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When Does Artificial Intelligence Improve Academic Achievement? The Moderating Role Of Academic Self-Efficacy: Evidence From Hierarchical And Moderated Regression Analyses Using R

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Abstract

The rapid integration of Artificial Intelligence (AI) in higher education presents new learning opportunities, yet its direct impact on academic achievement remains inconclusive. This study investigates the effect of AI utilization on students' academic achievement and examines the moderating role of academic self-efficacy. Employing a quantitative survey design, data were collected from 260 undergraduate students in Indonesia. Hierarchical and moderated regression analyses revealed that AI utilization does not exert a significant direct effect on academic achievement. Conversely, academic self-efficacy emerged as a robust positive predictor. Crucially, academic self-efficacy significantly moderated the relationship between AI use and academic achievement. Simple slope analysis demonstrated that AI utilization positively predicts academic achievement exclusively among students with low levels of academic self-efficacy, functioning as a compensatory support mechanism. For students with high self-efficacy, the marginal benefits of AI were non-significant. These findings indicate that the academic benefits of AI are highly conditional and dependent on learners' psychological characteristics. The study underscores the necessity of fostering academic self-efficacy alongside technological integration to optimize learning outcomes in the AI era.

Keywords: Artificial intelligence; Academic self-efficacy; Academic achievement

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INTRODUCTION

The rapid advancement of Artificial Intelligence (AI) has significantly transformed the landscape of higher education by offering personalized, accessible, and efficient learning support (Crompton & Burke, 2023; Wang et al., 2024). Generative AI tools, such as ChatGPT and Gemini, enable students to acquire information rapidly, receive instant feedback, and access diverse learning resources beyond traditional boundaries (Kasneci et al., 2023). Consequently, there is a growing optimism that integrating AI into educational environments can enhance learning engagement, foster personalized learning experiences, and substantially improve students' academic achievement (A. Y. Q. Huang et al., 2023).

Despite this technological optimism, empirical evidence regarding the direct impact of AI on academic achievement remains inconclusive. While some studies highlight the positive effects of AI on learning outcomes and academic productivity (Wang et al., 2024), others indicate that technology adoption does not automatically translate into improved academic performance (Kizilcec, 2023; Strzelecki, 2024). These inconsistent findings suggest that the mere availability and frequency of AI use are insufficient to guarantee academic success, pointing to the necessity of examining individual psychological factors that influence how students interact with and benefit from these technologies (X. Huang et al., 2025).

Viewed through the lens of contemporary educational psychology, the effectiveness of technological tools is heavily contingent upon students' psychological characteristics, particularly their academic self-efficacy. Academic self-efficacy—the belief in one's capability to organize and execute actions required to achieve academic goals—dictates students' learning choices, effort, and resilience in facing challenges (Schunk & DiBenedetto, 2020). In digital learning environments, students with high self-efficacy are better equipped to self-regulate, critically evaluate AI-generated information, and utilize technology as a cognitive scaffold rather than a mere shortcut (Panadero et al., 2022). Conversely, those with low self-efficacy may struggle to leverage AI optimally, potentially leading to cognitive offloading and AI dependency without deep conceptual understanding (Nzenwata et al., 2025).

Although the integration of AI in education has been extensively studied, the majority of existing literature has predominantly focused on technology acceptance, user perceptions, and behavioral intentions (Strzelecki, 2024; Tlili et al., 2023). There is a notable scarcity of empirical research investigating the psychological mechanisms underlying the relationship between AI utilization and actual academic achievement. Specifically, the moderating role of academic self-efficacy in determining *when* and *for whom* AI translates into tangible academic benefits remains

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largely unexplored in higher education contexts (Chan & Hu, 2024; Kizilcec, 2024).

To address this critical gap, this study aims to analyze the effect of AI utilization on students' academic achievement and to examine the moderating role of academic self-efficacy in this relationship. By shifting the paradigm from a purely technological perspective to an educational psychology approach, this research seeks to elucidate the conditional nature of AI's academic benefits. The findings will provide valuable insights for higher education institutions to design AI-integrated learning strategies that not only provide technological access but also foster the psychological readiness necessary for students to thrive in the AI era.

