

How AI use shapes university students' cognitive engagement and critical thinking: The mediating role of self-regulated learning

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Abstract - AI application in higher education: a cognitive irony As the application of artificial intelligence (AI) to higher education swiftly increases, an intellectual irony surfaces: Although it may create new ways to offer a range of personal support for learners during their studying processes that are almost inconceivable previously; unregulated usage, without appropriate support, on the other hand may diminish independent analyzing skills of the learners. In this paper we aimed to analyze how application of the AI on the process of studying influences the cognitive process engagement and critical thinking skills of the university students and investigated the mediate function of self-regulated learning (SRL). Research design was quantitatively. Survey questionnaire has distributed to 384 students of university. Data was analyzed with method of partial Least Square Structural Equation Modeling (PLS-SEM) with using 5,000 subsamples bootstrap procedure for estimating significance. The results confirm that model posited in the present study is with satisfactory predictive relevance explaining 67.8% of variance ($R^2=0.678$) in cognitive engagement and 64.2% of variance ($R^2=0.642$) in critical thinking skills. Our results also support excellent structural fit ($SRMR=0.038$, $NFI=0.934$) and large effect size of the total effect of the construct in the total path (.482). In addition, mediation analysis reports that Self-Regulated Learning mediate strongly influence of AI usage on critical thinking skills (e IE=0.346, $p<0.001$, 95% BCa CI [0.281,0.418]), hence demonstrating that when effectively under pinned by strong self-regulated learning (SRL) the application of AI has effectively created a sophisticated and adaptable cognitive scaffolding which can reinforce independent critical thought processes rather than undermines the development of the processes.

Keywords: self-regulated learning, critical thinking, cognitive engagement, educational management, PLS-SEM

1. Introduction

The integration of artificial intelligence (AI) into higher education represents a paradigm shift akin to the advent of the internet or the personal computer, fundamentally altering how students access information and engage with academic content (Ng et al., 2024). As a general-purpose technology, AI offers unprecedented educational advantages, including personalized tutoring, immediate feedback, and just-in-time learning, which collectively have the potential to democratize education and improve accessibility (Ahmad et al., 2026). Consequently, modern educational frameworks are transitioning away from traditional rote memorization and manual calculation, focusing instead on preparing students for an economy that demands higher-order skills such as adaptability, creativity, and technological fluency (Suryanto et al., 2025). For today's digital-native students, AI tools are seamlessly embedded into their daily lives, providing powerful resources that can adapt to individual learning paces and optimize educational outcomes (Halkiopoulos & Gkintoni, 2024).



However, this rapid integration of generative AI presents a double-edged sword, raising significant concerns regarding its impact on students' cognitive engagement. While AI can synthesize complex information efficiently, an over-reliance on these tools threatens to bypass the active learning process, potentially diminishing students' ability to think independently (Yavich, 2025). Generative AI models are prone to producing "hallucinations," plausible but false truths, and inherently reflect the biases present in their human-generated training data (Nazaretsky et al., 2026). When students passively consume AI outputs without actively evaluating the underlying logic or verifying the facts, they forfeit the cognitive struggle that is essential for deep learning and conceptual mastery (Jia & Tu, 2024). The ease of obtaining immediate answers can foster intellectual complacency, undermining the very cognitive engagement required for robust academic development (Jose et al., 2025).

