences and improve students'

engagement and efficiency. Recent studies have emphasized that AI integration can support higher-order thinking skills and academic achievement, particularly in digital learning environments (Badawi & Adiyono, 2026; Holmes et al., 2019; Ke et al., 2024; Zawacki-Richter et al., 2019). Despite these advancements, empirical evidence regarding how AI influences students' academic performance remains inconclusive, particularly in terms of the underlying learning mechanisms.

From a theoretical perspective, the Technology Acceptance Model (TAM) explains how users adopt and utilize technology based on perceived usefulness and ease of use (Davis, 1989). While TAM has been widely applied in educational technology research, it primarily focuses on technology adoption rather than learning outcomes. This limitation suggests the need to integrate cognitive and learning-based perspectives to better understand how technology contributes to academic performance (Dwivedi et al., 2023; Granić & Marangunić, 2019). In this regard, Self-Regulated Learning (SRL) theory provides a relevant framework for explaining how students actively manage their learning processes. SRL emphasizes students' ability to plan, monitor, and evaluate their learning, which has been consistently linked to academic success (Broadbent & Poon, 2015; Zimmerman, 2002). Recent studies further suggest that AI technologies can enhance SRL by providing real-time feedback and adaptive learning support (Azevedo et al., 2017; Viberg et al., 2018).

In addition to cognitive factors, motivational and technological competencies also play a crucial role in AI-supported learning. Motivation significantly influences learning outcomes in AI-supported environments. For example, self-determination theory highlights that intrinsic motivation, supported by teacher guidance, enhances students' competence and autonomy when using AI tools (Chiu et al., 2024; Lu, 2026; Zhen, 2025). Similarly, flow experiences mediated by psychological needs like autonomy and relatedness sustain engagement with AI systems (Lu, 2026). Meanwhile, digital literacy is often considered a key determinant of success in digital learning environments. However, recent evidence indicates that digital literacy may not directly improve academic performance but instead operates indirectly through learning processes (Thelma et al., 2024; Van Laar et al., 2019). These findings highlight an important gap in the literature, namely the lack of an integrative model that simultaneously explains the roles of motivation, technology use, and self-regulated learning in shaping academic performance.

Therefore, this study aims to address this gap by proposing and empirically testing a structural model that examines the role of artificial intelligence in influencing academic performance through self-regulated learning, while also incorporating learning motivation and digital literacy as key antecedents. Specifically, this study investigates how AI usage contributes to academic outcomes both directly and indirectly, and how motivational and cognitive factors interact within this process. In doing so, this study extends TAM by linking technology adoption to learning outcomes, advances SRL theory by positioning AI as a cognitive scaffold, and clarifies the indirect role of digital literacy in academic performance.

Based on this theoretical framework, several hypotheses are proposed. Learning motivation is expected to positively influence artificial intelligence usage (H1), while artificial intelligence usage is hypothesized to positively affect both academic performance (H2) and self-regulated learning (H3). Furthermore, self-regulated learning is expected to have a positive effect on academic performance (H4) and to mediate the relationship between artificial intelligence usage and academic performance (H5). In addition, digital literacy is hypothesized to positively influence self-regulated learning (H6) and to have a direct effect on academic performance (H7). Through this integrative framework, this study seeks to provide a more comprehensive understanding of how artificial intelligence contributes to academic performance in higher education.

Method

1. Research Design

This study employed a quantitative approach using a cross-sectional survey design to investigate the relationships between artificial intelligence usage, learning motivation, self-regulated learning, digital literacy, and students' academic performance. The study was designed to examine both direct and indirect effects within a structural model framework.

2. Participants and Data Collection

The study involved 547 undergraduate students from Institut Agama Islam Al-Jihad Shalahuddin Al-Ayyubi Jakarta, Indonesia. A proportionate random sampling technique was applied to ensure balanced representation across faculties and academic levels. Data were collected using an online questionnaire distributed via Google Forms. All respondents had prior experience using artificial intelligence tools, such as ChatGPT, to support their academic activities. Participation was voluntary, and informed consent was obtained prior to data collection.