This study employed a quantitative approach with an explanatory survey design grounded in Social Cognitive Theory to examine the relationships among artificial intelligence (AI) utilization, academic self-efficacy, and academic achievement. The participants comprised 260 undergraduate students enrolled in Integrated Science Education programs in the Special Region of Yogyakarta, Indonesia, selected based on specific inclusion criteria. The research model positioned AI utilization as the predictor variable, academic self-efficacy as the moderator, and academic achievement—measured objectively by the students' Grade Point Average (GPA)—as the criterion variable. Data for AI utilization and academic self-efficacy were collected using self-report questionnaires adapted from the Technology Acceptance Model and Bandura's self-efficacy framework, respectively. Both instruments were measured on a four-point Likert scale, a format specifically chosen to encourage decisive responses and minimize neutral response bias.

Data analysis was conducted using R software, beginning with descriptive statistics and Pearson correlation to map the initial bivariate relationships among the variables. To test the hypotheses, the study employed Hierarchical Regression Analysis to evaluate the sequential predictive contributions of the variables, followed by Moderated Regression Analysis (MRA) to assess the interaction effect between AI utilization and academic self-efficacy. Prior to computing the interaction term, the predictor and moderator variables were mean-centered to mitigate potential multicollinearity. The conditional effects of the moderation were further elucidated through simple slope analysis and the Johnson-Neyman technique to identify the specific regions of significance for the moderator. Additionally, relative importance analysis using the Lindeman, Merenda, and Gold (LMG) approach was applied to determine the proportional contribution of each predictor in explaining the variance in academic achievement, with all statistical tests evaluated at a 5% significance level.

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RESULTS AND DISCUSSION

Results

Descriptive Statistics of the Research Variables

The initial phase of the data analysis involved computing comprehensive descriptive statistics to establish a foundational understanding of the sampled undergraduate students enrolled in the integrated science education programs. This preliminary step was absolutely crucial for mapping the central tendencies and dispersion metrics across all measured constructs before proceeding to any complex inferential testing procedures. The calculated arithmetic means for all primary variables indicated a generally high level of technological engagement, psychological readiness, and overall academic performance among the participants. Furthermore, the standard deviation values suggested a moderate degree of variability within the dataset, ensuring that the subsequent regression models would adequately capture a diverse range of student experiences and psychological profiles. This comprehensive baseline mapping ensures that any subsequent anomalies or unexpected patterns in the inferential stages can be properly contextualized.

Table 1. Descriptive Statistics and Correlations Among Research Variables

Variable	M	SD	1	2	3
1. Artificial Intelligence	3.19	0.75	—		
2. Academic Self-Efficacy	3.32	0.64	0.013	—	
3. Academic Achievement	3.34	0.59	0.039	0.790***	—

The provided descriptive statistics reveal that the participants possessed a robust sense of academic self-efficacy, as evidenced by the highest mean score recorded among the measured variables. Concurrently, the students demonstrated a relatively high frequency of artificial intelligence utilization in their daily academic routines, reflecting the widespread integration of these digital tools in modern higher education environments. The academic achievement metric, represented by the cumulative grade point average, also reflected a strong overall performance level across the sampled population. These baseline metrics collectively portray a cohort of students who are both technologically adept and psychologically confident in their academic capabilities.

The relatively high mean scores across all constructs suggest that the modern university environment successfully fosters both technological adoption and psychological resilience among

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its students. However, the presence of moderate standard deviations indicates that despite this general trend, there remains a substantial subset of students who struggle with either technological integration or self-belief. This variability is particularly important for the current study, as it provides the necessary statistical variance required to detect potential interaction effects in the moderation analysis. Consequently, the descriptive profile confirms that the sample is highly representative of contemporary higher education students navigating the complexities of artificial intelligence integration.

Bivariate Correlation Analysis

Following the descriptive profiling, a bivariate correlation analysis was conducted to examine the preliminary linear relationships and associative strengths among the research variables. The Pearson correlation coefficients were computed to determine the direction and magnitude of the associations without imposing any causal assumptions at this exploratory stage. The analysis revealed a striking contrast between the relationships involving artificial intelligence utilization and those involving internal psychological constructs. Specifically, the technological variable showed virtually no linear association with either the psychological or the outcome variables, whereas the psychological construct demonstrated an exceptionally strong positive relationship with the academic outcome. Such preliminary mapping is essential for verifying the underlying assumptions of linearity and homoscedasticity required for parametric testing.

