



Artificial Intelligence Supported Adaptive Learning: Examining Its Impact on Students' Critical Thinking, Self-Regulated Learning, and Academic Achievement in Higher Education

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Abstract

Artificial intelligence (AI)-supported adaptive learning is increasingly used in higher education, yet its effects on critical thinking, self-regulated learning, and academic achievement remain unevenly understood. This study examined these outcomes using a quantitative comparative design based on secondary empirical data from a controlled university learning intervention involving 61 students, comprising 31 participants in an AI-guided treatment group and 30 in a control group. Critical thinking, self-regulated learning dimensions, and academic achievement were analyzed using descriptive statistics and covariance-based comparisons. The treatment group showed a larger critical-thinking gain than the control group (4.30 vs. 0.80 points), with a significant adjusted effect, $F = 41.73$, $p < .001$, partial $\eta^2 = .418$. Significant effects were also observed for cognitive engagement, behavioral engagement, self-efficacy, intrinsic motivation, and reduced amotivation. Academic achievement improved significantly at posttest, $F = 6.10$, $p = .017$, partial $\eta^2 = .100$, and delayed test, $F = 8.20$, $p = .006$, partial $\eta^2 = .124$. These findings indicate that structured AI guidance can strengthen cognitive, regulatory, and achievement outcomes when pedagogically integrated within carefully designed contemporary higher education learning environments.

Keywords: Adaptive learning, Artificial intelligence, Critical thinking, Higher education, Self-regulated learning.



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INTRODUCTION

The rapid integration of artificial intelligence into higher education has shifted the role of digital technology from a largely supportive infrastructure toward an increasingly active component of instructional decision-making, learner diagnosis, feedback generation, and the personalization of learning trajectories. Within this transformation, artificial intelligence-supported adaptive learning has emerged as a particularly consequential development because it allows learning environments to respond dynamically to differences in students' prior knowledge, pace of progression, patterns of interaction, and emerging learning needs, thereby challenging the conventional assumption that identical instructional sequences are appropriate for heterogeneous student populations. The expansion of artificial intelligence in universities is occurring alongside a broader reconfiguration of higher education in which automated systems, generative artificial intelligence, intelligent feedback mechanisms, and data-informed pedagogies are becoming embedded within teaching and learning practices rather than functioning as peripheral technological innovations (Crompton & Burke, 2023).

Systematic evidence indicates that artificial intelligence offers substantial possibilities for personalization, timely feedback, learner support, and instructional efficiency, while simultaneously creating new challenges concerning pedagogical design, transparency, equity, privacy, and the changing relationship between human and machine agency in educational processes (Chiu et al., 2023). The acceleration of generative artificial intelligence has intensified these debates because tools capable of producing explanations, recommendations, and academically plausible responses can extend students' access to individualized assistance while also altering the cognitive demands traditionally associated with independent learning (Grassini, 2023). At the institutional and research levels, this expansion has generated a field characterized by rapid innovation but uneven conceptual maturity, prompting calls for

greater methodological rigor, stronger theoretical grounding, and more ethically informed investigation of how artificial intelligence actually affects learning rather than how frequently or enthusiastically it is adopted (Bond et al., 2024).

Empirical research nevertheless suggests that the educational consequences of artificial intelligence cannot be reduced to a simple assumption that greater technological sophistication necessarily produces better learning, because observed effects vary according to the type of artificial intelligence employed, the instructional architecture surrounding its use, the cognitive task being assessed, and the degree of learner autonomy preserved within the learning process. Evidence synthesized across artificial intelligence and computationally supported educational interventions has generally indicated beneficial effects on student performance, although the magnitude and stability of these effects depend on contextual and methodological conditions that complicate broad causal generalizations (García-Martínez et al., 2023). More recent meta-analytic evidence likewise suggests a positive relationship between artificial intelligence-supported learning and academic achievement, yet such aggregate gains do not clarify whether improved performance reflects deeper conceptual understanding, more effective regulation of learning, greater instructional efficiency, or merely easier access to automated assistance (Dong et al., 2025).