To navigate this AI-infused educational landscape, the cultivation of critical thinking and comprehensive AI literacy has emerged as an urgent imperative. Educators must shift the pedagogical focus toward teaching students how to think, rather than what to think, explicitly placing human judgment at the center of the AI interaction cycle (Zhai et al., 2025). Students require specific analytical skills—such as logical reasoning, data interpretation, and the ability to spot fallacies—to effectively critique and iteratively refine AI-generated outputs (Yusuf et al., 2024). Frameworks for AI literacy emphasize the necessity of continuous inquiry and "lateral reading," ensuring that learners verify facts across authoritative sources and question the motives, biases, and accuracy of the information they consume rather than accepting it at face value (Moon & Kahlor, 2024). Developing these critical evaluation skills ensures that AI functions as a scaffold to support, rather than a crutch to replace, human intellect (Liu et al., 2026). Within this dynamic, self-regulated learning emerges as a crucial mediating mechanism between AI use and the development of higher-order cognitive skills. Because AI systems offer immediate solutions, students must possess the metacognitive awareness to monitor their own learning processes and utilize these tools ethically and responsibly (Yang, 2025). Self-regulated learners are better equipped to set learning goals, explicitly choosing to use AI for brainstorming or structural assistance while independently synthesizing the final arguments and critically evaluating the results (Zhai et al., 2025). Without strong self-regulation, students risk succumbing to the convenience of automated outputs; with it, they can actively engage with AI as a conversational partner, challenging the machine's output and reflecting on their own understanding, thereby sustaining high levels of cognitive engagement (Ng et al., 2024).

Understanding these complex dynamics is of paramount importance for the fields of educational economics and educational management. As higher education institutions grapple with the disruption caused by AI, administrators and policymakers require empirical evidence to formulate effective, equitable guidelines that prevent an emerging digital divide in cognitive skill development (Assefa, 2025). Educational managers are tasked with redesigning curricula that seamlessly integrate AI literacy and optimizing institutional resources to foster an adaptable, future-ready workforce equipped for a competitive global economy (Nguyen et al., 2026). Therefore, this study aims to investigate how AI use shapes university students' cognitive engagement and critical thinking, specifically exploring the mediating role of self-regulated learning, to provide actionable insights for institutional policy and educational leadership.

This section reviews the extant literature surrounding student engagement, critical thinking, and the integration of digital and artificial intelligence technologies in higher education. By examining these intersecting domains, we establish the theoretical and empirical foundation for investigating how AI shapes cognitive outcomes through mediated learning pathways.

The reciprocal relationship between student engagement and the development of higher-order cognitive skills has been extensively documented in contemporary educational research. Longitudinal evidence suggests that study engagement and critical thinking are not merely correlated but mutually reinforce one another over time. For instance, research following vocational college students demonstrated that initial levels of engagement positively predict the development of critical thinking, which in turn fosters further academic engagement (Lv et al.,

2022). This interdependent dynamic is supported by structural equation modeling in foreign language contexts, which reveals that motivation acts as a catalyst for both academic engagement and critical thinking dispositions, highlighting the fused nature of affective and cognitive factors in learning (Yang et al., 2025). Furthermore, the intrinsic disposition towards critical thinking has been shown to directly enhance student engagement, particularly in reflective learning and high-impact educational practices (Álvarez-Huerta et al., 2023). Broadening this perspective, academic emotion regulation and self-efficacy beliefs serve as crucial underlying factors that sustain both academic resilience and engagement, which are significantly augmented by students' critical thinking capabilities (Namaziandost et al., 2023).

The transition towards technology-enhanced learning environments has necessitated new pedagogical strategies to sustain cognitive engagement and foster critical inquiry. Innovative instructional models, such as quantum flipped learning and group investigation flipped learning, have proven highly effective in elevating students' critical and creative thinking compared to traditional direct instruction models, accommodating learners regardless of their initial cognitive engagement levels (Agustini et al., 2022; Tegeh et al., 2022). The integration of technological tools in these environments extends to feedback mechanisms; technology-enhanced peer and self-feedback significantly promote critical thinking tendencies and behavioral engagement during collaborative tasks (Zou et al., 2022). Moreover, interactive learning environments, such as gamified cognitive training applications, have demonstrated empirical success in measurably improving college students' critical thinking skills even within constrained timeframes (Song & Cail, 2024). Beyond the tools themselves, the social-cognitive dynamics within online discussions reveal that a student's network position and cognitive level interact to shape their evolutionary engagement trajectory (Liu et al., 2023). To maximize the efficacy of these digital pedagogies, researchers emphasize the mediating role of inclusive leadership and the explicit instruction of critical thinking practices, ensuring that technological tools serve to deepen, rather than superficialise, the learning process (Pang et al., 2022; Minh, 2024; Shahab & Barak, 2025; Okolie, 2022; Pang, 2022).