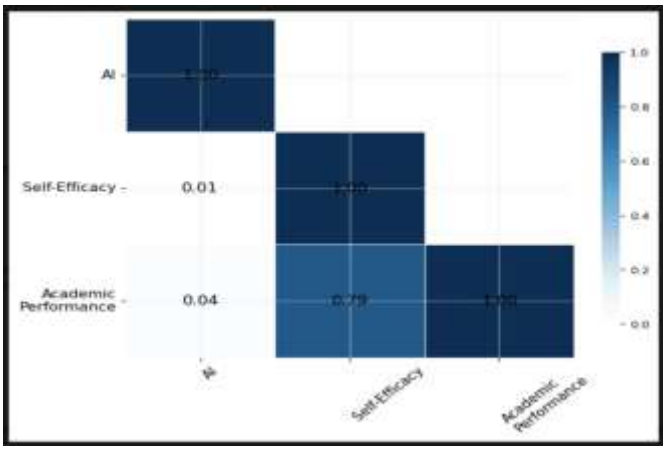


Figure 1. Correlation Matrix of Research Variables

The visual representation of the correlation matrix clearly highlights the dominant associative strength between the internal psychological construct and the academic outcome

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variable. The intense coloration and proximity in the network diagram emphasize that these two variables share a substantial amount of overlapping variance, confirming their strong empirical link. In stark contrast, the artificial intelligence utilization variable appears almost entirely disconnected from the other nodes, visually reinforcing its statistical independence from both the predictor and the criterion. This visual evidence strongly supports the initial numerical findings, illustrating that internal psychological factors overwhelmingly dictate the variance in student performance rather than mere technological exposure.

The near-zero correlation between artificial intelligence utilization and academic achievement suggests that the mere frequency of using digital tools does not inherently translate into better academic performance. This finding challenges the simplistic technological determinism that often pervades contemporary educational discourse, which assumes that increased access to advanced tools automatically yields superior learning outcomes. Instead, the exceptionally strong correlation observed for the psychological construct underscores the enduring importance of internal cognitive and motivational factors in determining academic success. Ultimately, these bivariate relationships establish the critical need for a more nuanced analytical approach that can uncover the conditional mechanisms governing technology effectiveness.

Hierarchical Regression Analysis

To systematically evaluate the unique and cumulative contributions of the predictor variables, a hierarchical regression analysis was executed in sequential steps. The first model isolated the direct predictive effect of artificial intelligence utilization on the academic outcome, revealing a statistically non-significant relationship with a negligible effect size. This initial finding confirmed the bivariate correlation results, demonstrating that the variance in student performance cannot be explained by the frequency of technology use alone. The extremely low coefficient of determination in this baseline model highlights the inadequacy of unidimensional technological metrics in capturing the complexities of academic success. This sequential approach allows researchers to observe the exact moment when additional variables significantly alter the explanatory power of the model.

The introduction of the psychological construct in the second model resulted in a dramatic and statistically significant transformation in the predictive power of the equation. The coefficient of determination surged to explain nearly two-thirds of the total variance in the academic outcome, underscoring the overwhelming dominance of internal psychological factors. Within this

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expanded model, the psychological construct emerged as a highly significant positive predictor, while the technological variable remained statistically insignificant and practically irrelevant. This stark contrast definitively establishes that a student's belief in their own academic capabilities is the primary engine driving their educational attainment, far surpassing the influence of external technological tools.

Table 2. Results of Hierarchical Regression and Moderated Regression Analysis

Variable	Model 1	Model 2	Model 3
Artificial Intelligence	0.030	0.022	0.024
Academic Self-Efficacy	–	0.728***	0.718***
AI × Academic Self-Efficacy	–	–	−0.163***
R^2	0.002	0.626	0.642
ΔR^2	–	0.624***	0.017***

The detailed regression coefficients presented in the table quantitatively substantiate the sequential enhancement of the predictive model across the three specified stages. The incremental change in the coefficient of determination between the first and second models quantifies the massive explanatory power added by the psychological variable. Furthermore, the stability of the technological variable's coefficient across all models confirms its consistent lack of direct predictive utility in this specific educational context. These hierarchical results firmly establish the baseline for testing the interaction effect, ensuring that the subsequent moderation analysis is built upon a robust understanding of the main effects.