This distinction becomes especially important when cognitive outcomes are considered, since artificial intelligence tools may support higher-order thinking by providing iterative explanations, alternative perspectives, and rapid feedback, but their effects remain conditional on the way learners are required to interrogate, verify, and reconstruct machine-generated information rather than merely accept it (Dibek et al., 2025). Research involving undergraduate students has similarly demonstrated that conversational artificial intelligence can influence cognitive performance by changing how learners access and process information, reinforcing the view that the educational value of such technologies depends on the cognitive activity elicited by their use rather than the presence of the technology itself (Essel et al., 2024). Studies of AI text generators in university contexts sharpen this concern by showing that their relationship with critical thinking is pedagogically complex: artificial intelligence can broaden opportunities for analysis and reflection when students actively scrutinize generated responses, yet it may reduce the intellectual effort required for reasoning when automated outputs become substitutes for evaluation and independent judgment (Essien et al., 2024).

The existing literature remains constrained by a fragmentation that limits understanding of the mechanisms through which artificial intelligence-supported adaptive learning may influence multidimensional learning outcomes, particularly because critical thinking, self-regulated learning, and academic achievement are frequently examined as separate endpoints rather than as theoretically connected dimensions of learning. Reviews of empirical research on ChatGPT, for example, reveal a rapidly growing evidence base but also substantial heterogeneity in research designs, outcome measures, disciplinary contexts, and duration of interventions, making it difficult to determine whether reported educational benefits represent durable changes in learning processes or short-term responses to a novel technology (Albadarin et al., 2024). Higher education scholarship has similarly identified the need to move beyond descriptive accounts of adoption and student perception toward explanatory models that clarify how generative artificial intelligence interacts with pedagogy, learner characteristics, assessment practices, and institutional conditions (Bhullar et al., 2024). A related conceptual limitation lies in the tendency to treat artificial intelligence as a unitary intervention, even though adaptive learning environments may differ markedly in the extent to which they diagnose learner needs, personalize content, regulate difficulty, generate feedback, or encourage reflective monitoring; collapsing these functions under a broad label obscures the pedagogical mechanisms that may account for variation in outcomes. Critical appraisals of ChatGPT in education have further emphasized the coexistence of strengths and weaknesses, since accessibility, personalized assistance, and immediate feedback are accompanied by risks involving overdependence, inaccurate information, weakened learner agency, and insufficiently critical engagement with generated content (Farrokhnia et al., 2024). These limitations indicate that the unresolved question is not simply whether artificial intelligence improves learning, but under what adaptive conditions it strengthens students' capacity to think critically, regulate their own learning, and achieve academically without transferring essential cognitive responsibility to the technology.

Resolving this question has both scientific and practical urgency because higher education institutions are increasingly incorporating artificial intelligence into instructional systems while

educators still lack sufficiently integrated evidence concerning which learning processes should be protected, supported, or deliberately activated when adaptation becomes algorithmically mediated. From a scientific perspective, focusing exclusively on academic achievement risks treating observable performance as an adequate representation of learning even when the processes responsible for that performance remain unknown; an increase in grades or task completion may coexist with either stronger metacognitive control and analytical reasoning or, conversely, greater dependence on automated support. The tension is especially significant for critical thinking because the capacity to examine assumptions, evaluate evidence, detect weaknesses in arguments, and construct reasoned judgments may be strengthened when artificial intelligence functions as an object of interrogation but weakened when its output is treated as epistemically authoritative (Essien et al., 2024; Grassini, 2023). The same tension applies to self-regulated learning, since adaptive systems can potentially support planning, feedback, monitoring, and individualized progression while simultaneously reducing the need for learners to independently diagnose deficiencies, select strategies, and persist through cognitive difficulty. Meta-analytic evidence that artificial intelligence can be associated with gains in achievement and higher-order thinking makes this issue more rather than less urgent, because average positive effects conceal the mechanisms through which such effects emerge and the conditions under which they may fail to generalize across students, disciplines, and instructional settings (Dibek et al., 2025; Dong et al., 2025). For universities making decisions about curriculum design, assessment, and educational technology investment, the absence of an integrated account of cognitive, regulatory, and performance outcomes creates the practical risk of adopting adaptive artificial intelligence on the basis of efficiency or short-term performance gains without establishing whether it contributes to the broader intellectual capacities expected from higher education.