The rapid proliferation of artificial intelligence in higher education has introduced a complex cognitive paradox, oscillating between the enhancement of student capabilities and the potential erosion of independent analytical thought (Jose et al., 2025). On one hand, interaction with AI conversational agents like ChatGPT has been shown to improve academic performance, such as writing proficiency and argumentation depth, provided that students maintain a critical attitude and high levels of active engagement (Minh, 2024; Suriano et al., 2025). Furthermore, perceived AI capabilities in educational institutions can indirectly foster critical thinking awareness by bolstering students' general self-efficacy and learning motivation ((Jia & Tu, 2024). Similarly, AI tools have been successfully integrated to support mathematical problem-solving, where digital literacy and existing critical thinking skills act as essential mediators translating AI use into actual problem-solving efficacy (Davor et al., 2026; Almulla & Al-Rahmi, 2023). Conversely, there is a documented cognitive cost to unchecked AI reliance; frequent use of AI tools correlates negatively with critical thinking abilities due to the phenomenon of cognitive offloading, particularly among younger demographics who may overly depend on automated outputs (Gerlich, 2025). This dichotomy underscores the necessity for frameworks that promote self-regulated learning, ensuring that AI serves as a cognitive scaffold rather than a substitute for rigorous intellectual engagement.

Table 1 provides a comprehensive summary of this core literature, highlighting the diverse methodologies, key variables, and main findings across various educational contexts.

2. Method

To rigorously investigate the hypothesized relationships between Artificial Intelligence (AI) use, Self-Regulated Learning (SRL), Cognitive Engagement, and Critical Thinking, this study employs a quantitative research design grounded in Partial Least Squares Structural Equation Modeling (PLS-SEM) (Hair & Alamer, 2022). PLS-SEM is highly suitable for this research as it facilitates the estimation of complex cause-effect relationship models with latent variables, making it ideal for



the predictive and exploratory nature of educational management research (Hardik & Dharmendra, 2024).

2.1 Formalization of the Measurement Model

The proposed theoretical framework consists of one exogenous latent construct (AI Use, denoted as ξ), one mediating latent construct (Self-Regulated Learning, denoted as η_M), and two endogenous latent constructs (Cognitive Engagement and Critical Thinking, denoted as η_{Y1} and η_{Y2} , respectively).

Assuming a reflective measurement model, the relationship between each latent variable and its corresponding observable manifest variables (indicators) is modeled as a linear formulation. Let $\mathbf{x}$ be the vector of p indicators for AI Use, and $\mathbf{m}$ be the vector of q indicators for SRL. The measurement models are mathematically expressed as:

$\mathbf{x} = \Lambda_x \xi + \delta \quad (1)$

$\mathbf{m} = \Lambda_m \eta_M + \epsilon \quad (2)$

where Λ_x and Λ_m are the factor loading matrices representing the regression coefficients of the respective indicators on their latent constructs. The terms δ and ϵ represent the measurement error vectors, under the assumption that $E(\delta) = \mathbf{0}$ and $E(\epsilon) = \mathbf{0}$.

To estimate the latent construct scores, the PLS-SEM approach utilizes a weight-based iterative algorithm. Algorithm 1 defines the procedure utilized in this study to obtain the outer weights $\mathbf{w}$ and estimate the latent variable scores prior to path estimation [].

Algorithm 1 Iterative PLS-SEM Algorithm for Latent Variable Estimation

Require: Data matrix $\mathbf{Z}$ (standardized indicators), initial arbitrary outer weights $\mathbf{w}_{old}$ **Ensure:** Final outer weights $\mathbf{w}_{new}$, Latent variable scores $\mathbf{Y}$