3. Measurement Instruments

The instrument consisted of 36 items distributed across five constructs, developed based on established theoretical frameworks and adapted to the context of AI-assisted learning. All items were measured using a five-point Likert scale ranging from 1 (*strongly disagree*) to 5 (*strongly agree*). The distribution of measurement items across constructs is presented in Table 1.

Table 1. Distribution of Measurement Items Across Constructs

No.	Construct	Number of Items	Dimensions	Item Codes
1	Artificial Intelligence Usage	8 items	Frequency of Use, Perceived Usefulness, Perceived Ease of Use, Learning Support	AI1–AI8
2	Learning Motivation	6 items	Intrinsic Motivation, Persistence, Goal Orientation	LM1–LM6
3	Self-Regulated Learning	8 items	Planning, Monitoring, Control, Self-Evaluation	SRL1–SRL8
4	Digital Literacy	6 items	Technical Skills, Information Evaluation, Digital Ethics	DL1–DL6
5	Academic Performance	8 items	Academic Achievement, Task Completion, Understanding, Productivity	AP1–AP8
Total		36 items		AI1–AP8

4. Data Analysis Technique

The data were analyzed using covariance-based structural equation modeling (CB-SEM) to examine the relationships among artificial intelligence usage, learning motivation, self-regulated learning, digital literacy, and academic performance. The analysis was conducted using JASP (Version 0.96), which utilizes the lavaan package for structural equation modeling, with maximum likelihood (ML) estimation.

Prior to the main analysis, data screening procedures were performed to ensure data quality and suitability. This included examining missing values, detecting potential outliers, and assessing the normality of the data distribution. Descriptive statistics and correlation analyses were also conducted to provide an initial overview of the relationships among variables.

Given that the data were collected using a single-source, self-reported survey, the potential for common method bias (CMB) was assessed. Harman's single-factor test was first conducted as an initial diagnostic, and the results indicated that no single factor accounted

for the majority of the variance. However, this technique has been widely criticized for its limited sensitivity in detecting method bias. Therefore, several procedural remedies were implemented during data collection, including ensuring respondent anonymity, reducing evaluation apprehension, and carefully designing questionnaire items to minimize ambiguity and social desirability bias (Podsakoff et al., 2003). Nevertheless, more advanced statistical techniques, such as marker variable analysis or the inclusion of a common latent factor in confirmatory factor analysis, were not applied. As such, the possibility of residual common method bias cannot be entirely ruled out.

A two-step analytical approach was employed. First, confirmatory factor analysis (CFA) was conducted to evaluate the measurement model, including the assessment of factor loadings, construct reliability, and convergent validity. Reliability was examined using Cronbach’s alpha and composite reliability, while convergent validity was assessed through average variance extracted (AVE). Second, the structural model was evaluated to test the hypothesized relationships among constructs.

Model fit was assessed using multiple goodness-of-fit indices, including the chi-square statistic (χ^2), Comparative Fit Index (CFI), Tucker–Lewis Index (TLI), Root Mean Square Error of Approximation (RMSEA), and Standardized Root Mean Square Residual (SRMR). The significance and strength of path coefficients were examined to determine the direct effects among variables. In addition, mediation effects were tested using bootstrapping procedures with 5,000 resamples to estimate indirect effects and their corresponding confidence intervals, providing a robust assessment of the mediating role of self-regulated learning.

5. Ethical Considerations

All participants were informed about the purpose of the study and provided consent prior to participation. The data were collected anonymously and used solely for academic purposes to ensure confidentiality and ethical compliance.

Result and Discussion

1. Result

a. Descriptive Statistics

A total of 547 valid responses were analyzed. The descriptive statistics and correlations among the study variables are presented in Table 1.

Table 1. Descriptive Statistics and Correlations

Variable	M	SD	AI	LM	SLR	DL	AP
1. AI	3.164	0.956	—				
2. LM	3.169	0.945	0.459	—			
3. SRL	3.154	0.959	0.375	0.543	—		
4. DL	3.166	0.936	0.750	0.369	0.199	—	
5. AP	3.159	0.947	0.607	0.535	0.628	0.368	—

Note. AI = Artificial Intelligence Usage; LM = Learning Motivation; SRL = Self-Regulated Learning; DL = Digital Literacy; AP = Academic Performance.