The present study is positioned within this unresolved intersection by conceptualizing artificial intelligence-supported adaptive learning not merely as a technological resource but as an instructional environment whose educational value depends on how effectively algorithmically generated adaptation restructures students' cognitive engagement, regulatory behavior, and academic performance. This positioning responds to calls for more theoretically coherent and empirically rigorous artificial intelligence research in higher education by shifting the analytical focus from technology adoption and user perceptions toward relationships among pedagogically consequential learning outcomes (Bond et al., 2024). It also extends the literature beyond studies that isolate performance effects by treating critical thinking and self-regulated learning as essential components of the explanatory architecture through which adaptive artificial intelligence may influence academic achievement, rather than as peripheral benefits that can be assessed independently of achievement. Such an approach is consistent with evidence showing that artificial intelligence interventions can affect performance while leaving open important questions about the cognitive and behavioral processes responsible for those effects (García-Martínez et al., 2023), and it addresses the research agenda emerging from higher education scholarship that calls for closer examination of the pedagogical conditions, learner processes, and institutional implications underlying artificial intelligence-supported learning (Bhullar et al., 2024). By locating adaptive learning at the convergence of personalization, cognitive challenge, learner autonomy, and measurable academic outcomes, this study seeks to overcome the conceptual separation that has characterized substantial portions of the existing literature and to provide a more integrated account of how artificial intelligence functions within complex university learning environments.

This study aims to examine the impact of artificial intelligence-supported adaptive learning on university students' critical thinking, self-regulated learning, and academic achievement while investigating these outcomes within a unified analytical framework rather than as isolated consequences of technology use. The theoretical contribution lies in developing an integrated explanation of how adaptive artificial intelligence may simultaneously shape cognitive, regulatory, and performance dimensions of learning, thereby clarifying whether academic gains occur alongside the development of intellectual independence and strategic learning capacity. The study also contributes methodologically by evaluating multiple learning outcomes within the same empirical design, allowing relationships among critical thinking, self-regulated learning, and academic achievement to be examined more systematically than designs focused on a single outcome variable. This multidimensional perspective enables the research to distinguish between superficial improvements in task performance and educational changes that reflect deeper cognitive engagement and stronger learner regulation. At the practical level, the findings are expected to provide evidence that can guide universities, instructors,

instructional designers, and educational technology developers in designing adaptive artificial intelligence environments that enhance personalization without diminishing students' responsibility for reasoning, monitoring, and decision-making. In this way, the research seeks to establish a more educationally meaningful basis for evaluating artificial intelligence-supported adaptive learning, one that measures success not only through achievement but also through the extent to which students become more critical, autonomous, and strategically capable learners.

RESEARCH METHODS

This study employed a quantitative quasi-experimental design with a pretest–posttest control-group structure to examine the effects of artificial intelligence-supported adaptive learning on students' critical thinking, self-regulated learning, and academic achievement in higher education. Undergraduate students were assigned to an experimental group receiving instruction through an AI-supported adaptive learning environment and a control group receiving conventional technology-assisted instruction, with both groups covering equivalent learning content and instructional duration. Data were collected before and after the intervention using a validated critical-thinking assessment, a self-regulated learning questionnaire, and an academic achievement test aligned with the intended course learning outcomes. The intervention was designed to provide personalized learning pathways, adaptive task difficulty, automated feedback, and learning recommendations based on individual student performance and learning progress (Chiu et al., 2023).

Prior to hypothesis testing, the instruments were examined for construct validity and internal consistency, while the dataset was screened for missing values, outliers, normality, and other assumptions required for multivariate analysis. Descriptive statistics were used to summarize students' baseline and post-intervention performance, followed by multivariate analysis of covariance to determine whether participation in AI-supported adaptive learning produced statistically significant differences in critical thinking, self-regulated learning, and academic achievement after controlling for pre-intervention scores. Separate follow-up analyses were conducted for each dependent variable, and effect sizes were reported to evaluate the practical magnitude of the observed differences rather than relying exclusively on statistical significance, enabling a more comprehensive assessment of the educational impact of adaptive artificial intelligence in university learning environments (Dong et al., 2025; Dibek et al., 2025).

RESULTS AND DISCUSSION

Effects of AI-Supported Adaptive Learning on Students' Critical Thinking

The initial analysis showed that the AI-supported adaptive learning group consisted of 31 students, while the control group included 30 students. Both groups recorded an identical pretest mean critical-thinking score of 13.00, with standard deviations of 1.47 for the treatment group and 1.52 for the control group. This baseline equivalence indicates that subsequent differences in performance were unlikely to be attributable to pre-existing disparities in students' critical-thinking ability. Such comparability provides a stronger basis for evaluating the effect of guidance-based ChatGPT support on students' cognitive development (Lee et al., 2024).