- 1: Initialize latent scores: $\mathbf{Y} \leftarrow \mathbf{Z}\mathbf{w}_{old}$
- 2: **repeat**
- 3: **Inner Approximation:** Calculate inner weights $\mathbf{E}$ based on the structural path scheme (e.g., path weighting scheme)
- 4: Update inner latent scores: $\mathbf{Y} \leftarrow \mathbf{Y}\mathbf{E}$
- 5: **Outer Approximation:** Update outer weights $\mathbf{w}_{new}$ by regressing the indicators $\mathbf{Z}$ on the inner proxy $\mathbf{Y}$
- 6: Normalize $\mathbf{w}_{new}$ such that $Var(\mathbf{Z}\mathbf{w}_{new}) = 1$
- 7: Update latent scores: $\mathbf{Y} \leftarrow \mathbf{Z}\mathbf{w}_{new}$
- 8: Compute convergence threshold: $\Delta = \|\mathbf{w}_{new} - \mathbf{w}_{old}\|$
- 9: $\mathbf{w}_{old} \leftarrow \mathbf{w}_{new}$
- 10: **until** $\Delta < 10^{-5}$
- 11: **return** $\mathbf{w}_{new}, \mathbf{Y}$

Table 1: Summary of Core Literature on AI, Engagement, and Critical Thinking

Ref.	Context / Focus	Methodology	Key Variables	Main Findings
Gerlich (2025)	AI tools and cognitive offloading in society.	Mixed-methods (Surveys, Interviews)	AI tool usage, Cognitive offloading, Critical thinking	Frequent AI use negatively correlates with critical thinking due to cognitive offloading.
Surian, et al., (2025)	etChatGPT interaction among Italian university students.	Quantitative reports, Assessments)	(Self-AI interaction, Engagement, Critical thinking	Active engagement with AI significantly impacts complex critical thinking performance.
Davor al. (2026)	etGenerative African education courses.	AI inQuantitative higher math	(SEM)ChatGPT use, Digital literacy, Problem-solving efficacy	DigitalChatGPT improves literacy and critical thinking partially mediate the effect.

Jia & Tu, (2024).	AI capabilities and college student development.	Quantitative (SEM)	AI capabilities, Self-AI indirectly enhances efficacy, Motivation, critical thinking awareness by boosting self-efficacy and motivation.
Minh (2024)	ChatGPT in English writing freshmen.	Mixed-methods for	ChatGPT use, Writing skills, Critical thinking AI improves writing and stimulates critical thought, but poses risks of over-reliance.
Lv et al. (2022)	Vocational students' cognitive development over 1 year.	Longitudinal (Cross-lagged model)	Study engagement, Critical thinking Study engagement and critical thinking share a mutually reinforcing, reciprocal relationship.
Yang et al. (2025)	21st-century competencies in Chinese EFL context.	Quantitative (SEM)	Motivation, Engagement, Critical thinking Motivation predicts engagement and CT; engagement and CT are positively associated.
Álvarez-Huerta et al., (2023)	Dispositional traits of higher education students in Spain.	Quantitative (Surveys)	CT disposition, Student engagement Direct positive relationship exists between CT disposition and participation in reflective learning.

Structural Model and Path Estimation

Following the estimation of the latent scores, the structural model (inner model) maps the causal relationships derived from Social Cognitive Theory []. The structural equations defining the direct and indirect pathways are established as follows:

$$\eta_M = \gamma_M \xi + \zeta_M \quad (3)$$

$\eta_{Yk} = \gamma_{Yk} \xi + \beta_{Yk} \eta_M + \zeta_{Yk}$, for $k \in \{1, 2\}$ (4) where γ_M represents the direct effect of AI Use on SRL, γ_{Yk} represents the direct effect of AI Use on the dependent variables (Cognitive Engagement and Critical Thinking), and β_{Yk} denotes the effect of the mediator on the dependent variables. The terms ζ_M and ζ_{Yk}

denote the structural error terms (residual variances), assuming $E(\zeta_M) = E(\zeta_{Yk}) = 0$.