The results indicate that all variables have mean values around the midpoint ($M \approx 3.15$), suggesting moderate levels across all constructs. The relatively similar standard deviations (approximately 0.93–0.96) indicate a consistent distribution of responses. The correlation analysis reveals positive relationships among all variables, with the strongest association observed between artificial intelligence usage and digital literacy ($r = 0.750$). In addition, self-regulated learning shows a strong relationship with academic performance ($r = 0.628$), highlighting the importance of cognitive learning processes in academic achievement.

b. Confirmatory Factor Analysis

Confirmatory factor analysis (CFA) was performed using maximum likelihood estimation. The model demonstrated good fit: $\chi^2 = 588.103$ (df = 517, $p = .016$), CFI = 0.993, TLI = 0.992, RMSEA = 0.016, and SRMR = 0.026 (see Table 5).

All standardized factor loadings were significant ($p < .001$) and ranged from 0.675 to 0.788. Reliability estimates were satisfactory, with Cronbach’s alpha values ranging from 0.836 to 0.910 and composite reliability (ω) values ranging from 0.836 to 0.910 (see Table 3 and 4).

Table 3. Measurement Model: Factor Loadings

Construct	Item	Loading	Construct	Item	Loading
AI	AI1	0.747	SRL	SRL5	0.745
	AI2	0.779		SRL6	0.704
	AI3	0.734		SRL7	0.776
	AI4	0.747		SRL8	0.770
	AI5	0.759	DL	DL1	0.741
	AI6	0.705		DL2	0.716
	AI7	0.773		DL3	0.687
	AI8	0.736		DL4	0.758
LM	LM1	0.768	AP	DL5	0.719
	LM2	0.731		DL6	0.675
	LM3	0.716		AP1	0.747
	LM4	0.730		AP2	0.728
	LM5	0.724		AP3	0.676
	LM6	0.701		AP4	0.784
SRL	SRL1	0.731	AP5	0.740	
	SRL2	0.741	AP6	0.723	
	SRL3	0.724	AP7	0.775	
	SRL4	0.788	AP8	0.746	

The factor loading results presented in Table 3 indicate that all measurement items load significantly on their respective constructs, with values exceeding the acceptable threshold. This suggests that each indicator adequately represents its underlying latent variable. To further assess the internal consistency of the constructs, reliability analysis was conducted, and the results are presented in Table 4.

Table 4. Measurement Model: Reliability

Construct	Cronbach’s α	Composite Reliability (ω)
Artificial Intelligence Usage (AI)	0.910	0.910
Learning Motivation (LM)	0.871	0.872
Self-Regulated Learning (SRL)	0.900	0.901
Digital Literacy (DL)	0.836	0.836
Academic Performance (AP)	0.906	0.906

As shown in Table 4, all constructs demonstrate satisfactory levels of internal consistency, with Cronbach’s alpha and composite reliability values exceeding the recommended threshold of 0.70. These results confirm that the measurement model is reliable. To further evaluate the overall adequacy of the model, goodness-of-fit indices were examined, as presented in Table 5.

Table 5 Model Fit Indices

Model	χ^2	df	p	CFI	TLI	RMSEA	SRMR
CFA	588.103	517	.016	0.993	0.992	0.016	0.026
SEM	621.400	581	.119	0.996	0.996	0.011	0.026

The model fit indices presented in Table 5 indicate that both the measurement and structural models demonstrate an excellent fit to the data. The high values of CFI and TLI, combined with the low RMSEA and SRMR, confirm the robustness of the model. These findings provide strong empirical support for the validity of the measurement model, thereby justifying its use for subsequent structural model analysis.

c. Model Fit and Explained Variance

The structural model also demonstrated good fit ($\chi^2 = 621.400$, $df = 581$, $p = .119$, $CFI = 0.996$, $TLI = 0.996$, $RMSEA = 0.011$, $SRMR = 0.026$; see Table 3). The model explained 34.4% of the variance in Artificial Intelligence Usage, 42.7% in Self-Regulated Learning, and 63.5% in Academic Performance.