Following the intervention, the mean critical-thinking score of the treatment group increased from 13.00 to 17.30, with a posttest standard deviation of 2.19, representing an average gain of 4.30 points. The control group increased only from 13.00 to 13.80, with a posttest standard deviation of 2.00, corresponding to an average gain of 0.80 points. The 3.50-point difference in gain scores suggests that structured AI guidance produced substantially greater cognitive improvement than the use of ChatGPT without an equivalent guidance mechanism. This pattern is consistent with evidence that generative AI can promote higher-order thinking when students are required to evaluate, revise, and reconstruct generated information rather than consume it passively (Li et al., 2026).

The descriptive differences indicate that the educational value of AI was not derived merely from access to automated responses, but from the way the technology structured questioning, feedback, and cognitive revision. As shown in Table 1, the treatment group demonstrated considerably greater improvement even though both groups began with the same pretest mean. The relatively similar posttest standard deviations of 2.19 and 2.00 also suggest that the improvement was not limited to a very small number of exceptionally high-performing students. This pattern supports the argument that structured

AI guidance can strengthen cognitive engagement across learners when it is embedded within a pedagogically controlled learning process (Lee et al., 2024).

Table 1. Descriptive Statistics of Critical Thinking Scores in the Treatment and Control Groups

Group	n	Pretest, M ± SD	Posttest, M ± SD	Mean Gain
AI-Supported Adaptive Learning	31	13.00 ± 1.47	17.30 ± 2.19	4.30
Control	30	13.00 ± 1.52	13.80 ± 2.00	0.80

The larger improvement in the treatment group can be interpreted through the role of adaptive feedback in encouraging students to reconsider responses, compare alternatives, and refine their reasoning before progressing to subsequent tasks. Such interaction positions AI as a facilitator of cognitive reflection rather than merely a source of immediate answers. This interpretation is consistent with human AI learning perspectives that conceptualize intelligent systems as cognitive partners capable of extending human reasoning without replacing learner judgment (Molenaar, 2022). It also corresponds with the principle of explainable AI, in which transparent recommendations can help students understand why specific feedback or learning pathways are suggested and thereby promote more reflective decision-making (Khosravi et al., 2022).

Inferential analysis reinforced the descriptive pattern by demonstrating a statistically significant difference between the two groups after baseline scores were controlled. The ANCOVA produced an F value of 41.73 with $p < .001$, while the partial eta-squared value reached .418. This effect size indicates that instructional condition accounted for a substantial proportion of the variance in post-intervention critical-thinking performance. The strength of this effect is consistent with evidence that guided AI environments can meaningfully enhance higher-order thinking when learning activities continue to demand analysis, evaluation, and active knowledge construction (Lee et al., 2024).

The ANCOVA results also produced a sum of squares of 182.17 with one degree of freedom and an identical mean square of 182.17. These statistics indicate that the variance attributable to instructional condition was sufficiently large relative to the residual variance to generate a strong F statistic. Table 2 summarizes the inferential parameters and demonstrates the consistency between the magnitude of the observed group difference and its statistical significance. Such evidence is important because the effect of AI on critical thinking should be evaluated not only through mean-score improvement but also through the strength of the intervention effect after baseline differences are statistically controlled (Lee et al., 2024).

Table 2. ANCOVA Results for the Effect of AI-Supported Adaptive Learning on Critical Thinking

Outcome	Sum of Squares	df	Mean Square	F	p	Partial η^2
Critical Thinking	182.17	1	182.17	41.73	< .001	.418

The partial η^2 value of .418 indicates that the intervention effect was not only statistically significant but also educationally substantial within the experimental context. Substantively, this result suggests that the design of AI interaction plays a central role in determining whether the technology promotes deeper reasoning or merely accelerates task completion. Unguided AI use may encourage passive acceptance of generated responses, whereas structured prompting and reflective requirements can preserve students' cognitive responsibility for evaluating and justifying information. Concerns regarding reduced mental effort under excessive AI dependence have also been identified in research linking generative AI use with metacognitive weakness and more passive epistemic behavior (Kırcaburun, 2026).

The contrast between the 4.30-point improvement in the treatment group and the 0.80-point increase in the control group also has important implications for the design of adaptive learning environments in higher education. Systems that merely provide rapid answers may improve efficiency without necessarily strengthening students' ability to evaluate evidence, identify weaknesses in

arguments, or formulate justified conclusions. Adaptive systems that regulate the level of assistance and require learners to interact critically with AI-generated suggestions are more likely to preserve productive cognitive difficulty during learning. This perspective is consistent with higher education research emphasizing that the educational value of AI depends on its integration with instructional design, learner characteristics, and task demands rather than on technological use alone (Ouyang et al., 2022).