Moderated Regression Analysis

Building upon the hierarchical results, the third model incorporated the interaction term to test the central hypothesis regarding the conditional nature of technological benefits. The inclusion of the interaction between the technological and psychological variables yielded a statistically significant coefficient, indicating the presence of a meaningful moderation effect. This significant interaction term demonstrates that the relationship between technology utilization and academic performance is not uniform across the student population but fluctuates depending on their psychological profiles. Consequently, the psychological construct functions not merely as an independent predictor but as a critical boundary condition that shapes the efficacy of digital learning tools. By testing this interaction, the study moves beyond simple main effects to explore

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the complex, conditional dynamics of modern digital learning environments.

The negative sign of the interaction coefficient provides profound theoretical insights into how internal beliefs alter the utility of external technological resources. This inverse relationship suggests that as the students' psychological readiness increases, the marginal benefit derived from frequent technology utilization progressively diminishes. For students possessing robust internal confidence and self-regulatory skills, the additional scaffolding provided by digital tools offers minimal incremental value to their already optimized learning strategies. Conversely, for those lacking strong internal academic beliefs, the technology serves as a vital compensatory mechanism that significantly bridges the gap in their cognitive and motivational resources.

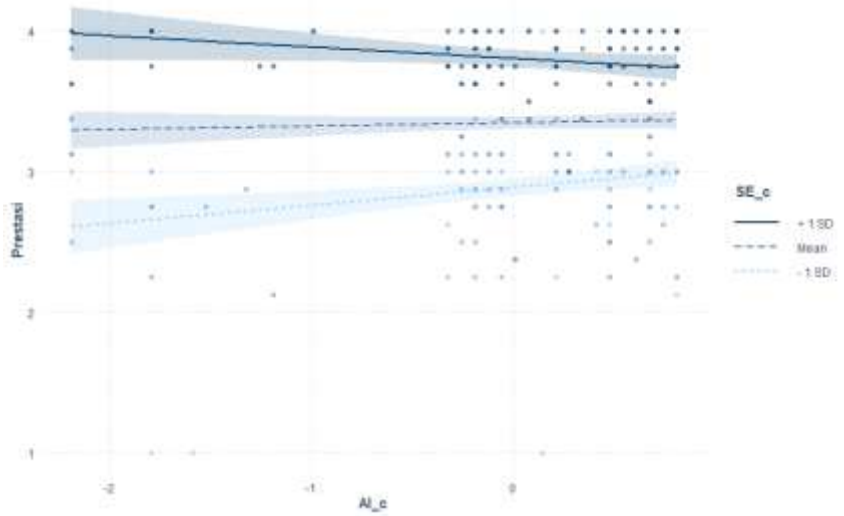


Figure 2. Moderating Effect of Academic Self-Efficacy on the Relationship Between Artificial Intelligence Use and Academic Achievement

The graphical illustration of the moderating effect vividly captures the divergent slopes representing the relationship between technology use and academic performance across different psychological profiles. The steep positive gradient observed for the low-confidence group visually confirms that these students derive substantial academic benefits from increased technological engagement. In contrast, the flattened and slightly negative trajectory for the high-confidence group illustrates the concept of diminishing returns, where advanced tools provide little to no additional advantage. This visual representation perfectly encapsulates the core finding that the academic utility of artificial intelligence is highly contingent upon the user's pre-existing psychological characteristics.

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Simple Slope Analysis

To decompose the complex interaction effect and understand its practical implications, a simple slope analysis was conducted at specific levels of the moderator variable. This technique allowed for the isolation of the technological variable's effect on the academic outcome at low, average, and high levels of the psychological construct. The analysis revealed that the positive predictive effect of technology utilization was only statistically significant for the subgroup of students exhibiting low levels of internal academic confidence. For students with average or high levels of psychological readiness, the slopes were statistically indistinguishable from zero, indicating no meaningful impact of technology on their performance. This granular approach is necessary because global interaction terms can sometimes obscure the specific conditions under which effects are actually present.