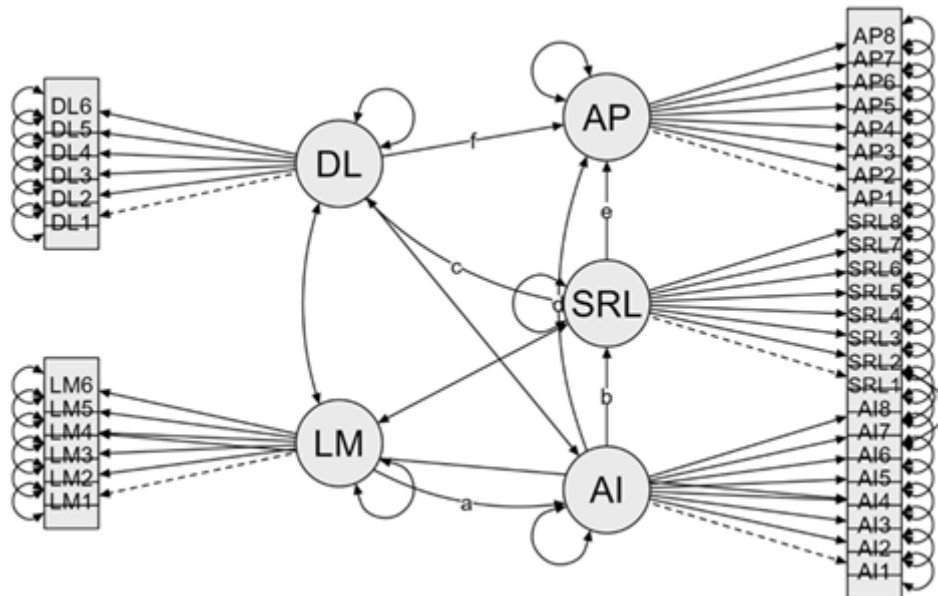


Figure 1. Presents the structural model illustrating the relationships among the latent variables: Learning Motivation (LM), Artificial Intelligence Usage (AI), Self-Regulated Learning (SRL), Digital Literacy (DL), and Academic Performance (AP). Value in table 6.

The structural model presented in Figure 1 demonstrates a well-fitting model with strong explanatory power. The results indicate that the model explains 34.4% of the variance in artificial intelligence usage and 42.7% in self-regulated learning, suggesting moderate explanatory capability for these constructs. Notably, the model accounts for 63.5% of the variance in academic performance, indicating a substantial level of predictive power.

These findings suggest that the proposed model is effective in capturing the key determinants of students’ academic performance. In particular, the relatively high explained variance in academic performance highlights the important role of artificial intelligence usage and self-regulated learning in shaping academic outcomes. Overall, the model demonstrates strong explanatory relevance, supporting its suitability for examining the hypothesized relationships among the variables.

d. Path Coefficients

The standardized path coefficients are presented in Table 6. Learning Motivation significantly predicted Artificial Intelligence Usage ($\beta = 0.322, p < .001$). Artificial Intelligence Usage significantly predicted Self-Regulated Learning ($\beta = 0.314, p < .001$) and Academic Performance ($\beta = 0.404, p < .001$). Self-Regulated Learning also significantly predicted Academic Performance ($\beta = 0.488, p < .001$). Digital Literacy significantly predicted Self-Regulated Learning ($\beta = 0.115, p < .001$) but did not significantly predict Academic Performance ($\beta = -0.065, p = .225$).

Table 6. Structural Model Results

Path	β	p
LM \rightarrow AI	0.322	< .001
AI \rightarrow SRL	0.314	< .001
DL \rightarrow SRL	0.115	< .001
AI \rightarrow AP	0.404	< .001
SRL \rightarrow AP	0.488	< .001
DL \rightarrow AP	-0.065	.225

The results presented in Table 6 provide clear evidence of the direct structural relationships among the study variables. Learning motivation significantly predicts artificial intelligence usage, indicating that students with higher intrinsic drive are more inclined to engage with AI-based learning tools. This finding reinforces the role of motivational factors as a primary driver of technology adoption in educational contexts.