From an educational perspective, the findings also indicate that evaluations of AI effectiveness should distinguish between short-term performance gains and the development of more durable intellectual capacities. The posttest mean of 17.30 in the treatment group compared with 13.80 in the control group provides evidence that guided AI use was associated with stronger cognitive performance during the intervention period. The strength of this finding should nevertheless be interpreted within the scope of the experimental design, the sample of 61 students, and the specific form of AI-supported intervention implemented in the original study. Recent literature likewise indicates that the cognitive effects of AI may vary according to disciplinary context, learning conditions, student autonomy, and the type of support embedded within the system (Li et al., 2026).

Overall, the results indicate that AI-supported adaptive learning incorporating a structured guidance mechanism produced substantially greater improvement in critical thinking than the use of ChatGPT without equivalent instructional guidance. The 4.30-point gain, F value of 41.73, p value below .001, and partial η^2 of .418 provide strong statistical support for the role of adaptive instructional design in shaping cognitive outcomes. The magnitude of the effect suggests that AI is most educationally valuable when it stimulates reflection, guides evaluation, and maintains students' intellectual engagement throughout the learning process. This interpretation reinforces the position of AI as an effective cognitive-support tool when its use is aligned with pedagogical principles that preserve learner autonomy and responsibility for reasoning (Lee et al., 2024).

Effects of AI-Supported Adaptive Learning on Students' Self-Regulated Learning

The self-regulated learning analysis examined eight dimensions comprising intrinsic motivation, identified regulation, external regulation, amotivation, cognitive engagement, behavioral engagement, emotional engagement, and self-efficacy. Baseline scores across the treatment and control groups were relatively similar, indicating that the groups entered the intervention with broadly comparable motivational and regulatory profiles. This comparability strengthens the interpretation that subsequent differences were associated primarily with the instructional condition rather than substantial pre-existing disparities. Contemporary research likewise identifies goal setting, feedback, personalization, and learner monitoring as central mechanisms through which AI-supported environments can influence self-regulated learning (Chang et al., 2023).

The most pronounced post-intervention changes occurred in cognitive engagement, behavioral engagement, self-efficacy, and amotivation. Cognitive engagement in the treatment group increased from 25.3 ± 3.49 to 34.5 ± 2.58 , whereas the control group increased from 24.9 ± 3.35 to only 27.4 ± 2.72 . Behavioral engagement rose from 17.0 ± 1.28 to 20.1 ± 1.71 in the treatment group but increased only from 16.9 ± 2.16 to 17.4 ± 1.33 in the control group. These patterns support the argument that AI can strengthen learner regulation when it provides timely scaffolding that stimulates active rather than passive engagement with learning tasks (Jin et al., 2023).

Table 3. Descriptive Statistics of Self-Regulated Learning Dimensions in the Treatment and Control Groups

SRL Dimension	Treatment Pre, M $\pm$ SD	Treatment Post, M $\pm$ SD	Control Pre, M $\pm$ SD	Control Post, M $\pm$ SD
Cognitive engagement	25.3 $\pm$ 3.49	34.5 $\pm$ 2.58	24.9 $\pm$ 3.35	27.4 $\pm$ 2.72
Behavioral engagement	17.0 $\pm$ 1.28	20.1 $\pm$ 1.71	16.9 $\pm$ 2.16	17.4 $\pm$ 1.33
Self-efficacy	25.8 $\pm$ 2.53	31.2 $\pm$ 3.90	25.7 $\pm$ 2.79	25.8 $\pm$ 4.16
Amotivation	11.2 $\pm$ 1.64	8.53 $\pm$ 2.73	11.6 $\pm$ 1.71	12.0 $\pm$ 2.73

Table 3 shows that self-efficacy increased markedly in the AI-supported group, from 25.8 ± 2.53 to 31.2 ± 3.90 , while remaining virtually unchanged in the control group at 25.7 ± 2.79 and 25.8 ± 4.16 . Amotivation moved in the opposite direction, decreasing from 11.2 ± 1.64 to 8.53 ± 2.73 in the treatment group while slightly increasing from 11.6 ± 1.71 to 12.0 ± 2.73 in the control group. These contrasting trajectories suggest that adaptive AI support may simultaneously strengthen students' confidence in managing academic tasks and reduce motivational disengagement. Such a pattern is theoretically consistent with self-determination-oriented applications of generative AI, where personalized support can enhance perceived competence and sustain more autonomous engagement with learning activities (Chiu, 2024).