Table 3. Results of Simple Slope Analysis

Level of Academic Self-Efficacy	Slope	t	P
Low (−1 SD)	0.13	3.02	0.003
Average	0.02	0.81	0.419
High (+1 SD)	−0.08	−1.92	0.056

The tabulated simple slope coefficients provide precise empirical evidence regarding the conditional effectiveness of artificial intelligence across the spectrum of student psychological profiles. The significant positive t-value for the low-confidence subgroup confirms that technological integration serves as a powerful equalizer for those who initially struggle with academic self-belief. Meanwhile, the non-significant coefficients for the average and high-confidence subgroups mathematically validate the notion that these students do not rely on external tools to maintain their academic excellence. These specific slope values are crucial for translating the abstract interaction effect into actionable insights for targeted educational interventions.

The nuanced findings from the simple slope analysis challenge the universalist approach to educational technology implementation by highlighting the necessity of differentiated instructional strategies. The fact that artificial intelligence significantly boosts the performance of only the low-confidence subgroup suggests that these tools are most effective when deployed as targeted scaffolding rather than blanket solutions. Students who already possess strong self-

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regulatory mechanisms and high academic confidence likely utilize the technology in fundamentally different, perhaps more superficial, ways that do not directly impact their grades. Therefore, the true value of these advanced digital tools lies in their capacity to support vulnerable learners rather than enhancing the capabilities of already successful students.

Johnson-Neyman Technique for Regions of Significance

To further refine the understanding of the moderation effect and identify the exact thresholds where the technological effect becomes significant, the Johnson-Neyman technique was applied. Unlike the simple slope analysis, which only tests the relationship at arbitrary standard deviation points, this method maps the continuous regions of significance across the entire spectrum of the moderator variable. The analysis determined that the predictive effect of artificial intelligence utilization on academic performance becomes statistically significant only when the psychological construct falls below a specific upper threshold. This precise boundary delineates the exact psychological conditions under which digital tools transition from being merely accessible resources to being critical determinants of academic success. This advanced statistical procedure provides a much more precise and continuous understanding of the moderation effect compared to traditional categorical slicing.