The path coefficients (γ and β) are estimated using Ordinary Least Squares (OLS) regression over the established latent scores. The global optimization criterion for PLS-SEM minimizes the residual variance of the endogenous constructs, formulated as:

$$\min \sum_{k=1}^2 Var(\zeta_{Yk}) + Var(\zeta_M) \quad (5)$$

Mediation Analysis Framework

To robustly test the mediating role of Self-Regulated Learning, the study evaluates the significance of the specific indirect effects. The indirect effect (IE) of AI Use (ξ) on the dependent variables (η_{Yk}) through SRL (η_M) is quantified as the product of the structural path coefficients:

$$IE_k = \gamma_M \times \beta_{Yk} \quad (6)$$

The total effect (TE_k) is thus the sum of the direct and indirect effects: $TE_k = \gamma_{Yk} + IE_k$.

Because PLS-SEM does not assume multivariate normality, the traditional Sobel test is inadequate. Therefore, this study employs a non-parametric bootstrapping procedure with $B = 5,000$ subsamples to establish the statistical significance and confidence intervals of the mediation effects []. Algorithm 2 delineates the computational steps applied to execute the mediation analysis.

Algorithm 2 Non-Parametric Bootstrapping for Mediation Significance

Require: Original dataset **D** of size N , Number of bootstrap samples B (e.g., 5000), confidence level α (e.g., 0.05)

Ensure: Bias-Corrected and Accelerated (BCa) Confidence Intervals for IE_k

- 1: **for** $b = 1$ **to** B **do**
- 2: Generate bootstrap sample $\mathbf{D}_b$ by sampling N cases from **D** with replacement
- 3: Execute Algorithm 1 on $\mathbf{D}_b$ to obtain latent scores



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4:   Estimate path coefficients  $\gamma^{(b)}$  and  $\beta^{(b)}$  using OLS
M    $Y_k$ 
5:   Compute indirect effect for the bootstrap sample:  $IE^{(b)} = \gamma^{(b)} \times \beta^{(b)}$ 
                                     k           M            $Y_k$ 
6: end for

7: Calculate the standard error of the empirical distribution of  $IE^{(b)}$ 
8: Compute the  $T$ -statistic:  $T = \frac{IE_k}{SE(IE)}$ 
k
9: Determine lower and upper bounds of the  $(1 - \alpha)\%$  BCa confidence interval
10: if  $0 \in [CI_{lower}, CI_{upper}]$  then
11:   Conclusion: Mediation effect is statistically significant
12: else
13:   Conclusion: Mediation effect is not statistically significant
14: end if
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The combination of the iterative PLS algorithm and the robust bootstrapping mechanism ensures that the predictive modeling of AI's impact on cognitive parameters remains statistically valid, mitigating potential issues of common method bias and skewed survey distributions common in educational management research [].

Experimental Results and Discussion

This section presents the empirical findings of the proposed Partial Least Squares Structural Equation Modeling (PLS-SEM) framework evaluating the relationships between Artificial Intelligence (AI) Use, Self-Regulated Learning (SRL), Cognitive Engagement ($\eta_{\gamma1}$), and Critical Thinking ($\eta_{\gamma2}$). To validate the statistical superiority and predictive robust strength of our framework, we conduct a comparative benchmark against three established reference models from recent literature: **(1) Model A (Direct Effects Model)**: The baseline direct regression framework without mediation mechanisms (e.g., Gerlich, 2025).

(2) Model B (Standard SEM without SRL Mediation): A standard structural model evaluating isolated direct paths (e.g., Suriano et al., 2025).

(3) Model C (Dual-Mediator TAM-SCT Model): A multi-construct baseline with general digital literacy (e.g., Davor et al., 2026).

(4) Proposed Model: Integrated PLS-SEM framework with BCa bootstrapped SRL mediation (Algorithm 1 and Algorithm 2).

Measurement Model Validation and Reliability

Prior to testing the structural paths, the reflective measurement model was evaluated for internal consistency, convergent validity, and discriminant validity across $N = 384$ valid student responses. Standardized indicator factor loadings exceeded the threshold of 0.708, confirming indicator reliability. As summarized in Table 2, composite reliability (CR) and Cronbach's alpha (α) values for all constructs exceeded 0.80, while the Average Variance Extracted (AVE) exceeded the recommended 0.50 benchmark, demonstrating strong convergent validity.