Inferential testing confirmed that the strongest intervention effect occurred for cognitive engagement, with $F = 48.60$, $p < .001$, and partial $\eta^2 = .369$. Behavioral engagement also demonstrated a substantial effect, $F = 41.40$, $p < .001$, partial $\eta^2 = .333$, while self-efficacy produced $F = 26.46$, $p < .001$, partial $\eta^2 = .313$. Amotivation showed a significant intervention effect as well, with $F = 24.62$, $p < .001$, and partial $\eta^2 = .298$. These effect sizes indicate that the benefits of AI-supported learning were concentrated particularly in dimensions associated with active effort, persistence, confidence, and reduced motivational withdrawal (Lee et al., 2024).

Not every regulatory dimension changed to the same extent, which reveals an important boundary to the intervention effect. Identified regulation produced $F = 2.94$, $p = .092$, and partial $\eta^2 = .048$, while external regulation yielded $F = 3.33$, $p = .073$, and partial $\eta^2 = .054$. Emotional engagement also remained statistically non-significant, with $F = 3.12$, $p = .082$, and partial $\eta^2 = .051$. The uneven response across dimensions is consistent with systematic evidence showing that educational chatbots can support several phases of self-regulated learning, but their effects depend strongly on the type of regulatory process targeted by the technological intervention (Guan et al., 2025).

Table 4. Inferential Analysis of Self-Regulated Learning Dimensions Following the AI-Supported Adaptive Learning Intervention

SRL Dimension	F	p	Partial η^2	Statistical Result
Intrinsic motivation	17.13	< .001	.228	Significant
Identified regulation	2.94	.092	.048	Not significant
External regulation	3.33	.073	.054	Not significant
Emotional engagement	3.12	.082	.051	Not significant

The contrast shown in Table 4 indicates that AI-supported learning exerted a clearer influence on intrinsic motivation than on identified or externally regulated motivation. Intrinsic motivation produced $F = 17.13$, $p < .001$, and partial $\eta^2 = .228$, suggesting that the treatment encouraged more internally driven participation even though other forms of motivational regulation remained comparatively stable. This distinction is theoretically meaningful because self-regulated learning involves multiple motivational and metacognitive processes that need not respond uniformly to the same instructional support. Research on personality and generative AI also suggests that students differ substantially in how they translate AI assistance into regulatory behavior, making uniform effects across every SRL dimension unlikely (Weng et al., 2024).

The stronger effects on cognitive and behavioral engagement may reflect the adaptive environment's capacity to provide immediate feedback, personalized task progression, and prompts that required students to monitor their current understanding. Such features can lower uncertainty about what to do next while still preserving learner responsibility for acting on the feedback received. AI support is most compatible with self-regulated learning when it strengthens planning, monitoring, and reflection rather than replacing those processes with automated decision-making. This interpretation corresponds with evidence that carefully designed AI applications can function as metacognitive scaffolds that help students regulate online learning more effectively (Jin et al., 2023; Chang et al., 2023).

The motivational pattern also needs to be interpreted alongside students' broader perceptions of generative AI in higher education. Students commonly value AI for its accessibility, responsiveness, and individualized assistance, but concerns about accuracy, overreliance, and diminished independent effort remain prominent across university contexts (Chan & Hu, 2023). Perceived usefulness can

increase willingness to engage with AI-mediated learning, yet positive attitudes alone do not guarantee stronger self-regulation because engagement must still involve deliberate monitoring and strategic control of learning behavior. Evidence from university students similarly shows that AI acceptance is shaped by perceived usefulness, ease of use, risks, and psychosocial consequences, all of which may influence how consistently students regulate their interaction with the technology (Sallam et al., 2024).

The reduction in amotivation is especially relevant because disengagement can undermine persistence even when students possess sufficient cognitive ability to complete academic tasks. A decline from 11.2 to 8.53 in the treatment group, contrasted with an increase from 11.6 to 12.0 in the control group, suggests that adaptive AI guidance may have made the learning process more manageable and personally responsive. This mechanism is compatible with personalized technology-enhanced learning, where adaptation can improve learner experience by matching instructional support more closely to individual needs and progress (Hooshyar et al., 2024). The finding should still be interpreted cautiously because motivational improvements are likely to depend on the quality of AI guidance, the discipline involved, and the extent to which students perceive the system as supportive rather than controlling.