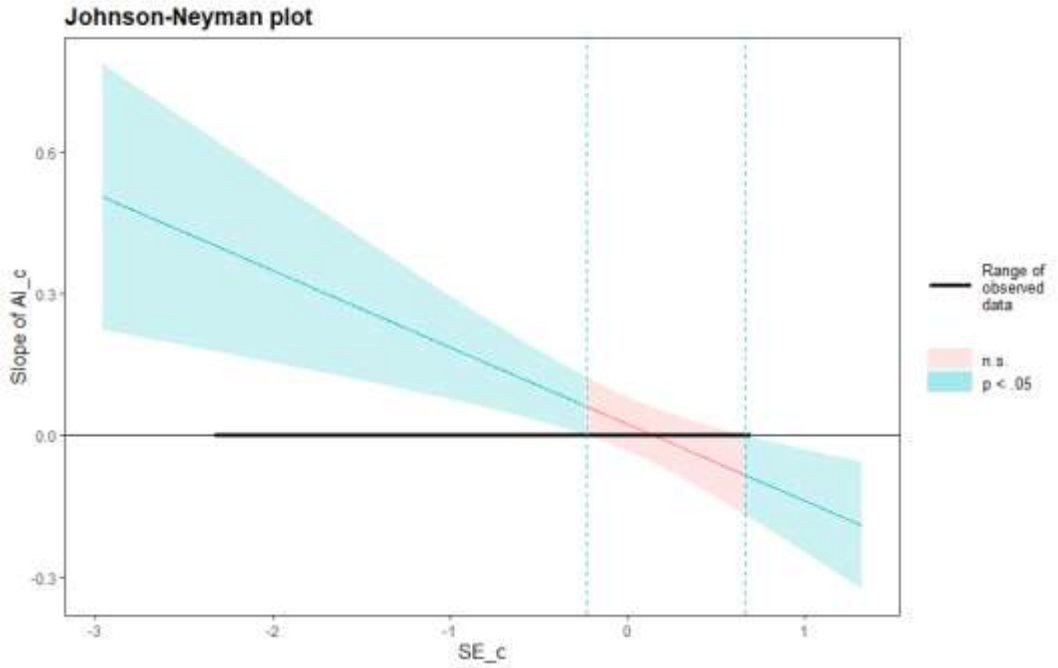


Figure 3. Johnson–Neyman Plot of Academic Self-Efficacy as a Moderator

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The resulting Johnson-Neyman plot provides a comprehensive visual map of the significance regions, clearly delineating the boundaries where the technological effect is statistically distinguishable from zero. The area where the confidence interval excludes the zero line corresponds precisely to the lower range of the psychological construct, confirming the simple slope findings. As the values of the moderator increase beyond the identified threshold, the confidence band rapidly encompasses the zero line, indicating a complete loss of statistical significance. This graphical output offers a rigorous, continuous validation of the compensatory mechanism hypothesis, proving that the utility of the technology is strictly bounded by the user's psychological state.

The synthesis of the hierarchical, moderated, and Johnson-Neyman analyses culminates in a robust empirical validation of the conditional nature of educational technology benefits. The comprehensive statistical evidence unequivocally demonstrates that artificial intelligence does not operate as a universal catalyst for academic improvement but rather functions as a highly context-dependent resource. The internal psychological characteristics of the students, specifically their academic self-efficacy, act as the primary gatekeepers that determine whether technological utilization will yield tangible academic dividends. Ultimately, these findings mandate a paradigm shift in educational policy, urging institutions to focus on cultivating students' psychological readiness alongside the provision of advanced technological infrastructure.

DISCUSSION

The finding that artificial intelligence (AI) utilization does not exert a direct, significant influence on students' academic achievement challenges the prevailing technological determinism that often accompanies the integration of digital tools in higher education. This null direct effect suggests that the mere frequency or intensity of using generative AI platforms, such as ChatGPT or Gemini, does not automatically translate into improved academic performance. This outcome aligns with recent literature indicating that while AI can significantly enhance task efficiency and provide instant feedback, it does not inherently foster the deep conceptual understanding required for higher grades (Alam et al., 2026; Hassen, 2025; Vieriu & Petrea, 2025). Furthermore, Tlili et al (2023) noted that although AI boosts learning productivity, its ultimate impact on academic achievement is heavily contingent upon individual characteristics and the specific pedagogical context. Supporting this view, Leite et al (2026) and Zhao et al (2025) argued that when students utilize generative AI primarily for task completion rather than knowledge construction, the technology serves as a shortcut that increases efficiency but fails to yield

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substantial improvements in actual academic achievement.

In stark contrast to the negligible impact of AI, academic self-efficacy emerged as the overwhelmingly dominant predictor of academic achievement, accounting for a massive proportion of the variance in students' Grade Point Average (GPA). This robust positive relationship underscores the enduring primacy of internal psychological factors over external technological resources in determining educational success. According to Krisnaresanti et al (2026), Maslakhah et al (2023), Miao et al (2025), and Rosiyanti et al (2025), self-efficacy fundamentally dictates a student's learning choices, the magnitude of their effort, and their resilience when confronting academic obstacles, which are critical behaviors for achieving high grades. In the context of modern digital learning environments, this psychological trait becomes even more vital; Navarro et al (2023) and Sui et al (2023) demonstrated that students with high academic self-efficacy are significantly better equipped to engage in self-regulated learning, critically evaluate the quality of digital information, and utilize technological tools productively without losing cognitive control. Consequently, the present study reinforces the notion that a student's belief in their own capabilities remains the most reliable engine for academic excellence, even in an era saturated with advanced artificial intelligence.

The most critical contribution of this study lies in the discovery that academic self-efficacy significantly moderates the relationship between AI utilization and academic achievement, effectively answering the question of *when* AI actually improves academic outcomes. The simple slope and Johnson-Neyman analyses revealed that AI utilization only yields a significant positive effect on academic achievement for students with low levels of academic self-efficacy. This phenomenon can be conceptualized through the lens of a compensatory support mechanism, where AI acts as a vital cognitive scaffold for vulnerable learners. Khalil et al (2026) and Sultana et al (2025) corroborate this finding, noting that the most profound benefits of AI-assisted learning are predominantly experienced by students who struggle with academic confidence or face learning difficulties. For these students, generative AI provides essential scaffolding—such as simplified explanations, brainstorming assistance, and immediate feedback—that helps bridge the gap between their current capabilities and the demands of the academic task, thereby directly translating into measurable improvements in their academic performance.