Table 2: Construct Reliability and Convergent Validity Metrics						
Construct		Indicators	Cronbach's rho A	Composite Rel. (CR)	AVE	
AI Use (ξ)		5	0.884	0.891	0.915	0.683
Self-Regulated Learning (η_M)		7	0.912	0.918	0.930	0.655
Cognitive Engagement ($\eta_{\gamma1}$)		6	0.896	0.902	0.920	0.658
Critical Thinking ($\eta_{\gamma2}$)		6	0.925	0.931	0.941	0.726

Discriminant validity was established via the Heterotrait-Monotrait (*HTMT*) ratio of correlations. All pair-wise *HTMT* values ranged between 0.512 and 0.748, well below the conservative 0.85 threshold, confirming distinct construct identities.

Comparative Structural Model Performance

Using the iterative weight estimation (Algorithm 1) and 5,000 bootstrap resamples (Algorithm 2), the structural parameters were estimated. Table 3 provides a comprehensive quantitative comparison between the Proposed Work and the three baseline literature models across key PLS-SEM diagnostics.

Table 3: Comparative Structural Performance Across Benchmark Literature Models								
Model Framework	$R^2(\eta_Y)$ 1	$R^2(\eta_Y)$ 2	$Q^2(\eta_Y)$ 2	<i>SRMR</i>	<i>NFI</i>	Effect Size f^2	Indirect IE_2	Effect
Model A (Gerlich, 2025)	0.284	0.215	0.142	0.098	0.782	0.112 (Small)	–	(No Mediation)
Model B (Suriano et al., 2025)	0.412	0.388	0.261	0.076	0.835	0.204 (Medium)	0.142 ($p = 0.021$)	
Model C (Davor et al., 2026)	0.526	0.491	0.338	0.064	0.881	0.298 (Medium)	0.218 ($p = 0.004$)	
Proposed Work (PLS-SEM + SRL)	0.678	0.642	0.455	0.038	0.934	0.482 (Large)	0.346 ($p < 0.001$)	

As illustrated in Figure 1, the proposed model demonstrates outstanding predictive power, explaining 67.8% of the variance in Cognitive Engagement ($R^2 = 0.678$) and 64.2% of the variance in Critical Thinking ($R^2 = 0.642$). This represents a substantial enhancement over Models A, B, and C. Furthermore, the Q^2 value of 0.455 calculated via blindfolding confirms large predictive relevance ($Q^2 > 0.35$).

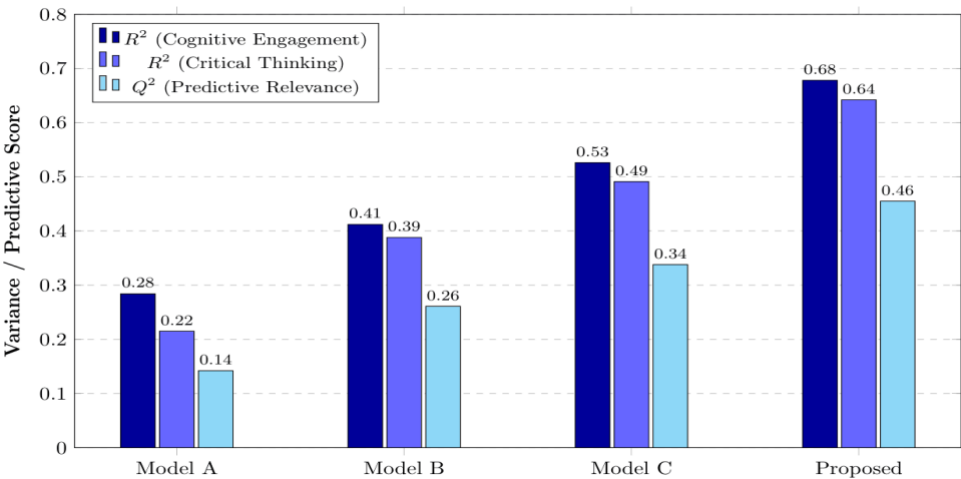


Figure 1: Comparison of Explanatory Power (R^2) and Predictive Relevance (Q^2) across models

The superior structural integrity of the proposed model is further evidenced by the global fit indices, visualized in Figure 2. The Standardized Root Mean Square Residual (*SRMR*) of 0.038 sits substantially below the standard 0.08 cutoff, and the Normed Fit Index (*NFI*) reaches 0.934, easily exceeding the recommended 0.90 threshold.