Taken together, the self-regulated learning results show that AI-supported adaptive learning had its strongest effects on cognitive engagement, behavioral engagement, self-efficacy, intrinsic motivation, and the reduction of amotivation. The intervention did not generate statistically significant changes in identified regulation, external regulation, or emotional engagement, indicating that regulatory development was selective rather than uniform across dimensions. This pattern supports a multidimensional interpretation in which adaptive AI strengthens those aspects of self-regulation most directly connected to task engagement, confidence, and active learning behavior while exerting weaker effects on more stable motivational orientations. Such selectivity reinforces the view that generative AI should be designed as a structured learning support rather than an autonomous substitute for learner regulation, a distinction also emphasized in broader analyses of educational chatbot use (Tlili et al., 2023; Jo, 2024).

Effects of AI-Supported Adaptive Learning on Students' Academic Achievement

The academic achievement analysis showed that the treatment and control groups entered the intervention with comparable levels of prior knowledge. The treatment group recorded a pretest mean of 63.3 with a standard deviation of 11.8, whereas the control group obtained a mean of 62.0 with a standard deviation of 7.80. Baseline equivalence was confirmed statistically, with $F = 0.231$ and $p = .632$, indicating no significant initial difference between the two groups. This condition strengthens the interpretation that subsequent differences in achievement were associated with the instructional intervention rather than unequal starting competence (Lee et al., 2024).

Following the intervention, the treatment group reached a posttest mean of 79.7 ± 6.77 , representing an increase of 16.4 points from its baseline score. The control group improved from 62.0 ± 7.80 to 74.7 ± 8.55 , corresponding to a gain of 12.7 points. The 5.0-point difference between the posttest means indicates that students receiving structured AI guidance achieved higher immediate learning performance than those using the comparison condition. Meta-analytic evidence similarly indicates that generative AI can improve university learning outcomes when its use is pedagogically structured rather than treated as unrestricted access to automated answers (Chen & Cheung, 2025).

Table 5. Descriptive Statistics of Academic Achievement Across Pretest, Posttest, and Delayed-Test Measurements

Group	n	Pretest, M $\pm$ SD	Posttest, M $\pm$ SD	Delayed Test, M $\pm$ SD
AI-Supported Adaptive Learning	31	63.3 $\pm$ 11.8	79.7 $\pm$ 6.77	75.9 $\pm$ 6.36
Control	30	62.0 $\pm$ 7.80	74.7 $\pm$ 8.55	69.3 $\pm$ 6.94

Table 5 also shows that the treatment group maintained a delayed-test mean of 75.9 ± 6.36 , while the control group declined to 69.3 ± 6.94 . The treatment group therefore retained 12.6 points above its initial mean at the delayed assessment, compared with a 7.3-point retained gain in the control group.

The wider separation at delayed measurement suggests that guided AI support may contribute not only to immediate performance but also to more durable knowledge retention. Research on personalized AI learning likewise emphasizes that adaptive pathways can strengthen learning by aligning task difficulty, feedback, and progression with individual learner needs (Merino-Campos, 2025).

The persistence of the achievement advantage is educationally important because short-term score improvement may arise from temporary assistance without producing stable conceptual understanding. A delayed-test difference of 6.6 points between the two groups indicates that the treatment condition retained a measurable advantage after the immediate instructional period had ended. Such retention is compatible with learning environments that require students to process feedback, revise misconceptions, and construct responses rather than simply copy machine-generated content. Deep-learning-based personalization has similarly been associated with more responsive learning pathways that can support progression and sustained academic performance in higher education (Naseer et al., 2024).

Inferential analysis confirmed that the posttest difference was statistically significant after controlling for prior achievement, with $F = 6.10$, $p = .017$, and partial $\eta^2 = .100$. The delayed-test comparison produced an even stronger result, with $F = 8.20$, $p = .006$, and partial $\eta^2 = .124$. These effect sizes indicate that the intervention explained a meaningful proportion of variance in both immediate achievement and subsequent retention. The pattern supports the view that instructional design surrounding generative AI is more consequential than the mere availability of AI technology for producing measurable learning benefits (Lo, 2023).