Conversely, for students possessing high levels of academic self-efficacy, the marginal academic benefits derived from AI utilization diminish substantially and become statistically non-significant. These students typically already possess robust self-regulatory strategies, strong critical thinking skills, and high intrinsic motivation, rendering the additional scaffolding provided

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by AI largely redundant for the purpose of grade improvement. Zhang et al (2026) emphasizes that the effectiveness of educational technology is strictly bounded by the psychological characteristics of the user, meaning that advanced tools cannot be assumed to provide universal benefits across all learner profiles. Furthermore, relying heavily on AI might even pose subtle risks for highly efficacious students; Zahid et al (2026) and Zhang et al (2026) warned that excessive AI dependency can lead to cognitive offloading, where students bypass deep mental processing, potentially reducing their cognitive engagement. Therefore, because high self-efficacy students already have optimized internal learning mechanisms, the introduction of AI does not significantly augment their academic achievement and may occasionally introduce the risk of superficial engagement if not carefully managed.

Ultimately, these findings necessitate a paradigm shift in how higher education institutions approach the integration of educational technologies, moving away from a purely access-based model toward a psychologically informed framework. The evidence clearly demonstrates that AI should not be viewed as a universal panacea for academic underperformance, but rather as a highly conditional, compensatory tool whose efficacy is gated by the user's psychological readiness. Wang et al (2024) highlighted in their systematic review that the successful integration of AI in education requires a holistic approach that considers human factors, pedagogical strategies, and learner diversity. Therefore, to maximize the potential of artificial intelligence in higher education, universities must implement interventions that not only provide technological infrastructure but also actively cultivate students' academic self-efficacy, digital literacy, and self-regulated learning skills, ensuring that all students are psychologically prepared to leverage these tools effectively.

CONCLUSION

In conclusion, this study demonstrates that the utilization of Artificial Intelligence (AI) in higher education does not exert a direct, universal impact on students' academic achievement, challenging the assumption that technological integration automatically yields academic success. Instead, academic self-efficacy emerges as the paramount predictor of academic performance, underscoring the enduring primacy of internal psychological factors over external technological tools. Crucially, the findings reveal that academic self-efficacy significantly moderates the relationship between AI utilization and academic achievement. Specifically, AI functions as a compensatory support mechanism, significantly improving the academic outcomes only for students with low levels of academic self-efficacy, while its marginal benefits diminish and become

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statistically non-significant for those with high self-efficacy who already possess robust self-regulatory and cognitive strategies.

These findings carry profound implications for educational policy and instructional design, indicating that the successful integration of AI must transcend mere technological access and prioritize the cultivation of students' psychological readiness. Higher education institutions should implement targeted interventions that foster academic self-efficacy, self-regulated learning, and critical thinking to ensure students can leverage AI as a cognitive scaffold rather than a mere shortcut. While this study provides critical empirical evidence regarding the conditional nature of AI's academic benefits, future research should employ longitudinal or experimental designs to establish causal pathways and explore additional psychological and contextual moderators to further elucidate the complex human-technology dynamics shaping the future of learning.

FUTURE DIRECTIONS

While this study provides critical empirical evidence regarding the conditional benefits of artificial intelligence in higher education, its cross-sectional design precludes definitive causal claims, necessitating future research to employ longitudinal or experimental designs to track the long-term developmental trajectories of AI-assisted learning. Furthermore, subsequent studies should adopt more granular measurements to differentiate between various AI applications and specific usage intentions—such as deep knowledge construction versus superficial task completion—to better understand how distinct modes of human-AI interaction uniquely impact cognitive engagement and learning outcomes. Additionally, future investigations must explore other critical psychological and cognitive constructs, including self-regulated learning, digital literacy, and critical thinking, to build a more comprehensive framework of the complex human-technology dynamics in educational settings. Finally, to establish the broader applicability of these findings, it is imperative to replicate this study across diverse academic disciplines, educational levels, and cultural contexts, thereby determining whether the compensatory role of AI for students with low self-efficacy is a ubiquitous phenomenon or a highly context-dependent mechanism.

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