Furthermore, artificial intelligence usage exerts a significant positive effect on both self-regulated learning and academic performance. This dual influence suggests that AI functions not only as a performance-enhancing tool but also as a facilitator of learning processes. Notably, self-regulated learning emerges as the strongest direct predictor of academic performance, highlighting its central role in determining learning outcomes.

In contrast, digital literacy demonstrates a limited direct impact. While it significantly contributes to self-regulated learning, its direct effect on academic performance is not statistically significant. This indicates that possessing digital skills alone does not automatically translate into improved academic outcomes, emphasizing the need to distinguish between technological competence and effective learning strategies.

e. Indirect Effects and Mediation

The indirect effects are presented in Table 7. Artificial Intelligence Usage had a significant indirect effect on Academic Performance through Self-Regulated Learning ($\beta = 0.129, p < .001$). Learning Motivation had significant indirect effects on Academic Performance through Artificial Intelligence Usage ($\beta = 0.192, p < .001$) and through the sequential pathway involving Artificial Intelligence Usage and Self-Regulated Learning ($\beta = 0.041, p < .001$). Additionally, Learning Motivation indirectly influenced Self-Regulated Learning through Artificial Intelligence Usage ($\beta = 0.102, p < .001$). Digital Literacy also showed a significant indirect effect on Academic Performance through Self-Regulated Learning ($\beta = 0.047, p < .001$).

Table 7. Indirect Effects (Mediation Analysis)

Path	Indirect Effect (β)	95% CI	p
AI \rightarrow SRL \rightarrow AP	0.129	[0.098, 0.160]	< .001
LM \rightarrow AI \rightarrow AP	0.192	[0.113, 0.270]	< .001
LM \rightarrow AI \rightarrow SRL \rightarrow AP	0.041	[0.029, 0.054]	< .001
LM \rightarrow AI \rightarrow SRL	0.102	[0.075, 0.128]	< .001

DL → SRL → AP	0.047	[0.022, 0.071]	< .001
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The mediation analysis presented in Table 7 offers deeper insight into the underlying mechanisms through which the variables interact. The significant indirect effect of artificial intelligence usage on academic performance via self-regulated learning confirms that the impact of AI is partially transmitted through students' ability to regulate their learning processes. This finding underscores that AI does not independently drive academic success but operates through cognitive and metacognitive engagement.

In addition, learning motivation demonstrates multiple indirect pathways influencing academic performance. Its effect is transmitted both directly through artificial intelligence usage and sequentially through artificial intelligence usage and self-regulated learning. This layered mediation structure indicates that motivation plays a foundational role in initiating a chain of learning behaviors that ultimately lead to improved academic outcomes.

Similarly, digital literacy shows a significant indirect effect on academic performance through self-regulated learning, despite its non-significant direct effect. This pattern highlights a fully mediated relationship, suggesting that digital literacy contributes to academic success only when it enhances students' capacity for self-regulation. Overall, these findings emphasize that self-regulated learning functions as the central mechanism that translates both technological engagement and individual competencies into meaningful academic performance.

Discussion

1. The Role of Artificial Intelligence in Enhancing Academic Performance

The findings of this study demonstrate that artificial intelligence (AI) plays a significant role in shaping students' academic performance, both directly and indirectly. The results show that AI usage positively influences academic performance, indicating that the integration of AI into learning activities enhances students' access to information, efficiency in completing tasks, and overall learning effectiveness. This finding is consistent with the Technology Acceptance Model, which suggests that perceived usefulness and ease of use drive positive outcomes (Davis, 1989). More recent studies also confirm that AI-supported learning environments can improve student engagement and academic achievement through adaptive and personalized learning systems (Holmes et al., 2019; Zawacki-Richter et al., 2019).