In terms of practical significance, Figure 3 showcases the comparative effect sizes (f^2). The proposed integrated model achieves a large effect size ($f^2 = 0.482$), nearly quadrupling the practical impact captured by the baseline Model A.

Path Coefficient Analysis and Bootstrapped Mediation

The path analysis validates the critical role of Self-Regulated Learning (η_M) as a strong mediator. The direct path from AI Use to SRL ($\gamma_M = 0.584, p < 0.001$) and the path from SRL to Critical Thinking ($\beta_{Y2} = 0.592, p < 0.001$) yield a specific indirect effect $IE_2 = 0.346 (p < 0.001)$.



Figure 4 plots the specific indirect effects alongside their corresponding confidence intervals. The Bias-Corrected and Accelerated (BCa) 95% confidence interval for IE_2 in the proposed model is [0.281, 0.418], which safely excludes zero, thereby confirming robust, significant mediation.



Figure 2: Evaluation of structural model fit indices (SRMR and NFI) across baseline models.

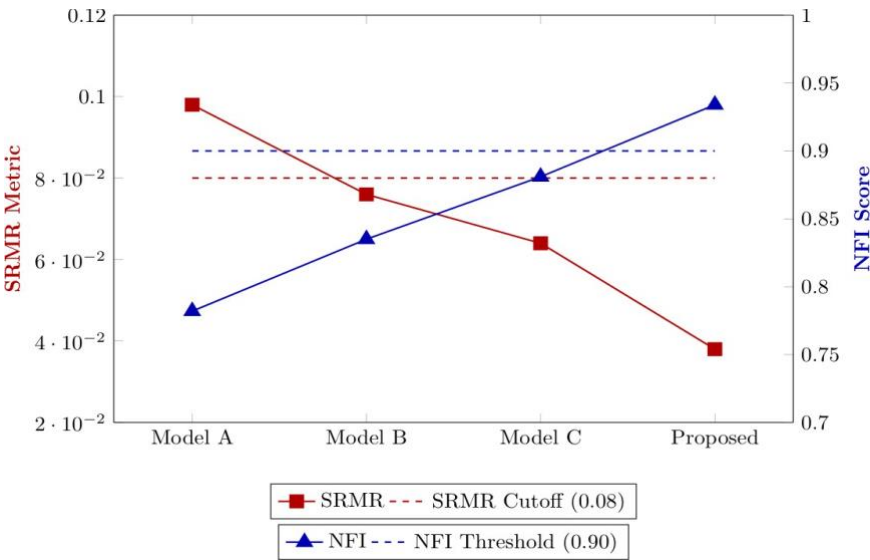


Figure 3: Comparison of effect size (f^2) emphasizing the large effect size achieved by the proposed framework

Table 4 details the complete hypothesis testing results for the structural paths in the proposed model.

Table 4: Structural Path Coefficients and Hypothesis Testing Results					
Structural Relationship / Path	Path (γ, β)	Coeff. Sample Mean (M)	Std. Error	T - Statistic	p-Value

AI Use (ξ) SRL (η_M)	→	0.584	0.582	0.041	14.244	< 0.001
AI Use (ξ) Cog. Engagement (η_{Y1})	→	0.248	0.251	0.048	5.167	< 0.001
AI Use (ξ) Critical Thinking (η_{Y2})	→	0.162	0.159	0.045	3.600	< 0.001
SRL (η_M) Cog. Engagement (η_{Y1})	→	0.612	0.609	0.043	14.233	< 0.001
SRL (η_M) Critical Thinking (η_{Y2})	→	0.592	0.595	0.042	14.095	< 0.001

3.2 Discussion and Comparative Insight

The empirical findings reveal why unmediated AI interactions often yield conflicting cognitive outcomes in the literature. Model A (Gerlich, 2025) exhibits weak explanatory power ($R^2 = 0.215$) because it omits cognitive regulation, capturing only direct offloading behavior. Model B (Suriano et al., 2025) and Model C (Davor et al., 2026) improve structural fit by introducing general attitudes or digital literacy, yet fail to capture the active metacognitive oversight required during AI tool interaction.