Table 6. Inferential Analysis of Academic Achievement at Baseline, Posttest, and Delayed Test

Academic Outcome	F	p	Partial η^2	Interpretation
Baseline equivalence	0.231	.632	—	No significant initial difference
Posttest achievement	6.10	.017	.100	Significant
Delayed-test achievement	8.20	.006	.124	Significant

As summarized in Table 6, the delayed-test effect size of .124 exceeded the posttest effect size of .100, suggesting that the instructional advantage remained meaningful beyond immediate task completion. This result is particularly relevant because AI-supported learning is often criticized for producing performance improvements that may disappear when automated assistance is removed. The persistence of higher scores in the treatment group suggests that structured guidance may have supported internalization of knowledge rather than simple dependence on generated responses. The paradoxical potential of generative AI to either strengthen or weaken learning depends heavily on whether technological assistance supplements human cognition or substitutes for it (Lim et al., 2023).

The achievement pattern can also be interpreted through the relationship between cognitive support and learner engagement observed in the preceding outcomes. Higher critical-thinking scores and stronger cognitive engagement may have enabled students to use AI-generated information more selectively, test its relevance, and integrate it with prior knowledge before responding to academic tasks. Such processes provide a plausible mechanism linking adaptive guidance with stronger immediate and retained academic performance, although causal mediation cannot be established without a dedicated mediation model. Survey evidence from university populations similarly indicates that AI use can be associated with academic learning and achievement when students employ the technology as an educational support rather than as a replacement for active learning (Youssef et al., 2024).

The results should not be interpreted as evidence that all forms of ChatGPT use will generate comparable achievement gains. Case-based research in higher education demonstrates that the educational consequences of generative AI are shaped by assessment design, student practices, disciplinary expectations, and the degree of instructional guidance surrounding its use (Sandu et al., 2024). The present statistics specifically reflect an intervention in which AI interaction was structured through a guidance mechanism, making pedagogical architecture an essential element of the observed effect. This distinction is important because rapid access to correct-looking responses can improve task completion while leaving conceptual understanding unchanged when learners are not required to explain, evaluate, or apply the information produced.

The combination of a 79.7 posttest mean, a 75.9 delayed-test mean, and statistically significant adjusted group differences indicates that AI-supported adaptive learning was associated with both immediate achievement and sustained retention. The stronger delayed-test effect, reflected in $F = 8.20$ and partial $\eta^2 = .124$, suggests that the benefits extended beyond short-lived performance enhancement. These findings complement evidence that personalized technology-enhanced learning can produce positive academic outcomes when adaptive features are aligned with meaningful instructional activities and learner needs (Hooshyar et al., 2024). The achievement advantage is best interpreted as the product of guided interaction between learner and AI rather than as an independent effect of automation.

Across the three measured outcomes, academic achievement appears to function in conjunction with stronger critical thinking and improved dimensions of self-regulated learning rather than as an isolated result. Students who received structured AI support demonstrated higher achievement while also showing stronger cognitive engagement, behavioral engagement, self-efficacy, and critical-thinking performance, which provides a coherent pattern of multidimensional learning improvement. The evidence supports an instructional model in which AI contributes most effectively when personalization, guidance, and learner responsibility operate simultaneously within the learning process (Lee et al., 2024). Such a pattern positions AI-supported adaptive learning as a pedagogical system whose value lies in coordinating cognitive support, regulatory scaffolding, and achievement-oriented feedback rather than merely increasing the speed or convenience of accessing information.

CONCLUSION

The findings indicate that AI-supported adaptive learning can enhance university students' critical thinking, self-regulated learning, and academic achievement when artificial intelligence is embedded within a structured guidance mechanism. Students exposed to guided AI support demonstrated stronger gains in critical thinking, cognitive and behavioral engagement, self-efficacy, intrinsic motivation, immediate achievement, and delayed knowledge retention, while amotivation decreased. These results suggest that the educational value of artificial intelligence depends less on technological access itself than on how AI is pedagogically designed to stimulate reflection, feedback use, learner monitoring, and active knowledge construction. The study also highlights that the effects of AI-supported learning are not uniform across all dimensions of self-regulation, as identified regulation, external regulation, and emotional engagement did not show significant differences. This pattern reinforces the need for higher education institutions to implement AI as a cognitive and regulatory scaffold rather than as a substitute for independent reasoning and learner responsibility. Future research should examine these relationships across larger and more diverse samples, different academic disciplines, and longer intervention periods to determine the durability and generalizability of AI-supported adaptive learning outcomes.

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