Beyond its direct effect, AI also significantly influences students' learning processes, particularly self-regulated learning. AI technologies provide real-time feedback, intelligent recommendations, and adaptive scaffolding that enable students to regulate their learning more effectively. This aligns with research suggesting that digital and AI-based tools can foster deeper learning engagement and metacognitive awareness (Badawi & Adiyono, 2026; Bond et al., 2021; Nurjanah et al., 2025; Rizvi et al., 2025). In this sense, AI functions not merely as a technological tool but as a facilitator of learning processes.

Furthermore, the dual role of AI as both a performance enhancer and a process facilitator highlights its transformative potential in higher education. Rather than serving solely as a productivity tool, AI reshapes how students interact with knowledge and manage their learning. In summary, AI's value lies not only in improving measurable outcomes but also in enhancing the processes that lead to those outcomes, such as personalized learning, real-time feedback, and skill development. This dual focus underscores AI's transformative potential in education (Badawi & Adiyono, 2026; Hubballi et al., 2025; Kushwah et al., 2025; Ntjamba & Ashipala, 2025).

2. Self-Regulated Learning as a Key Mechanism

One of the most important findings of this study is that self-regulated learning (SRL) emerges as the strongest predictor of academic performance. This result reinforces the central premise of Self-Regulated Learning theory, which emphasizes that students' ability to plan, monitor, and evaluate their learning is essential for academic success (Zimmerman, 2002). Prior studies consistently show that students with strong self-regulation skills achieve better academic outcomes across various learning environments (Broadbent & Poon, 2015).

In addition, AI usage was found to significantly enhance self-regulated learning, suggesting that AI can act as a cognitive scaffold that supports metacognitive development. AI systems can guide students in setting goals, tracking progress, and reflecting on their learning, thereby strengthening self-regulatory behaviors. This finding is supported by previous research indicating that technology-enhanced learning environments can promote SRL by providing structured support and feedback (Azevedo et al., 2017).

The mediation analysis further confirms that SRL plays a critical role in linking AI usage to academic performance. This suggests that the effectiveness of AI depends on how students use it within their learning processes. In other words, AI serves as a tool, but SRL functions as the mechanism that transforms technological use into meaningful academic outcomes. This mechanism-based perspective contributes to the literature by integrating technological and cognitive dimensions into a unified explanatory model.

3. The Conditional Role of Digital Literacy and Learning Motivation

The non-significant direct effect of digital literacy on academic performance requires critical interpretation, as it challenges the dominant assumption that digital competence inherently leads to improved learning outcomes. This finding suggests that possessing digital skills does not automatically translate into academic success, particularly in AI-supported learning environments.

One plausible explanation lies in the distinction between digital skills and learning strategies. Digital literacy primarily reflects students' ability to access, navigate, and evaluate digital information; however, it does not guarantee that these capabilities are applied in cognitively meaningful ways. Without strong self-regulated learning, digital competence may remain procedural rather than strategic, limiting its direct contribution to academic performance (Nassar & Khattab, 2024; Van Laar et al., 2019; Victor & Ujir, 2025).

Moreover, the result highlights a potential gap between surface-level engagement and deeper cognitive processing. Students with high digital literacy may efficiently interact with digital platforms and retrieve information, yet this efficiency does not necessarily foster critical thinking, conceptual understanding, or knowledge integration. In this context, digital literacy facilitates access to information but does not ensure meaningful learning (Kirschner & De Bruyckere, 2017; OECD, 2021).

Another important consideration is the increasing reliance on artificial intelligence tools in academic tasks. While AI can enhance efficiency, excessive dependence on such technologies may reduce students' cognitive effort and active engagement. As a result, digital proficiency may shift from being a learning enabler to a shortcut mechanism, weakening its direct impact on academic performance. This phenomenon aligns with emerging concerns that overreliance on intelligent systems may hinder deep learning and metacognitive development (Dwivedi et al., 2023; Kasneci et al., 2023).

Overall, this finding calls for a reconsideration of the linear assumption that digital competence directly leads to academic success. Instead, it supports a more nuanced perspective in which digital literacy contributes to academic performance only when mediated by self-regulated learning, highlighting the central role of cognitive and metacognitive

processes in AI-supported education.