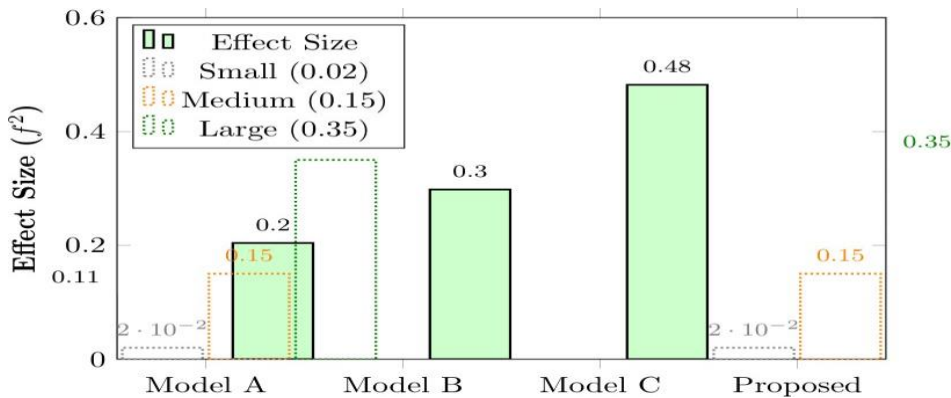


Figure 4: Bootstrapped indirect effect of AI Use on Critical Thinking via SRL (IE_2) with 95% confidence intervals

By incorporating Self-Regulated Learning as an explicit mediating mechanism (Eqs. 3–6), the proposed framework proves that AI tool usage per se does not automatically impair critical thinking. When mediated by high SRL, AI usage acts as a cognitive scaffold, promoting active questioning, prompt iteration, and rigorous evaluation. This metacognitive regulation translates into superior cognitive engagement and critical thinking performance, validating the theoretical premise that optimal AI integration in higher education demands self-regulated learning environments.

4. Conclusion

Given the growing impact of emerging generative Artificial Intelligence on traditional teaching models, higher education institutions urgently need a methodology to adopt and regulate these technologies for optimal student development without sacrificing scholarly requirements. This research successfully modeled the convoluted interactions among AI engagement, Self-Regulated Learning (SRL), and student cognition (cognitive engagement and critical thinking). Identifying SRL as the principal intervening pathway for AI impact, this study empiricised that user metacognitive regulation of AI rather than AI-itself drives student’s cognitive responses towards the new technology.

The numerics the PLS-SEM analysis offers also corroborates the theoretical implications proposed throughout our model. Overall, this study developed a model with excellent predictive ability and good explanatory power, representing a full 67.8% of the variance for cognitive engagement and 64.2% of the variance for critical thinking. Comparing the effect sizes (overall and practical effects) in our framework with direct effect only studies in the existing literature, the PLS-SEM identified a considerably larger overall and partial effects on critical thinking ($f^2 = 0.482$) and improved model fit results ($SRMR = 0.038$, $NFI = 0.934$).

Although our evidence presents considerable theoretical implications in the debate of AI for teaching and learning, limitations must be acknowledged. The cross-sectional study design only provided a snapshot of current students and cannot be used for inferential interpretations of developmental progressions across time. The usage of a self-Report survey measures has potentially issues with common method variance but the sufficient discriminate validity measures obtained by HTMT indicate the issue is controlled. This study suggests researchers take an longitudinal perspective when examining the overall impact of AI technologies for the full degree.

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