4. Theoretical Contribution

This study advances a mechanism-based reconceptualization of how artificial intelligence (AI) contributes to academic performance, challenging the prevailing tendency in the literature to treat technology adoption as an end rather than a process. Existing research grounded in the Technology Acceptance Model has largely emphasized perceived usefulness and ease of use while offering limited explanation of how technology translates into measurable learning outcomes. By introducing self-regulated learning (SRL) as a mediating mechanism, this study addresses this conceptual limitation. It repositions AI from a passive technological artifact to an active component within a cognitively mediated learning system. This shift is critical, as it redirects the analytical focus from adoption metrics toward learning mechanisms, which remain underdeveloped in prior empirical models.

Moreover, this study provides a substantive extension to Self-Regulated Learning by situating it within an AI-supported learning environment. While SRL has been widely recognized as a predictor of academic success, its role as a mechanistic bridge between technology use and performance outcomes has not been sufficiently theorized. The findings demonstrate that AI enhances academic performance only to the extent that it strengthens students' metacognitive regulation, underscoring that technological effectiveness is contingent upon learners' cognitive engagement rather than inherent in the technology itself. This challenges deterministic assumptions about AI in education and reinforces the need to embed technological innovation within established learning theories.

Finally, the study offers a critical re-evaluation of digital literacy by demonstrating its non-significant direct effect on academic performance, a finding that problematizes the dominant narrative that digital competence is inherently beneficial. Instead, the results suggest that digital literacy operates indirectly through SRL, implying a hierarchical dependency between technological skills and cognitive processes. This insight exposes a theoretical oversimplification in prior studies that conflate access and competence with learning effectiveness. By integrating motivational, technological, and cognitive dimensions into a unified model, this study not only bridges fragmented theoretical perspectives but also establishes a more analytically rigorous framework for understanding academic performance in AI-mediated educational contexts.

5. Limitations and Future Research

This study is subject to several limitations that should be acknowledged. First, the use of a cross-sectional design restricts the ability to draw causal inferences, as the observed relationships reflect associations rather than temporal dynamics. Second, the reliance on self-reported data raises concerns regarding common method bias and potential response inflation, particularly in measuring constructs such as academic performance and AI usage. Third, the sample was drawn from a single institution, which may limit the generalizability of the findings across different educational contexts and cultural settings. In addition, the study does not differentiate between types or intensity of AI usage, thereby overlooking potential variations in how specific AI tools influence learning processes. These limitations suggest that future research should employ longitudinal or experimental designs, incorporate objective performance indicators, and examine diverse institutional contexts as well as more nuanced dimensions of AI engagement.

Another limitation concerns the potential presence of common method bias due to the use of self-reported data collected from a single source. Although Harman's single-factor test suggested that common method variance is unlikely to be a serious concern, this

technique is considered insufficient as a standalone diagnostic tool. Future research is therefore encouraged to employ more robust statistical approaches, such as marker variable techniques or common latent factor modeling, to better control for and assess common method bias (Podsakoff et al., 2003).

Conclusion

This study demonstrates that artificial intelligence (AI) contributes to students' academic performance through both direct and indirect pathways, with self-regulated learning (SRL) emerging as the central mechanism linking technology use to learning outcomes. The findings indicate that while AI can enhance efficiency and access to learning resources, its effectiveness is not inherent but depends on students' ability to actively regulate their learning processes. In this regard, SRL functions as the primary driver that transforms AI usage into meaningful academic gains.

Furthermore, the results highlight that learning motivation plays a crucial role in encouraging students to engage with AI technologies, whereas digital literacy does not directly improve academic performance but operates indirectly through SRL. This suggests that technological competence alone is insufficient to enhance learning outcomes without the support of strong cognitive and metacognitive skills. Therefore, the integration of AI in education should not be approached solely as a technological intervention but as part of a broader pedagogical strategy that fosters students' self-regulation and motivation.

Overall, this study underscores the importance of adopting a holistic approach to AI integration in higher education by aligning technological tools with students' learning processes. Future research is encouraged to further investigate the dynamic interplay between AI, cognitive engagement, and contextual factors across diverse educational settings to develop more robust and generalizable models of AI-supported learning.

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